From the holdings of the Department of Special Collections , Princeton University Library, Princeton, NJ

These documents are either in the public domain, or can only be used for educational and research purposes (Fair use) as per U.S. Copyright law (text below). By accessing this file, all users agree that their use falls in the public domain or within fair use as defined by the copyrightlaw. We do not charge any permission or usage fees for the publication of images of material inour collections, including those provided by Princeton University Library, via our website, catalog, or directly from staff.For more information regarding copyright, credit, and citation please review the information onthe Copyright, Credit and Citation Guidelines page of our website.
https://library.princeton.edu/special-collections/policies/copyright-credit-and-citation-guidelines. If you have any questions, including how to order higher-quality images from the collection, contact Special Collections Public Services via our Ask Us! Form. https://library.princeton.edu/special-collections/ask-us

---

Doctoral Dissertations, 2011-2026 Population Studies

2025

THREE ESSAYS ON POPULATION AGING, FAMILY AND WELL-BEING

Wang, Xueqing

Princeton, NJ : Princeton University

---

http://arks.princeton.edu/ark:/88435/dsp01pv63g372d

U.S. Copyright law: The copyright law of the United States (Title 17, §108, United States Code) governs the making of photocopies or other reproductions of copyrighted material. Under certain conditions specified in the law, libraries and archives are authorized to furnish a photocopy or other reproduction. One of these specified conditions is that the photocopy or reproduction is not to be used for any purpose other than private study, scholarship, or research. If a user makes a request for, or later uses, a photocopy or reproduction for purposes in excess of fair use that user may be liable for copyright infringement. This institution reserves the right to refuse to accept a copying order if, in its judgment, fulfillment of the order would involve a violation of copyright law. https://www.copyright.gov/title17/title17.pdf

THREE ESSAYS ON POPULATION AGING, FAMILY AND WELL-BEING

Volume I

XUEQING WANG

A DISSERTATION

PRESENTED TO THE FACULTY

OF PRINCETON UNIVERSITY

IN CANDIDACY FOR THE DEGREE

OF DOCTOR OF PHILOSOPHY

RECOMMENDED FOR ACCEPTANCE BY

THE OFFICE OF POPULATION RESEARCH

Adviser: James M. Raymo

September 2025

© Copyright by Xueqing Wang, 2025. All rights reserved.

Abstract

Population aging represents one of the most significant demographic shifts of the twenty-first century, occurring within contexts of increasing social heterogeneity, massive migration flows, and changing family structures. This dissertation examines three interconnected dimensions of how demographic processes affect the life trajectories and well-being of older adults: socioeconomic differentials in mortality, social connections and emotional well-being, and family structures and living arrangements. Using data from China and the United States, the three essays reveal how demographic transformation creates distinct challenges across different societies. In China, survey attrition systematically biases mortality estimates, while massive internal migration reshapes family structures and drives population-level patterns of loneliness, with projections showing that parents of one-child policy cohorts will face unprecedented rates of complete family separation and elevated burden of loneliness. In the United States, racial and ethnic minorities follow different family trajectories than whites, increasingly diverging from the traditional norm of lifelong marriage and spousal coresidence in later life. Together, these findings show how the global demographic trends—population aging, family change, and migration—manifest as fundamentally different challenges across societies and social groups.

Acknowledgments

This dissertation would not have been possible without the guidance of my advisor, James M. Raymo. Our advisor-advisee relationship began when I reached out to him via email in the summer of 2020. We started with a project on life tables, and my interest in this methodology has never diminished since. Jim has played the dual role of encouraging friend and colleague while maintaining rigorous academic standards as an advisor, which I have deeply appreciated. Throughout these years, I have benefited immensely from our conversations about research papers, academic careers, and many other topics, including how to be a good researcher and colleague.

My gratitude also extends to my committee members, Arun Hendi and Yu Xie. I learned greatly from Arun's introductory and advanced demographic methods classes, and Yu Xie has consistently provided valuable advice on research, the job market, career choices, and academic life more broadly. I am particularly grateful to my external committee member, Emma Zang at Yale University, who has always been a role model to me. Emma visited the Office of Population Research during 2021-2022 and played an important role in my PhD journey. Not only did we develop a fruitful collaborative relationship, but she also taught me, step by step, how to write effectively and how to be a good scholar. I have also benefited from professors with whom I have taken classes or field exams: Noreen Goldman, Anne Case, Alicia Adsera, and Alyssa Sharkey.

I would also like to thank the staff members who supported me throughout these years. Lynne Johnson has always been kind and encouraging, and I loved how she translated my first name—though hard to pronounce for many English speakers—into the cute nickname "Sunshine Snow." Her gift to me, a cup with the words "I'm enough," lifted my spirits and gave me faith when I encountered difficulties in the earlier years of my PhD. The final stages of completing my dissertation would not have been as smooth without Lynne's heartwarming support and creative

problem-solving. Boriana Pratt, the statistical programmer, became a good friend from our first meeting when I asked for help with STATA questions. I would also like to thank the staff at Stokes Library, where I spent significant time working throughout my PhD years.

I would like to thank my parents who set an example for me with their dedication to graduate school when I was a young child. I remember those days in my childhood when I would see my father sitting in front of his computer working on his dissertation at midnight while everyone else had gone to sleep, then waking up early in the morning to work at his day job because he had a family to raise. Later, as I started my own academic journey, I always remembered my dad's story about how he failed English tests many times as the last requirement for his PhD degree, but how he never gave up trying until he managed to pass on his final attempt. He taught me perseverance: the idea of giving up never occurred to me when I encountered challenges that I once couldn't believe I would overcome. Studying abroad was his dream, but he never had such an opportunity as the eldest son to his parents. Yet he did not hesitate to send me abroad. My mom has always believed in me for no reason during times of self-doubt and bad luck, and she always encourages me to think positively and look at the brighter side. She is truly my role model in being a good teacher to her students throughout her career.

My heart goes out to my grandmother, a strong person as she has always been, who dedicated most of her life to taking care of the family. In my childhood, she primarily took care of me when both of my parents were busy pursuing their graduate degrees. My heart also goes to my late grandfather, who was always a wonderful companion in my childhood and taught me Chinese calligraphy hand by hand. He was born in 1940 during wartime in Tianjin and almost got killed. He passed away in March 2022, another chaotic period in this world. Due to COVID-related travel restrictions during 2019-2023, I was never able to fulfill my promise of celebrating his 80th

birthday with him, and it remains my forever regret that I could not say farewell to him in person before he is gone to another world.

All my thanks go to the friends who have supported me throughout this journey, with each friendship lasting more than 10 years since we first met as college freshmen: Shuang Gao, Demi Zhang, Rocky Li, Yinan Zhou, Suqing Wang, and Yuqiao Tang. Thanks also to my friends, office mates, and organizers and regular attendees of the Demography Working Group: Angela, Katie, Micah, Ha-Joon, Rama, Marrielle, and many more. Another important person I would like to thank is Andrew Francis-Tan, my advisor at my undergraduate institution. We keep in touch after graduation, and he has always supported and encouraged me to pursue the field of demography and health.

I would also like to thank the Max Planck Institute for Demographic Research (MPIDR) for hosting me during a wonderful summer research stay. Being able to spend a summer in Rostock, Germany, and meet fellow demographers really gave me fresh perspectives after five consecutive years living in Princeton. Being surrounded by demographers gave me a sense of community, and I was fed with fascinating research by them every week, if not every day. The friends and colleagues I met during the Summer Incubator program were wonderful, and some of us continue to build new relationships. Working on a collaborative project reminded me of the joy of doing research that drew me to academia in the first place, and that project later became a source of inspiration for additional analyses in Chapter 1. The first draft of Chapter 2 was completed at my assigned working space, which later became my favorite spot in MPIDR's library. During writing breaks, I would watch ferries coming and going through the library window.

Thanks to my furry friend, Ferris, whom I adopted in December 2023 and who has since become a beloved family member.

Beyond my growth as a scholar and the knowledge and skills I have gained, both hard and soft, I am grateful for everything I have encountered on this journey—the ups and the downs. This experience has taught me that nothing is certain nor uncertain, and I always have the chance to turn bitter experiences sweet and transform difficulties into lessons. The world has not been quiet during these years, with COVID, travel bans, wars, recessions, and recent unsettling times regarding funding cuts in science. Life's certainties have become uncertainties. Regardless, life continues. I feel grateful to have had the opportunity to spend years doing research at Princeton, and I wish to continue to do so as I move to the next stage.

TABLE OF CONTENTS

Page

INTRODUCTION..... 9

CHAPTER 1: Gone for Good: How Survey Attrition Affects Old-Age Mortality Estimates in China..... 15

CHAPTER 2: Migration and the Demography of Loneliness: How Internal Migration Shapes the Landscape of Late-Life Loneliness in China..... 73

CHAPTER 3: Beyond Lifelong Marriage and Spousal Coresidence: A Research Note on Racial and Ethnic Differences in Late-Life Family and Living Arrangements..... 132

CONCLUSION.....159

Introduction

Population aging represents one of the most significant demographic shifts of the twenty-first century, fundamentally altering the structure of societies worldwide. The global population aged 65 and over is projected to more than double from 771 million in 2022 to 1.6 billion by 2050, with the most rapid increases occurring in developing countries that previously experienced younger age structures (United Nations, 2024).

This demographic shift presents new challenges for understanding population dynamics as aging occurs within contexts of increasing social and demographic heterogeneity, changing family structures, and growing inequality. Large-scale migration patterns now separate millions of families across vast distances, fundamentally altering traditional support networks and creating new forms of vulnerability among aging populations. Persistent socioeconomic disparities in health and mortality outcomes require careful measurement, yet the very populations most at risk may be systematically excluded from the surveys used to document these patterns, potentially obscuring our understanding of inequality in aging experiences. Meanwhile, family structures have become increasingly diverse and fluid, with rising rates of divorce, remarriage, cohabitation, childlessness, and non-traditional family forms that challenge conventional assumptions about available support systems in later life. These intersecting social forces—migration-driven family separation, challenges in accurately measuring socioeconomic disparities in aging outcomes, and evolving family structures—create complex new realities for understanding how populations age and the resources available to support well-being in later life.

This dissertation examines three interconnected dimensions of how demographic shifts affect the life trajectories and well-being of older adults, each representing a core area identified in the National Academy of Sciences' future research agenda for the demography of aging:

socioeconomic differentials in mortality, social connections and emotional well-being, and family structures and living arrangements (National Academies of Sciences, Engineering, and Medicine, 2018).

Socioeconomic Differentials in Mortality represent the most well-established area in the demography of aging, with research consistently documenting persistent and often widening gaps in health and survival across socioeconomic groups. Recent evidence shows that educational differentials in mortality are "significant and continue over time," with those having the least schooling experiencing increases in mortality risk (National Academies of Sciences, Engineering, and Medicine, 2018). However, understanding these differentials requires accurate measurement of mortality patterns and high-quality data, which becomes complicated when mortality data are primarily collected through surveys and survey attrition is systematically related to both socioeconomic status and mortality risk.

Chapter 1: "Gone for Good: How Survey Attrition Affects Old-Age Mortality Estimates in China" examines how survey attrition biases mortality estimates in Chinese aging surveys (CHARLS and CFPS). Using WHO life tables as benchmarks, this chapter demonstrates that systematic survey attrition leads to substantial mortality underestimation, particularly among higher socioeconomic groups. The finding that approximately 78% of survey attritors would need to be classified as deceased to match benchmark mortality levels, and that attrition patterns correlate with socioeconomic characteristics, reveals how methodological issues may systematically bias our understanding of both mortality levels and socioeconomic differentials without proper analytical corrections.

Social Connections and Emotional Well-being have emerged as critical determinants of health and mortality in later life, with loneliness and social isolation now recognized as having

health impacts comparable to traditional risk factors (Hawkley and Cacioppo, 2010; Holt-Lunstad et al., 2015). This represents a priority research agenda in the demography of aging, as "social well-being and health in the older population" intersect in complex ways, with lonely older adults facing increased risks of chronic inflammation, cardiovascular disease, cognitive decline, and mortality (National Academies of Sciences, Engineering, and Medicine, 2018). Beyond individual health impacts, demographic processes like migration and changing family structures systematically reshape the social landscapes within which aging occurs, creating new forms of vulnerability in aging societies. A particularly understudied area is how these demographic shifts affect the population-level prevalence and distribution of loneliness across different groups and communities.

Chapter 2: "Family Separation, Internal Migration, and the Rising Burden of Loneliness in China's Aging Population" examines how large-scale internal migration creates population-level patterns of family separation and loneliness. Using China Health and Retirement Longitudinal Study (CHARLS) data from 2011-2018, it demonstrates how children's migration drives changes in loneliness prevalence, distinguishing between partial separation (some children migrated) and complete separation (all children migrated). Projections show that one-child policy cohorts will face unprecedented rates of complete family separation, suggesting a growing loneliness burden as these cohorts age and their single children migrate for economic opportunities.

Family Structures and Living Arrangements constitute a third core area in this dissertation. Contemporary aging populations are characterized by increasingly diverse family histories, with growing proportions entering later life having experienced divorce, remarriage, cohabitation, or lifelong singlehood rather than stable, lifelong marriages. Rising rates of late-life divorce and the emergence of non-traditional living arrangements mean that traditional

assumptions about spending one's later life in stable, nuclear families increasingly diverge from contemporary realities. While China's context illuminates how migration disrupts traditional family support systems, the United States provides a particularly compelling case for examining the diversity of family formation and living arrangement trajectories, as historical patterns of discrimination and contemporary socioeconomic stratification have created vastly different pathways through marriage, divorce, and household formation across racial and ethnic groups.

Chapter 3: "Beyond Lifelong Marriage and Spousal Coresidence: Racial and Ethnic Differences in Late-Life Family and Living Arrangements" applies a novel multi-state life table method to document these diverse family trajectories across racial and ethnic groups. Using Health and Retirement Study (1992-2018), it shows stark disparities in how different groups experience later life: White adults largely follow traditional patterns of stable marriage and spousal co-residence, while Black adults experience shorter marriage durations and spend more time living alone, and Hispanic adults maintain substantial marriage duration while relying more heavily on multigenerational households. These patterns demonstrate how racial and ethnic minorities are increasingly diverging from the traditional model of lifelong marriage and spousal coresidence, instead exhibiting greater diversity in family arrangements and living configurations throughout later life.

Together, these chapters reveal how demographic processes operate across multiple levels, connecting individual experiences and population-level patterns. Findings illuminate both the diversity of aging experiences across different social contexts and the need for future research that can capture the dynamic, interconnected nature of contemporary population change.

References

Brown, S.L., and Lin, I.F. (2012). The gray divorce revolution: rising divorce among middle-aged and older adults, 1990-2010. *The Journals of Gerontology Series B: Psychological Sciences and Social Sciences*, 67(6), 731-741.

Chan, K.W., and Zhang, L. (1999). The hukou system and rural-urban migration in China: Processes and changes. *The China Quarterly*, 160, 818-855.

Colby, S.L., and Ortman, J.M. (2015). *Projections of the Size and Composition of the U.S. Population: 2014 to 2060* (Current Population Reports P25-1143). Washington, DC: U.S. Census Bureau.

Hawkley, L.C., and Cacioppo, J.T. (2010). Loneliness matters: A theoretical and empirical review of consequences and mechanisms. *Annals of Behavioral Medicine*, 40(2), 218-227.

Holt-Lunstad, J., Smith, T.B., Baker, M., Harris, T., and Stephenson, D. (2015). Loneliness and social isolation as risk factors for mortality: A meta-analytic review. *Perspectives on Psychological Science*, 10(2), 227-237.

National Academies of Sciences, Engineering, and Medicine. (2018). *Future Directions for the Demography of Aging: Proceedings of a Workshop*. Washington, DC: The National Academies Press.

National Bureau of Statistics of China. (2022). *China Statistical Yearbook 2022*. Beijing: China Statistics Press.

United Nations, Department of Economic and Social Affairs, Population Division. (2024). *World Population Prospects 2024: Highlights* (ST/ESA/SER.A/452). New York: United Nations.

Williams, D.R., and Mohammed, S.A. (2009). Discrimination and racial disparities in health: Evidence and needed research. *Journal of Behavioral Medicine*, 32(1), 20-47.

Chapter 1: Gone for Good: How Survey Attrition Affects Old-Age Mortality Estimates in China

Abstract

China's unique demographic history has motivated an increasing number of research on how social changes affect population processes, including socioeconomic mortality differentials, yet the accuracy of mortality data from Chinese population surveys remains understudied. This study investigates to what extend mortality is underrepresented due to attrition, and to what extend selective attrition bias estimation of SES-mortality differentials in China. This research examines mortality underrepresentation in two major surveys of older Chinese adults. This study shows that the overestimation stems from death underreporting due to attrition and attrition among potential reporters of older household member's death. Notably, panel attrition in both surveys correlates positively with characteristics typically associated with lower mortality, such as being aged 50-60, urban residence, and higher educated. This pattern selective attrition skews estimates of socioeconomic mortality differentials, highlighting the need for caution when using surveys to analyze Chinese old-age mortality.

Key words: Old-Age Mortality, Aging, China, SES Mortality Differential, Panel Attrition

Introduction

China has the world's largest older population, and it is growing rapidly. China's population aged 65 and over—which has more than tripled from 4% in the 1960s to 13% in 2021—roughly equals the entire population of Bangladesh, the world's eighth most populous country. China's annual recorded deaths in 2020 alone exceeded Sweden's total population (United Nations 2022). With projections indicating that 30% of China's population will be 65 or older by 2050, this profound demographic shift presents significant challenges for managing social security and healthcare systems, underscoring the need for accurate mortality estimates to guide policy making. Thus, the need for accurate mortality estimates is particularly pressing.

However, accurate, consistent, and reliable mortality information on China remains challenging for researchers to access and utilize (Zhao, Chen and Jin 2016; Zhao et al. 2014). For example, the country's vital statistics system significantly underreports deaths, with an estimated 17.4% undercount at the national level (Wang et al. 2011). While Census data is more accessible, it also suffers from substantial underreporting of deaths among those aged 60 and above (Wang 2013), possibly due to families' reluctance to report older family member's deaths in order to continue receiving social security benefits (Wu and He 2015). Moreover, vital statistics data remains largely inaccessible to scholars and are thus rarely used in mortality research (Zhao et al. 2014). Given the limited access and questionable accuracy of registration data, researchers must rely on longitudinal surveys to describe mortality levels and differentials.

Large-scale population-representative surveys modeled after the Health and Retirement Study (HRS), along with household panels similar to the Panel Study of Income Dynamics (PSID), have emerged as key data sources for studying mortality in China. The availability of these surveys, combined with growing interest in examining the impact of profound social and economic changes

on population processes, has generated substantial scholarship on socioeconomic (SES) differentials in mortality. These studies have identified variations in mortality based on educational attainment and other SES correlates, such as family structure, living arrangements, and geographic location (Feng et al. 2017; Liang et al. 2000; Luo and Xie 2014; Luo, Zhang and Gu 2015; Yi, Gu and Land 2007; Zhu and Xie 2007). However, the mortality information from these surveys has not been systematically evaluated against reliable national records to verify the accuracy of their mortality estimates.

This validation is particularly crucial because longitudinal household surveys face a fundamental challenge: attrition. This process, where respondents are permanently lost from the study, can lead to underreported mortality estimates (Eisner et al. 2019; Uhrig 2008; Timæus 1991; Sirken and Royston 1970). In studies of older populations, attrition commonly results from death, severe illness, institutionalization, or mobility limitations (Lillard and Panis 1998). Without linking respondents to death registration, researchers cannot determine the survival status of attritors. In case of extensive attrition, mortality levels can thus be substantially underestimated.

Moreover, attrition is typically not random. In lower- and middle-income countries (LMICs), attrition often stems from difficulty tracking respondents (Alderman et al. 2001; Defo 1992; Thomas, Frankenberg and Smith 2001; Thomas et al. 2012) and is shaped by a complex interplay of factors: individual mobility (often associated with SES), household processes, and potentially unobserved early life experiences (Thomas et al. 2012). These patterns of selective attrition create systematic differences between the retained sample and the population of interest. When estimating SES-based mortality differentials, such selective attrition can lead to differential underreporting of deaths across SES groups, potentially biasing mortality differential estimates.

The choice of statistical methods for handling attrition bias fundamentally depends on understanding the underlying attrition process itself. This understanding shapes three critical aspects. First, it informs the plausibility of missing data assumptions (MCAR, MAR, or MNAR) that underpin different correction methods. For instance, if we understand that attrition is related to unobserved factors, this would suggest MNAR mechanisms and point toward using pattern mixture or shared parameter models rather than simpler MAR-based approaches. Second, knowledge of the attrition process helps identify which variables might make the MAR assumption more plausible or serve as good predictors in imputation models. Third, understanding potential drivers of attrition helps researchers formulate realistic scenarios for sensitivity analyses and choose appropriate sensitivity parameters. For example, if we understand that attrition is likely related to declining health, we can specify sensitivity parameters that model how unobserved health status might differ between dropouts and completers. Instead of arbitrary sensitivity parameters, we can ground them in substantive knowledge about the attrition process.

China's distinctive patterns of population mobility create unique challenges for tracking respondents. The country's substantial "floating" migrant population—approximately one-tenth of the total population (Goodkind and West 2002) —lacks valid urban hukou status, leading to their exclusion from social security benefits, healthcare, and housing in cities (Huang et al. 2014). This exclusion triggers two forms of mobility that complicate survey tracking. First, migrants frequently move within urban areas in search of housing and work opportunities (Wu 2006), making them particularly vulnerable to survey attrition. Second, approximately one-third of these migrants eventually return to their rural hometowns upon reaching retirement age to access social benefits tied to their original hukou location (Liu, Dou and Perry 2020). The challenge for mortality estimation is particularly acute because migrants, especially males, often engage in precarious

professions that may subject them to higher mortality (Donnelly 2022). Consequently, these mobile populations may be both more likely to die and harder to track: they may be lost to follow-up during their working years in cities, while their eventual return migration can disrupt the continuity of mortality tracking, potentially leading to systematic underestimation of mortality among specific population subgroups.

Beyond migration patterns, attrition in China is further complicated by evolving household arrangements that vary distinctly between urban and rural areas and by SES. The living arrangements of older adults have undergone significant changes in recent decades, with patterns varying by SES and urban/rural residence. In urban areas, increasing financial independence has led to a rise in nuclear families and older couples living near (rather than with) their adult children, a trend more common among those with better economic conditions (Lei et al. 2015; Sereny 2011). These changes in living arrangements typically involve residential moves that complicate survey tracking. When deaths occur among these older adults, they often go unreported in surveys. Meanwhile, rural areas have seen a decline in multi-generational households driven by adult children's migration to cities for employment opportunities (He and Ye 2014). In intergenerational households, adult children typically serve as the main reporters of parental deaths. Therefore, when the adult children in the household are lost to attrition, deaths of older family members in the survey may go unreported. These contrasting patterns suggest different attrition risks by SES groups: in urban areas, higher-SES older adults with greater residential mobility may be more likely to be lost to follow-up, while in rural areas, lower-SES families affected by labor migration may be harder to track.

This complex interplay of migration patterns, changing living arrangements, and socioeconomic transitions reveals two key mechanisms through which attrition affects mortality

estimation: failing to observe deaths among attritors themselves and losing accurate reporters of household members' deaths due to mobility. Moreover, these patterns of death underreporting likely vary systematically by SES groups. However, to date, no study has systematically assessed how selective attrition affects our understanding of mortality levels and differentials in old-age survival.

This study addresses this gap through three objectives: (1) assessing the accuracy of mortality estimates from two widely-used Chinese surveys against life tables provided by World Health Organization (WHO); (2) identifying key mechanisms of underreporting through mortality-based attrition and mobility-based attrition where potential reporters of older family members' death are lost; and (3) examining how selective attrition affects SES-based mortality differentials. While focusing on China, these findings have broader implications for understanding attrition and mortality underreporting in other LMICs with similar longitudinal household surveys, particularly those in the Health and Retirement Study (HRS) network. The results are especially relevant for improving mortality data collection through household surveys and strengthening evidence-based policymaking in rapidly aging societies that depend on these surveys for mortality estimation.

Data and Method

Data

I use two surveys: the Chinese Health and Retirement Longitudinal Study (CHARLS) waves 2011-2018, and the Chinese Family Panel Studies (CFPS) waves 2010-2018. CHARLS is designed to be representative of the Chinese population aged 45 and above (Zhao et al. 2013), whereas the CFPS is a sample of Chinese families, including older family members residing within the household (Xie and Hu 2014; Xie et al. 2017). CHARLS is the most widely used national survey

of older Chinese and CFPS is an important household panel that will become increasingly relevant for studying health outcomes at older ages as respondents age. The two surveys have distinct sampling strategies: CHARLS sampled age-eligible respondents in the household (Zhao et al. 2013) and recruited one respondent to answer individual- and family-level questions, while CFPS interviewed every household member in sampled families (Xie and Lu 2015). Both surveys collected mortality information through exit interviews. Deceased respondents' next-of-kin (CHARLS) or other surviving household members (CFPS) reported the date, cause, location of death, and demographic information of the decedent. However, the reported date, cause, and location of death were not matched with any official document or registration data as is common practice in many longitudinal surveys of aging in the US.

Defining Attrition

In CHARLS, attritors are identified using the interview status variable, with those marked as "no response" considered attrited. In contrast, defining panel attrition in CFPS is more complex due to the dynamic nature of household membership, as new members may join after the baseline wave—such as through marriage or moving into the household. To standardize the definition of attrition across the two surveys, I included all core family members reported by the household head in any wave between 2011 and 2018 as part of the sample. These individuals were expected to have their survival status tracked in every subsequent wave following their initial appearance. Thus, in CFPS, attrition was defined as respondents whose last recorded observation occurred before the end of the observation period in 2018, mirroring the approach used in CHARLS. A key difference in CFPS is that interviewers actively tracked and re-interviewed households that had relocated. In contrast, there is no documented effort in CHARLS to follow up with respondents who did not initially respond.

Both surveys have non-trivial levels of panel attrition. 5,312 (23.6%) CHARLS respondents attrited between 2011 and 2018, and 4,662 (22.3%) CFPS respondents attrited between 2010 and 2018 (Table 1). The absence of information about the survival status of these attritors is a critical concern for research on mortality levels and differentials. It is likely that some respondents died before or after attrition, but it is impossible to know the date and cause of death in such cases.

[Table 1 About Here]

Benchmark

I use the WHO life table for China as the benchmark. I consider this life table to be the best mortality data on China that is readily accessible to researchers for the following reasons. First, the WHO draws from a combination of data sources that include the National Census, vital registration, and sample surveys from the Disease Surveillance Point, United Nations, and WHO mortality database (World Health Organization 2020). This approach minimizes the potential bias that comes from using a single data source. In addition, mortality information used in the WHO life table was adjusted for incompleteness that may exist in vital registration data (World Health Organization 2020).

One limitation of the WHO life table is that it sets the oldest open-ended age interval at 85+, which is not ideal given that approximately one-fourth of the Chinese population survives to age 85. To address this issue, *Mortpack*'s BESTFIT function was used to determine that the mortality pattern of the Chinese population mostly closely aligns with the Western Model Life Table. Using this model, I borrowed age-specific survival proportions for ages 85 to 100 in five-year intervals and then disaggregated them into single-year age groups using the UNABR function.

However, two caveats should be noted for ages beyond 85. First, some studies suggest that the mortality patterns of the oldest-old in East Asian populations do not align with the Western Model Life Table, but instead follow a Kannisto model, which better captures mortality trends at oldest-old ages (Gu et al. 2013; Zeng and Vaupel 2003). Therefore, extending the life table using the Western Model may not accurately reflect the mortality experience of the oldest-old in China. Second, mortality in the WHO life table beyond age 85 are themselves derived from models rather than observed data, making them inherently less reliable. Consequently, any comparisons involving mortality estimates beyond age 85 should be interpreted with caution due to the greater uncertainty.

Analytical Strategy

Levels of Mortality Underreporting

The first objective is to estimate age-specific mortality rates ${}_nm_x$. The conventional method for calculating ${}_nm_x$ involves dividing the observed number of deaths (${}_nd_x$) by the observed person-years of exposure to the risk of death. However, previous research has indicated that obtaining reliable mortality estimates for single years of age in China is challenging due to small cell sizes at oldest-old ages (Gu and Dupre 2008). My own analysis of the two surveys confirms that sample sizes are limited beyond age 80. Consequently, I turn to the model-based approach to generate smoothed estimates of ${}_1m_x$.

Previous studies have shown that parametric Gompertz and Weibull models provide the most accurate descriptions of mortality patterns for older Chinese individuals up to age 96, while the Kannisto model better fits mortality patterns beyond age 96 (Gu and Dupre 2008; Zeng and Vaupel 2003). Given the limited number of observed deaths after age 90 in the samples, I employ

both Gompertz and Weibull models. While these two models yield highly comparable results, the Gompertz model yields slightly higher mortality estimates within specific age groups. To address potential differences in model estimates due to model selection, I follow the practice outlined by Gu and Dupre (2008) and average age-specific mortality rate estimates from the two models. These age-specific rates are then converted into survival probabilities using the standard conversion formula (Equation 1).

$$ {}_1p_{x,i} = 1 - {}_1q_{x,i} = 1 - \frac{1 \cdot {}_1m_{x,i}}{1+(1- {}_1a_x) {}_1m_{x,i}} \quad (1) $$

where ${}_1p_{x,i}$ denotes the probability of survival from age x to age $x+1$ for data source i. ${}_1m_{x,i}$ denotes the estimated mortality rate from age x to age $x+1$ for data source i. The average number of person-years lived by those dying between exact age x and exact age $x+1$, ${}_1a_x$, is assumed to equal 0.5.

Next, I demonstrate the underrepresentation of deaths by comparing the estimated survival proportions to the WHO benchmark. To quantify the extent of mortality underreporting, I calculate the percentage difference between the estimated age-specific survival proportions and the benchmark values, using the benchmark as the reference point. The degree of underrepresentation is expressed as the percentage deviation from the benchmark.

While the two surveys have a roughly similar age distribution (see Table 1), the CHARLS sample is slightly older in its age distribution. To ensure a consistent visual representation, I use a common base population. More specifically, I multiply the sex- and age-specific population counts from the 2015 1% Population Micro Census by the estimated mortality rates (Equation 2). The results can be interpreted as the deaths that would have been observed had China's population in 2015 been subject to the age-specific mortality rates estimated from CHARLS and CFPS.

$$ {}_1D_{x,i} = {}_1m_{x,i} \cdot {}_1N_x \quad (2) $$

Where ${}_1D_{x,i}$ denotes the expected number of deaths between age x and $x+1$ based on mortality from data source i. ${}_1N_x$ denotes the observed Census population count between age x and $x+1$. For brevity, I only present results for the female population.[1]

Understanding How Attrition Contributes to Mortality Underreporting

The second objective explores how attrition affects mortality underreporting through a two-step approach. First, I estimate logistic regression models for attrition in both surveys as a function of key demographic characteristics (age, gender, education attainment, and marital status) and family characteristics (living arrangement and household income), as in prior studies on attrition (Becketti et al., 1988; Fitzgerald et al., 1998; Lillard and Panis, 1998; Zapel, 1998). To explore the extent of mortality underreporting due to attrition, I then perform imputations based on assumptions about two mechanisms: mortality-based attrition and mobility-based attrition. For mortality-based attrition, the imputation operates on the assumption that if mortality is the cause of individuals being lost to follow-up, their deaths should follow an age-specific mortality pattern similar to the general population, albeit with potential variations, as attritors are often selective and may exhibit different mortality rates compared to the rest of the sample. According to this assumption, the proportion of attritors that eventually ended up dying in each age group should reflect the corresponding age-specific death pattern.

Ideally, age-specific mortality among attritors can be obtained through linkage to vital registration. This type of data is available in the Health and Retirement Study (HRS), which tracks attritors and verifies their survival status using the National Death Index. Given the comparability between HRS and the CHARLS in terms of sampling methods and scale, and acknowledging that

[1] Results were similar for the male population and are available upon request.

attritors in China and the U.S. may differ in terms of selectivity, I use the age-specific percentage of deaths among HRS attritors to impute corresponding death percentages among CHARLS attritors for each age group. The attritors are randomly assigned as either alive or dead based on these age-specific proportions (Scenario 1).

In CHARLS waves 1 and 2, some attritors were marked as alive, though the source of this information is unclear. While this does not provide data on those who have died, it offers age-specific percentages of attritors confirmed as alive (see Appendix Table A1). I use this information to calculate the alive-to-death ratio for each age group, where "alive" represents the percentage of confirmed living attritors and "dead" the percentage of observed deaths in the same age group. The remaining attritors with unknown status are then randomly assigned as either alive or dead based on this ratio (Scenario 2)[2].

In addition, I consider an alternative approach (Scenario 3) where attritors are imputed as deceased if they self-reported poor health during their last observation. This scenario operates on the assumption that individuals with poor health at their last recorded observation have a significantly higher likelihood of subsequent death, based on the well-established link between poor self-reported health and increased mortality risk (Benyamini 2011; Franks, Gold and Fiscella 2003; Lorem et al. 2020). By using self-reported health status as an individual-level predictor of death, Scenario 3 contrasts with the first two scenarios, which rely on group-level proportions of death based on age. Together, these three scenarios facilitate assessment of whether mortality-

[2] However, this approach has limitations, as it assumes that the reasons for being lost to follow-up and the likelihood of dying are the same for both observed deaths and those with unknown status.

related attrition contributes to underreported mortality. I then re-estimate the survival curves incorporating these imputations for missing data.

Beyond mortality-based attrition, I examine how mobility-based attrition affects death underreporting through patterns of family-based reporting (Scenario 4). This scenario builds on the assumption that when accurate reporters—typically adult children—are lost due to mobility, deaths among older household members may go unreported. I test this assumption using CFPS data, which surveys every household member regardless of age. Specifically, when both a younger (under 70) and older (over 70) family member are lost to follow-up in the same wave, I impute the older member as deceased. This approach captures how family mobility patterns might contribute to death underreporting among older adults. Appendix Table A2 summarizes all four imputation scenarios.

To assess the robustness of our findings, we conduct sensitivity analyses that vary key assumptions in each scenario. For mortality-based attrition (Scenario 1), we test variants where attritor death rates differ from HRS-based rates by ±20% to account for potential differences in selectivity between US and Chinese contexts. For health-based imputation (Scenario 3), we vary both the definition of poor health and the assumed mortality risk associated with poor health status. For family-based reporting (Scenario 4), we test different age thresholds for older family members (65+, 70+, 75+) and varying temporal windows for co-occurring attrition. These sensitivity analyses help identify which findings are robust across different assumptions about the attrition process.

Understanding the Impact of Selective Attrition on SES-Mortality Differential

The last objective is to demonstrate how mortality underreporting due to attrition affects the estimation of SES-mortality differentials. I estimate and compare the survival probabilities between individuals with less than a high school education and those with a high school education or higher under the four different scenarios described above. I use Cox proportional hazard models to estimate the observed time to death. The proportional hazards assumption is evaluated and confirmed using the *phtest* command in STATA. This analysis aims to assess the sensitivity of SES-mortality differentials under different scenarios involving mortality-based or mobility-based attrition.

To further explore the impact of differential underreporting and its interaction with varying levels of death underreporting due to attrition, I extend the analysis using an approach similar to that employed for estimating bias from response misclassification in binary regression (Neuhaus 1999), which has been applied to underreporting contexts such as abortion (Lindberg et al. 2020). I conducted Monte Carlo simulations using reported death as the outcome. Specifically, I modeled a hypothetical study estimating how a binary demographic characteristic (η) affects an individual's likelihood of death. Without underreporting, this relationship is defined by the logistic regression model:

$$\log\left(\frac{p(Y=1)}{1-p(Y=1)}\right) = \beta_0 + \beta_1\eta, \tag{3}$$

where β_1 is the covariate of interest, and Y is whether the respondent died. However, Y is measured with error; only Y* is observed, a measurement that has perfect specificity (all respondents reporting death have died) but poor sensitivity (high levels of underreporting).

To illustrate the bias introduced by using Y*, I repeatedly sample 10,000 individuals from a hypothetical population in which 15% had the characteristic η, reflecting the actual proportion of respondents with a high school or higher education in the samples. In this population, 10% of

individuals died, representing a fixed mortality level. The bias induced by underreporting is the difference between the estimated relationship $\widehat{\beta_1}$ (using Y* as the response) and the true value of β_1 (which I set at a constant value of 1). In each simulation, I systematically vary two factors: the extent of differential underreporting (the degree to which η increases the likelihood of reporting) and the overall prevalence of underreporting. Each scenario is run 50 times, and I calculate the average bias across simulations.

Results

Levels of Mortality Underreporting

Figure 1 shows the estimated proportions surviving between ages 55 and 100. Panel A indicates that proportions surviving based on CHARLS (blue dashed line) and CFPS (red dashed line) are higher than the benchmark (solid black line). Compared to the CHARLS data, the survival curve based on CFPS is characterized by substantially higher proportions surviving between ages 65 and 90. This overestimation of surviving proportions translates into a large difference in the expected number of deaths, illustrated in Appendix Figure A1 (Panel A), assuming that the Chinese population was subject to the mortality rates estimated from CHARLS and CFPS data. Relative to the WHO benchmark, both surveys generate far lower expected number of deaths.

[Figure 1 About Here]

These substantial gaps in survival and expected number of deaths are presumably due to unreported deaths among panel attritors in the two surveys. Although it is impossible to observe survival status once a person attrites from the survey, I evaluate the potential impact of attrition on mortality estimates by making the extreme, and clearly unrealistic, assumption that all panel attritors died, with the age of death being age at the last observation. Using this extreme assumption,

re-estimated proportions surviving can be interpreted as upper bounds on the actual values (or lower bounds on estimates of proportions surviving).

Panel B of Figure 1 shows that the re-estimated CHARLS survival curve closely matches the benchmark survival curve. This match requires approximately 78% of CHARLS respondents lost to panel attrition to be classified as deceased across all age groups. This percentage was calculated through three steps: For each age group, I computed the expected number of deaths by multiplying the benchmark age-specific death probabilities by the total number of CHARLS respondents. I then calculated under-observed deaths by subtracting actual CHARLS-observed deaths from these expected deaths. Finally, I divided the under-observed deaths by the total number of attritors in each age group, yielding age-specific proportions of attritors that should be classified as deceased (detailed in Appendix Figure A2). The overall 78% represents the average of these age-specific proportions.

In contrast, the re-estimated CFPS curve does not align with the benchmark. The fact that the CHARLS curve closely matches the benchmark while the CFPS curve does not suggests that mortality-based attrition is likely the primary factor contributing to death underreporting in CHARLS, whereas other processes are at work in CFPS.

Appendix Figure A3 displays the age distribution of attritors in both surveys, highlighting a heavy skew towards the younger age group of 50-60. This extensive attrition among young-old respondents raises an important question about whether these individuals often serve as key reporters of death statuses for their older family members in the household-based CFPS. When respondents in this age group are missing due to attrition, the deaths of older family members may go unreported.

I test this possibility using logistic regression to analyze whether families with an attritor aged 50-60 are more likely to lose older household members (aged 70+ or 80+) to follow-up in the same wave. Table 2 presents odds ratios from the logistic regression model, using the family as the unit of observation. The results show that among families with multiple attritors, having an attritor aged 50-60 significantly increases the odds of losing an older household member to follow-up, even after controlling for household characteristics. This association is particularly pronounced in rural areas (Appendix Table A3), suggesting a higher likelihood of missing older family members when a household member aged 50-60 is lost to follow up in rural villages. Taken together, these results suggest that mobility-based attrition of younger family members may lead to systematic underreporting of deaths in CFPS, as these individuals often serve as key reporters about older family member's death.

[Table 2 About Here]

To further test whether mortality-based attrition and mobility-based loss of reporters contribute to death underreporting, Figure 2 examines how different imputation scenarios affect mortality estimation by presenting the percentage deviation between re-estimated survival curves and the benchmark. In both the upper and lower panels, applying either the alive-to-death ratio from CHARLS or the percentage of death among attritors from HRS yields reasonably accurate estimates of age-specific survival proportions for both Chinese men and women between ages 50 and 85. In this age range, the percentage deviation from the benchmark generally falls between 0% and -1% (lower panel), indicating only a slight overestimation of mortality and underestimation of survival. However, beyond age 85, survival proportions are consistently underestimated compared to the benchmark, raising questions about the accuracy of WHO life tables or other model life tables in capturing mortality patterns among the oldest-old in East Asian populations (see

discussion in Gu et al. 2011). Notably, despite cultural and demographic differences between China and the United States, the results are strikingly similar when applying the age-specific alive-to-death ratio or percentage of deaths among attritors from either country. This consistency in mortality patterns across different populations suggests that attrition-related mortality may be primarily driven by biological aging processes rather than country-specific factors.

[Figure 2 About Here]

In Scenario 4, attritors aged 70 and above in CFPS were imputed as deceased if they resided in a household with at least one younger household member aged 50 to 60, and this younger member was also lost to follow-up in the same wave as the older attritor. Similar to Scenarios 1 and 2, the upper panel of Figure 2 shows that this approach accounts for most of the underreported deaths among individuals aged 50 to 85. The lower panel zooms in on this age range, showing that Scenario 3 slightly underestimates female mortality (overestimates female survival) compared to males. This likely reflects the fact that more women live alone, meaning the assumption used in this scenario fails to capture some deaths among women living in single-person households.

Explaining Attrition Patterns

The results so far suggest that mortality-based attrition is a key factor driving death underreporting in CHARLS. However, an apparent contradiction emerges: younger older adults (those below age 70), where mortality is less common, are more prone to attrition than those aged 70 and above. This trend is illustrated in the age distribution of attritors (Appendix Figure A3) and the proportion of attritors among all respondents (Appendix Figure A4). Specifically, Appendix Figure A4 shows that attrition peaks in the 50-60 age group, with around 35% of urban residents experiencing attrition compared to approximately 15% of rural residents.

One possible explanation for the higher levels of attrition among urban residents aged 50-60 is return migration to rural hometowns. This explanation is empirically supported by Table 3. Model 1 in the upper panel indicates that being a migrant—loosely defined as respondents with rural hukou living in urban areas—is associated with a 24% increase in the odds of attrition in the next wave. This relationship holds even after controlling for factors such as age, gender, marital status, education, self-rated health, and living arrangements. Migrants are disproportionately less educated, and those with less than a high school education face significantly higher odds of attrition, as evidenced by the significant interaction term in Model 5. However, Model 3 shows that return migration does not follow a specific age pattern, as the interaction between being a migrant and being aged 50-60 is not significant. This suggests that migrants may be lost to follow-up at various ages, not just between 50 and 60.

[Table 3 About Here]

Migrants may contribute to the underreporting of deaths, particularly among male migrants, since migrant workers may face an elevated risk of premature mortality (Zimmer, Kaneda and Spess 2007), especially male migrant workers, who are often employed in physically demanding and precarious jobs, such as construction (Swider 2015). The lower panel of Table 2 presents odds ratios from a discrete-time logistic model where death is the outcome. Being a migrant is associated with a 9% higher odds of dying, controlling for age and gender (Model 1). However, when controlling for age, male migrants show a 14% higher odds of death, significant at the 0.05 level (Model 2), while no difference in mortality risk is observed for female migrants (Model 3).

For ages beyond 70, residential mobility likely explains the underreported deaths among urban attritors. Older adults with illness often move to their adult children's household to receive care; in many cases, their adult children are migrants themselves residing in cities with better

employment prospects and medical resources (Zimmer and Korinek 2010). This change in living arrangements may lead to attrition resulting from change of address (which may be accompanied by subsequent mortality). Some older adults in good health conditions may engage in seasonal migration (Li and Alencar 2023), which is less likely to contribute to death underreporting but nevertheless elevates the risk of attrition. However, the change of address makes it hard to empirically test whether residential mobility and mobility with seasonal migration contributes to the underreporting of death.

Implications for SES-Mortality Differentials

Table 4 presents the odds ratios from logistic regression models examining the likelihood of attrition in the next wave. The results clearly show that attrition is not random with respect to key demographic characteristics. In both CHARLS and CFPS, individuals aged 50-60 exhibit significantly higher odds of attrition compared to those aged 70-80. Similarly, having a high school education or above is associated with a significantly higher likelihood of attrition. Additionally, living in urban areas is linked to higher odds of attrition compared to living in rural villages. These findings suggest that attritors are more likely to be younger, more educated, and living in urban areas at the time of their last available observation.[3] An indirect implication of this pattern is that presumed (unobserved) deaths among attritors may be disproportionately concentrated among individuals with higher SES. It is therefore crucial to understand how underreporting of deaths among attritors affects our interpretation of SES-mortality differentials in analyses based on these surveys.

[Table 4 About Here]

[3] Results using characteristics measured at baseline observation were similar (not shown).

Panel A of Figure 3 shows educational differentials in mortality when the most common practice is adopted – i.e., attrition is ignored. Respondents with at least a high school education have higher survival probabilities between ages 65 and 100. This is consistent with existing evidence showing a mortality advantage among the higher educated (Hummer and Hernandez 2013). In Panels B and C, the educational differential in mortality is estimated after applying age-specific alive-to-dead ratios, either directly observed in CHARLS or borrowed from the HRS. The resulting curves are virtually indistinguishable, likely due to the random imputation of deceased status among a subset of attritors, who are disproportionately better educated. Thus, a larger proportion of deaths were imputed among respondents with higher education compared to those with lower education. Panel D presents a different scenario in which individuals who self-reported poor health were imputed as deceased. In this case, while the survival advantage for the more educated remains, the gap between the higher and lower educated narrows slightly compared to Panel A. Additional analyses by urban/rural residence (Appendix Figure A5) reveal that mortality differentials can either converge or enlarge when stratified by urban/rural residence.

[Figure 3 About Here]

Estimation of Bias from Differential Mortality Underreporting

While Figure 3 demonstrates how mortality differentials by SES vary under different mortality-based attrition scenarios, it cannot reveal the true bias in these differentials since the truth of mortality differential remains unknown. To further explore the impact of differential underreporting, I turn to a simulation exercise, with particular attention to how bias changes under varying levels of death underreporting as well as the differential degree of underreporting between groups. Figure 4 illustrates the bias introduced by underreporting deaths in logistic regression models where death is the outcome. Each panel corresponds to a different level of death

underreporting: low (10% of deaths not reported), medium (45% not reported), and high (80% not reported). The y-axis shows the average bias (the difference between the estimated and true relationships, expressed in log odds), while the x-axis represents the degree of differential reporting between groups. Higher positive x-values indicate that individuals with characteristic η were less likely to have their deaths underreported compared to those without that characteristic.

[Figure 4 About Here]

At each level of underreporting, even when there is no differential reporting between groups (i.e., when the x-axis equals 0), there is substantial bias in the estimated relationship between characteristic η and the likelihood of death. This bias tends to result in an overestimation of mortality differentials (as indicated by a positive bias), and the magnitude of the bias increases as the level of missing deaths rises.

Differential reporting can either mitigate or exacerbate the bias caused by underreporting. In some cases, the two sources of bias counterbalance each other. For instance, in the low and medium missingness scenarios, when highly educated individuals are more likely to have missing deaths (represented by negative x-values), there may be a point where the biases offset each other, resulting in an unbiased estimate (bias = 0 on the y-axis). This reflects a balance between the proportion of missing deaths and the differences in underreporting between individuals with and without characteristic η. However, when the differences in underreporting are large and negative (e.g., highly educated individuals are much more likely to have unreported deaths), the estimated education-mortality differential could be underestimated compared to the true differential[4].

[4] It is important to note that this simulation assumes η represents 15% of the population, approximating the proportion of highly educated older adults in China. In supplementary analyses, similar tests were conducted with η set to 70%, reflecting the proportion of individuals with at least a high school education among those aged 50 and above in the HRS dataset from 1994 to 2018. The results were highly similar, and they do not alter the conclusions drawn from the original analysis. Additional tests were performed under a scenario where a greater proportion of respondents eventually died. While the current set of tests assumes a mortality rate of 10%, the supplementary tests used a mortality

Discussion

Accurate mortality estimates are fundamental to understanding population aging and developing effective health and social policies. This need is particularly pressing as most developing countries experience unprecedented demographic transitions without reliable or accessible mortality data. In China, which faces one of the world's most rapid population aging and has the largest population of older adults, researchers frequently rely on household surveys to examine mortality trends and differentials. However, the mortality information from these surveys has not been systematically validated against existing benchmarks. In this study, I quantified the underrepresentation of mortality in two widely used household surveys of the older Chinese adults: the Chinese Health and Retirement Study (CHARLS) and China Family Panel Study (CFPS). When compared with life tables produced by World Health Organization (WHO), age-specific survival proportions for ages 65-90 produced from the two surveys are substantially overestimated (equivalent of underestimating of age-specific probability of dying).

Failing to capture deaths among attritors results in an underrepresentation of mortality at older ages. In both surveys, attrition is extensive, with 23.6% of respondents lost to follow-up in CHARLS and 22.3% for CFPS. Researchers using these surveys should be mindful of individuals—and potentially their deaths—excluded from the data due to attrition. Imputation scenarios reveal that in CHARLS, mortality-based attrition is the main driver of underreporting, whereas in CFPS, there is evidence of a link between mobility-based and mortality-based attrition. Specifically, the attrition of young-old household members in CFPS likely results in the loss of key reporters of older members' deaths.

rate of 60%, simulating a hypothetical population with a much older age structure. In this scenario, the degree of overestimation bias decreased significantly compared to the magnitude of bias shown in Figure 7.

Attrition is a challenge for almost all longitudinal surveys. Still, most studies using these two surveys assume (at least implicitly) that attrition is random and adopt the common practice of ignoring attrition. My analysis of attrition patterns in both surveys suggests that attrition among older Chinese adults is correlated with characteristics linked to higher SES, such as having a high school education or above and living in urban areas. These characteristics, along with being in the young-old age range (50-60), are also associated with greater mobility, indicating that attrition is not random but systematic. This selective attrition can lead to differential underreporting of deaths across SES groups, which introduces bias into the estimated SES-mortality differentials.

When death underreporting is due to mortality-based attrition, estimates of education-mortality differentials are highly sensitive to how researchers conceptualize and handle mortality among attritors. When applying a general age pattern of mortality, borrowed from internal or external data to reflect the age-specific mortality patterns among attritors, the education-mortality differential appeared non-existent, with indistinguishable survival curves between higher- and lower-educated individuals. This occurred because a random selection of respondents to impute as deceased disproportionately included those with higher education. Conversely, when assuming that attritors with poor self-rated health at their last observation were deceased, the mortality differential between education groups narrowed but did not disappear, with higher-educated individuals still maintaining a survival advantage. This is likely because one's self-reported health is strongly linked to education attainment, and poor health is disproportionately more present among the lower educated.

The sensitivity of SES-mortality differentials is driven by the interplay between the magnitude of differential death underreporting across education groups and the overall level of underreporting. The results from simulation, illustrated in Figure 7, reveal this complex interaction.

When higher-educated groups have more deaths underreported compared to lower-educated groups (as the x-axis becomes more negative), the bias shifts from a positive overestimation to a negative underestimation of the mortality differential. Conversely, when higher-educated groups have fewer underreported deaths compared to lower-educated groups (as the x-axis becomes more positive), the bias consistently remains a positive overestimation. This finding underscores the need for caution when interpreting mortality differentials in the presence of significant selective attrition, particularly in the context of China, where attrition is closely tied to characteristics associated with higher SES.

The evidence I present in this study likely extends beyond mortality reporting to other health-related variables affected by sample attrition. Selective attrition can lead to significant biases in health estimates, especially when individuals who drop out are systematically less healthy than those who remain. Conditions such as hypertension, diabetes, or mental health disorders are often underreported due to undiagnosed cases or stigma (Adair, Li and Rao 2024; Lopes et al. 2024; Mason et al. 2023), and when respondents with these health issues are more likely to leave the survey, it impacts the estimates of disease prevalence and overall health status. This not only underestimates the true burden of disease but also obscures the relationship between health outcomes and SES. However, accurately assessing the extent of these biases is challenging without reliable benchmarks for comparison.

The analysis has several limitations. First, the findings about mortality-based attrition and mobility-based attrition through loss of death reporters may only apply to ages below 85. As illustrated in Figure 4, survival proportions beyond age 85 are consistently underestimated compared to the benchmark across all imputation scenarios, indicating mortality overestimation. However, no definitive conclusion can be drawn for ages beyond 85 since the WHO life table

benchmark might not reflect accurate mortality levels in this age group. This limitation is significant because approximately one-fourth of the Chinese population survives to age 85. A related limitation concerns the life table construction: I set $_1a_x$ to 0.5 across all age groups. While this approach is straightforward, it may overestimate $_1a_x$ in age groups older than 85, potentially leading to overestimated survival probabilities at 85+.

Second, when using CHARLS's observed age-specific alive-to-death ratio, I assume the ratio of survivors to deaths at each age group does not systematically differ between those with known and unknown survival status. While this assumption cannot be directly tested without complete mortality data, its violation – for example, if attritors with unknown status are more likely to be deceased—would lead to underestimated mortality levels in this study. A related assumption is that deaths among attritors occur at the same age as their last observation. However, some respondents, particularly those with higher SES, may have died considerably later after being lost to follow-up due to better health conditions and access to healthcare. Together, these assumptions suggest that the true patterns of mortality underreporting due to attrition may be more complex than our estimates indicate, especially when examining mortality patterns across SES groups.

Third, the mobility-based attrition scenario assumes that when both young and old household members are lost to follow-up simultaneously, the older member's absence indicates death rather than co-migration. While Table 2 supports the correlation between young-old and old-old attrition within households, this approach could overestimate mortality if families actually migrate together – for instance, when adult children relocate with their older parents for caregiving purposes. Nevertheless, as shown in Figure 4, the re-estimated survival curve from this imputation matches the benchmark reasonably well for ages below 85, suggesting that older family members' attrition is more likely due to death rather than migration.

Despite these limitations, the patterns of mortality underreporting and attrition observed in Chinese surveys have broader implications for other LMICs. As the Health and Retirement Study (HRS) network expands to countries like Thailand, Mexico, India, and Brazil, a critical methodological challenge emerges: how accurately do household surveys capture mortality in aging populations? This question becomes particularly pressing because attrition patterns in LMICs may differ fundamentally from those in high-income countries. While attrition in high-income countries primarily stems from participation refusal (Singh 1995), attrition in LMICs is often driven by difficulties in tracking respondents (Alderman et al. 2001; Defo 1992; Thomas et al. 2001; Thomas et al. 2012). These tracking challenges result in substantially higher attrition rates in LMICs—ranging from 20% to 45% (Alderman et al. 2001)—which may significantly affect mortality estimates.

The linkage between mobility-based attrition and mortality-based attrition identified in Chinese surveys—where the mobility of younger household members leads to the loss of death reporters for older adults—likely applies to other LMIC settings characterized by rapid urbanization and changing family structures. This pattern is particularly relevant as many LMICs share similar demographic transitions and resource constraints in survey implementation. Despite the importance of understanding attrition in these contexts, most existing studies on attrition have focused on Western countries—particularly the United States—using data from non-aging panels or earlier periods when attrition rates were generally lower (Becketti et al. 1988; Fitzgerald, Gottschalk and Moffitt 1998; Lillard and Panis 1998; Zabel 1998). The current gap in understanding these dynamics outside Western contexts highlights the urgent need for systematic investigation of attrition patterns in LMIC aging surveys, especially regarding how they may affect

mortality estimates of older populations. Such research is critical for improving data quality and ensuring accurate documentation of demographic trends in developing populations.

References

Adair, T., Li, H., and Rao, C. (2024). Assessing the Accuracy of Reporting of Hypertension on Death Certificates in Australia. *American Journal of Hypertension*. https://doi.org/10.1093/ajh/hpae108

Alderman, H., Kohler, H.-P., Behrman, J., Watkins, S., and Maluccio, J.A. (2001). Attrition in Longitudinal Household Survey Data: Some Tests for Three Developing-Country Samples. *Demographic Research*, *5*(4), 79-124. https://doi.org/10.4054/DemRes.2001.5.4

Becketti, S., Gould, W., Lillard, L., and Welch, F. (1988). The Panel Study of Income Dynamics after Fourteen Years: An Evaluation. *Journal of Labor Economics*, *6*(4), 472-492. http://www.jstor.org/stable/2534852

Benyamini, Y. (2011). Why does self-rated health predict mortality? An update on current knowledge and a research agenda for psychologists. *Psychol Health*, *26*(11), 1407-1413. https://doi.org/10.1080/08870446.2011.621703

Defo, B.K. (1992). Mortality and Attrition Processes in Longitudinal Studies in Africa: An Appraisal of the Iford Surveys. *Population studies*, *46*(2), 327-348. https://doi.org/10.1080/0032472031000146266

Donnelly, R. (2022). Precarious work in midlife: Long-term implications for the health and mortality of women and men. *Journal of health and social behavior*, *63*(1), 142-158.

Feng, Z., Falkingham, J., Liu, X., and Vlachantoni, A. (2017). Changes in living arrangements and mortality among older people in China. *SSM - Population Health*, *3*, 9-19. https://doi.org/https://doi.org/10.1016/j.ssmph.2016.11.009

Fitzgerald, J., Gottschalk, P., and Moffitt, R.A. (1998). An analysis of sample attrition in panel data: The Michigan Panel Study of Income Dynamics. In: National Bureau of Economic Research Cambridge, Mass., USA.

Franks, P., Gold, M.R., and Fiscella, K. (2003). Sociodemographics, self-rated health, and mortality in the US. *Soc Sci Med*, *56*(12), 2505-2514. https://doi.org/10.1016/s0277-9536(02)00281-2

Goodkind, D.and West, L.A. (2002). China's Floating Population: Definitions, Data and Recent Findings. *Urban Studies*, *39*(12), 2237-2250. https://doi.org/10.1080/0042098022000033845

Gu, D., Andreev, K.F., Gerland, P., Spoorenberg, T., Li, N., and Heilig, G. (2013). Old age mortality in Eastern and South-Eastern Asia. *Demographic Research*, *29*(38), 999-1038. https://doi.org/10.4054/DemRes.2013.29.38

Gu, D.and Dupre, M.E. (2008). Assessment of Reliability of Mortality and Morbidity in the 1998-2002 CLHLS Waves In Y.Z.D.V.D.P.D. Gu (Ed.), *Healthy Longevity in China: Demographic, Socioeeconomic, and Psychological Dimensions*. Springer.

He, C.and Ye, J. (2014). Lonely sunsets: impacts of rural–urban migration on the left-behind elderly in rural China. *Population, Space and place*, *20*(4), 352-369.

Huang, X., Dijst, M., van Weesep, J., and Zou, N. (2014). Residential mobility in China: Home ownership among rural–urban migrants after reform of the hukou registration system. *Journal of Housing and the Built Environment*, *29*, 615-636.

Hummer, R.A.and Hernandez, E.M. (2013). The Effect of Educational Attainment on Adult Mortality in the United States. *Popul Bull*, *68*(1), 1-16. https://www.ncbi.nlm.nih.gov/pubmed/25995521

Lei, X., Strauss, J., Tian, M., and Zhao, Y. (2015). Living arrangements of the elderly in China: evidence from the CHARLS national baseline. *China Economic J*, *8*(3), 191-214. https://doi.org/10.1080/17538963.2015.1102473

Li, Y.and Alencar, A. (2023). A tale of two cities: digital place-making and elderly Houniao migration in China. *Journal of Ethnic and Migration Studies*, *49*(4), 1032-1049. https://doi.org/10.1080/1369183X.2022.2115630

Liang, J., McCarthy, J.F., Jain, A., Krause, N., Bennett, J.M., and Gu, S. (2000). Socioeconomic Gradient in Old Age Mortality in Wuhan, China. *The Journals of Gerontology: Series B*, *55*(4), S222-S233. https://doi.org/10.1093/geronb/55.4.S222

Lillard, L.A.and Panis, C.W. (1998). Panel attrition from the Panel Study of Income Dynamics: Household income, marital status, and mortality. *Journal of Human Resources*, 437-457.

Lindberg, L., Kost, K., Maddow-Zimet, I., Desai, S., and Zolna, M. (2020). Abortion Reporting in the United States: An Assessment of Three National Fertility Surveys. *Demography*, *57*(3), 899-925. https://doi.org/10.1007/s13524-020-00886-4

Liu, Y., Dou, X., and Perry, T.E. (2020). Return Migration in Later Life in Mainland China: Motivations, Patterns, and Influences. *Ageing Int*, *45*(1), 30-49. https://doi.org/10.1007/s12126-018-9336-8

Lopes, L.C.P., Medeiros, G.A., Wieczorek, M., Pinto, M., and Negrato, C.A. (2024). Underreporting of diabetes mellitus as the cause of death in Bauru, State of Sao Paulo, Brazil over 40 years: a documental study. *Arch Endocrinol Metab*, *68*, e230443. https://doi.org/10.20945/2359-4292-2023-0443

Lorem, G., Cook, S., Leon, D.A., Emaus, N., and Schirmer, H. (2020). Self-reported health as a predictor of mortality: A cohort study of its relation to other health measurements and

observation time. *Scientific Reports*, *10*(1), 4886. https://doi.org/10.1038/s41598-020-61603-0

Luo, W.and Xie, Y. (2014). Socio-economic disparities in mortality among the elderly in China. *Population studies*, *68*(3), 305-320. https://doi.org/10.1080/00324728.2014.934908

Luo, Y., Zhang, Z., and Gu, D. (2015). Education and mortality among older adults in China. *Soc Sci Med*, *127*, 134-142. https://doi.org/10.1016/j.socscimed.2014.09.039

Mason, J., Laporte, A., McDonald, J.T., Kurdyak, P., and de Oliveira, C. (2023). Health Reporting from Different Data Sources: Does it Matter for Mental Health? *J Ment Health Policy Econ*, *26*(1), 33-57. https://www.ncbi.nlm.nih.gov/pubmed/37029904

Neuhaus, J.M. (1999). Bias and Efficiency Loss Due to Misclassified Responses in Binary Regression. *Biometrika*, *86*(4), 843-855. http://www.jstor.org/stable/2673589

Sereny, M. (2011). Living arrangements of older adults in China: The interplay among preferences, realities, and health. *Research on Aging*, *33*(2), 172-204.

Singh, C. (1995). A comparative analysis of attrition in household panel studies.

Swider, S. (2015). Building China: precarious employment among migrant construction workers. *Work, Employment & Society*, *29*(1), 41-59. https://www.jstor.org/stable/26499232

Thomas, D., Frankenberg, E., and Smith, J.P. (2001). Lost but not forgotten: Attrition and follow-up in the Indonesia Family Life Survey. *Journal of Human Resources*, 556-592.

Thomas, D., Witoelar, F., Frankenberg, E., Sikoki, B., Strauss, J., Sumantri, C., and Suriastini, W. (2012). Cutting the costs of attrition: Results from the Indonesia Family Life Survey. *Journal of Development Economics*, *98*(1), 108-123.

United Nations, D.o.E.a.S.A., Population Division. (2022). World Population Prospects 2022. https://population.un.org/wpp/DataQuery/.

Wang, J. (2013). Trends in Life Expectancies and Mortality Patterns in China since 1990 A Further Examination and Analysis. *Population Research*, *37*(4), 3-18. http://rkyj.ruc.edu.cn/EN/abstract/article_3242.shtml

Wang, L., Wang, L.J., Cai, Y., Ma, L.M., and Zhou, M.G. (2011). Analysis of under-reporting of mortality surveillance from 2006 to 2008 in China. *Zhonghua Yu Fang Yi Xue Za Zhi*, *45*(12), 1061-1064.

World Health Organization. (2020). *WHO Methods and Data Sources for Life Tables 1990-2019*. World Health Organization, Department of Data and Analytics. https://cdn.who.int/media/docs/default-source/gho-documents/global-health-estimates/ghe2019_life-table-methods.pdf?sfvrsn=c433c229_5

Wu, W. (2006). Migrant Intra-urban Residential Mobility in Urban China. *Housing Studies*, *21*(5), 745-765. https://doi.org/10.1080/02673030600807506

Wu, X.and He, G. (2015). The Evolution of Population Census Undertakings in China, 1953-2010. *China Review-an Interdisciplinary Journal on Greater China*, *15*(1), 171-206. <Go to ISI>://WOS:000354227700007

Xie, Y.and Hu, J. (2014). An introduction to the China family panel studies (CFPS). *Chinese sociological review*, *47*(1), 3-29.

Xie, Y.and Lu, P. (2015). The sampling design of the China family panel studies (CFPS). *Chinese journal of sociology*, *1*(4), 471-484.

Xie, Y., Zhang, X., Tu, P., Ren, Q., Sun, Y., Lv, P., Ding, H., Hu, J., and Wu, Q. (2017). CFPS China Family Panel Studies.

Yi, Z., Gu, D., and Land, K.C. (2007). The association of childhood socioeconomic conditions with healthy longevity at the oldest-old ages in China. *Demography*, *44*(3), 497-518. https://doi.org/10.1353/dem.2007.0033

Zabel, J.E. (1998). An analysis of attrition in the Panel Study of Income Dynamics and the Survey of Income and Program Participation with an application to a model of labor market behavior. *Journal of Human Resources*, 479-506.

Zeng, Y.and Vaupel, J.W. (2003). Oldest Old Mortality in China. *Demographic Research*, *8*(7), 215-244. https://doi.org/10.4054/DemRes.2003.8.7

Zhao, Y., Strauss, J., Yang, G., Giles, J., Hu, P., Hu, Y., Lei, X., Park, A., Smith, J.P., and Wang, Y. (2013). China health and retirement longitudinal study–2011–2012 national baseline users' guide. *Beijing: National School of Development, Peking University*, *2*.

Zhao, Z., Chen, W., and Jin, Y. (2016). Recent Mortality Trends in China. In C.Z. Guilmoto and G.W. Jones (Eds.), *Contemporary Demographic Transformations in China, India and Indonesia* (pp. 37-53). Springer International Publishing. https://doi.org/10.1007/978-3-319-24783-0_2

Zhao, Z., Chen, W., Zhao, J., and Zhang, X. (2014). Mortality in China: Data Sources, Trends and Patterns. In I. Attané and B. Gu (Eds.), *Analysing China's Population: Social Change in a New Demographic Era* (pp. 205-225). Springer Netherlands. https://doi.org/10.1007/978-94-017-8987-5_11

Zhu, H.and Xie, Y. (2007). Socioeconomic Differentials in Mortality Among the Oldest Old in China. *Research on Aging*, *29*(2), 125-143. https://doi.org/10.1177/0164027506296758

Zimmer, Z., Kaneda, T., and Spess, L. (2007). An examination of urban versus rural mortality in China using community and individual data. *J Gerontol B Psychol Sci Soc Sci*, *62*(5), S349-357. https://doi.org/10.1093/geronb/62.5.s349

Zimmer, Z.and Korinek, K. (2010). Shifting coresidence near the end of life: comparing decedents and survivors of a follow-up study in China. *Demography*, *47*(3), 537-554. https://doi.org/10.1353/dem.0.0116

[This page is left in blank intentionally]

Table 1 Sample Characteristics of CHARLS (Waves 2011-2018) and CFPS (Waves 2010-2018)

	CHARLS	CFPS
N	22,471	20,720
Survivors	15,191 (67.6%)	13,643 (65.9%)
Observed deaths	1,968 (8.8%)	2,455 (10.8%)
Attritors§	5,312 (23.6%)	4,622 (22.3%)
Mean age*	58.1 (10.1)	59.9 (9.8)
Age group		
50-59	8,134 (36.2%)	7,788 (37.6%)
60-69	7,977 (35.5%)	6,685 (32.3%)
70-79	4,314 (19.2%)	4,002 (19.3%)
80-89	1,821 (8.1%)	1,900 (9.2%)
90+	225 (1%)	345 (1.7%)
Educational attainment		
Less than high school	19,432 (86.4%)	20,720 (82.9%)
High school and above	3,039 (13.5%)	3,546 (17.1%)
Marital status		
Married or partnered	19,727 (87.8%)	15,506 (76.5%)
Divorced or separated	317 (1.4%)	312 (1.5%)
Widowed	2,224 (9.9%)	2,676 (12.9%)
Never married	192 (0.9%)	1,776 (8.8%)
Self-reported health		
Excellent	300 (1.3%)	2,450 (11.8%)
Very good	2,216 (9.9%)	2,815 (13.6%)
Good	3,642 (16.2%)	6,342 (31.0%)
Fair	10,509 (46.8%)	3,535 (17.0%)
Poor	5,008 (22.3%)	4,999 (24.0%)
Missing	796 (3.5%)	579 (2.8%)
Place of residence		

Urban	9,895 (44.0%)	10,036 (48.4%)
Rural	12,576 (56.0%)	9,796 (47.3%)
Missing		888 (4.3%)
Hukou status		
Urban hukou	5,450 (24.3%)	6,158 (29.7%)
Rural hukou	16,181 (72.0%)	13,615 (65.7%)
Missing	840 (3.7%)	947 (4.6%)
Living arrangement		
Living with spouse only	6,838 (30.4%)	5,359 (25.9%)
Living alone	1,289 (5.7%)	1,414 (6.8%)
Living with >2 people	14,344 (63.8%)	13,947 (67.3%)
Home ownership		
Full or partial ownership	19,126 (85.1%)	16,912 (81.6%)
No ownership	2,258 (10.1%)	3,785 (18.3%)
Missing	1,087 (4.8%)	23 (0.1%)
Household income quartile†		
1 (Bottom 25%)	5,663 (25.2%)	6,125 (29.6%)
2	5,752 (25.6%)	4,615 (22.3%)
3	5,753 (25.6%)	4,714 (22.8%)
4 (Top 25%)	5,303 (23.6%)	5,222 (25.2%)
Retired	2,923 (13.0%)	723 (3.5%)
Currently working	13,944 (62.1%)	8,351 (40.4%)

Note: Percentage or standard errors in paratheses.
§2,317 Attritors in CHARLS were marked as 'non-response but alive'.
*Mean age and age group distributions were measured using the last observation available in each sample.
†Household income quartile was a constructed variable within each sample, determined by the total household income.

Table 2. Odds Ratios from Logistic Regression Models of Family Attrition, CFPS (Waves 2010-2018)

	70 and above			**80 and above**		
	OR	95% CI	*p*	OR	95% CI	*p*
Attrition of family member aged 50-60†	1.39	[1.05, 1.86]	0.024	8.04	[4.57, 14.15]	0.000
Household size‡	0.93	[0.76, 1.14]	0.492	1.11	[0.78, 1.59]	0.566
Urban (*ref: rural*)	1.22	[1.02, 1.44]	0.025	1.42	[0.97, 2.08]	0.075
Home ownership	0.66	[0.52, 0.82]	0.000	0.79	[0.50, 1.24]	0.303
Living with spouse§	0.58	[0.43, 0.79]	0.000	0.81	[0.44, 1.48]	0.495
Living with children¶	0.96	[0.78, 1.17]	0.670	0.85	[0.54, 1.33]	0.481
Max. age in the household	1.15	[1.14, 1.17]	0.000	1.18	[1.16, 1.21]	0.000
Min. age in the household	1.04	[1.03, 1.05]	0.000	1.07	[1.04, 1.09]	0.000
Household income quartile‡ (ref: bottom 25%)						
2	0.77	[0.61, 0.97]	0.029	0.82	[0.48, 1.41]	0.477
3	1.04	[0.83, 1.30]	0.712	1.05	[0.64, 1.72]	0.847
4 *(Top 25%)*	0.85	[0.67, 1.07]	0.172	0.89	[0.54, 1.49]	0.671
Constant	1.02e-06	[3.75e-07, 2.76e-06]	0.000	1.14e-06	[6.24e-11, 8.27e-09]	0.000
N	8,506			8,506		

Note: The logistic regression models examined the likelihood of having at least one family members aged 70 and above (or 80 and above) lost to follow-up among families with multiple attritors. The unit of analysis was family. Families that only had one respondent were excluded. In each family, I excluded family members who were less than age 50. Results were based on both male and female respondents.

†Defined as having at least one family member aged 50-60 attrited.

‡Household size in the sample ranged from 2 to 6 members. The odds ratio indicates how the likelihood of having at least two family members lost to attrition changes with each additional household member.

§Reference category was not living with spouse.

¶Reference category was not living with children.

Table 3. Odds Ratio from Logistic Regression Models of Sample Attrition and Death, CHARLS (Waves 2011-2018)

	Attrition		
	OR	95% CI	*p*
Model 1			
Migrant	1.24	[1.11, 1.39]	0.000
Model 2			
Migrant	1.22	[1.08, 1.37]	0.001
Model 3			
Migrant	1.28	[1.10, 1.50]	0.002
Age 50-60	1.21	[1.05, 1.39]	0.009
interaction	0.9	[0.71, 1.15]	0.409
Model 4			
Migrant	0.59	[0.39, 0.89]	0.013
<HS education	0.66	[0.54, 0.80]	0.000
interaction	2.24	[1.45, 3.46]	0.000
	Death		
	OR	95% CI	*p*
Model 1			
Migrant	1.09	[0.99, 1.19]	0.05
Model 2			
Migrant, male	1.14	[1.02, 1.28]	0.02
Model 3			
Migrant, female	1.01	[0.88, 1.15]	0.898

Note. The table presents odds ratios (ORs) and 95% confidence intervals (CIs) for attrition and death outcomes across different models. The upper panel examines characteristics at wave n and their association with attrition at wave n+1. Model 1 includes no

controls. Model 2 adjusts for age, gender, marital status, education, self-rated health, and living arrangement. Model 3 adds an interaction between age and migrant status to the controls from Model 2. Model 4 introduces an interaction between migration status and education, while controlling for the same factors as Model 2.The lower panel focuses on the relationship between migrant status and death. Model 1 adjusts for age and gender. Model 2 regresses on males only, controlling for age, while Model 3 regresses on females only, also controlling for age.

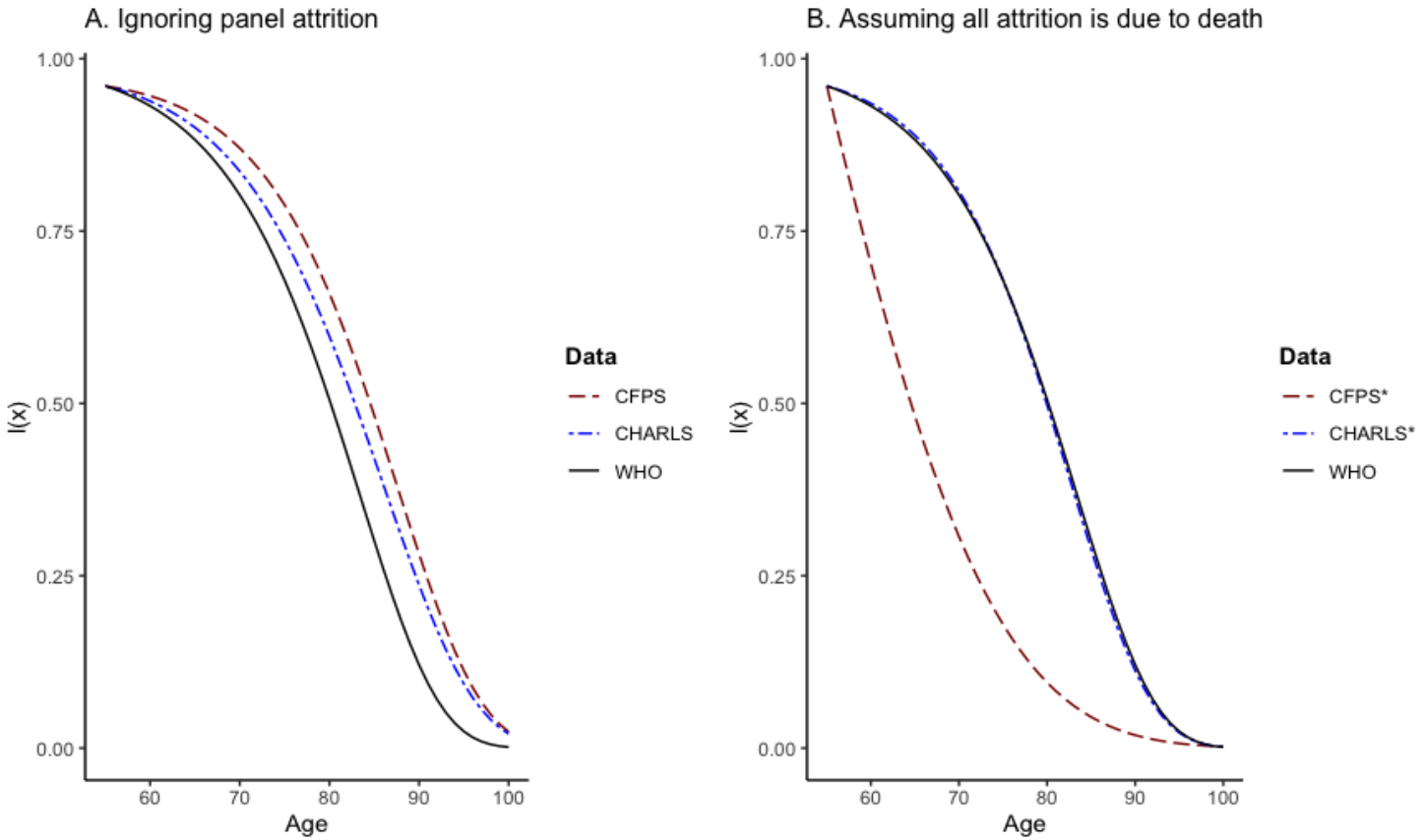
Table 4 Odds Ratios from Logistic Regression Models of Sample Attrition in CHARLS (Waves 2011-2018) and CFPS (Waves 2010-2018)

	CHARLS			CFPS		
	OR	95% CI	*p*	OR	95% CI	*p*
Female *(ref: male)*	0.96	[0.84, 1.09]	0.732	0.71	[0.63,0.81]	0.002
Age group (ref: 70-80)						
50-60	1.74	[1.44, 2.09]	0.000	2.13	[1.73, 2.62]	0.000
60-70	2.21	[1.74, 2.81]	0.047	0.94	[0.85, 1.04]	0.248
80-90	0.81	[0.58, 1.13]	0.210	0.71	[0.57, 0.89]	0.003
90+	0.68	[0.24, 1.91]	0.457	0.18	[0.02, 1.38]	0.099
Educational attainment (ref: less than high school)						
High school and above	1.29	[1.07, 1.56]	0.009	1.25	[1.05, 1.49]	0.012
Marital status (ref: married or partnered)						
Never married	1.68	[0.80, 3.55]	0.596	2.95	[2.34, 3.71]	0.000
Divorced or separated	0.71	[0.34, 1.49]	0.718	1.36	[1.03, 1.78]	0.029
Widowed	0.95	[0.70, 1.29]	0.206	1.33	[1.17, 1.52]	0.000
Place of residence (ref: rural)						
Urban	1.35	[1.11, 1.63]	0.002	1.10	[1.01, 1.19]	0.016
Hukou status (ref: rural hukou)						
Urban hukou	1.23	[0.96, 1.65]	0.102	0.95	[0.85, 1.05]	0.304
Self-rated health (ref: at least fair conditions)						
Poor	0.92	[0.69, 1.23]	0.568	0.84	[0.73, 0.96]	0.012
Living arrangement (ref: living with spouse only)						
Living alone	1.05	[0.67, 1.62]	0.843	0.72	[0.51, 1.02]	0.067
Living with at least 2 family members	1.07	[0.85, 1.35]	0.547	1.26	[1.09, 1.46]	0.001
Household income quartile† (ref: bottom 25%)						

2	0.93	[0.74, 1.17]	0.529	0.86	[0.78, 0.94]	0.113
3	1.06	[0.83, 1.34]	0.654	0.87	[0.80, 0.98]	0.015
4 *(Top 25%)*	1.28	[1.04, 1.57]	0.293	0.85	[0.77, 0.95]	0.003
Owning a home (ref: no ownership)	1.52	[1.16, 1.95]	0.000	1.23	[1.03, 1.48]	0.040
Currently working (*ref: not working*)	0.66	[0.55, 0.79]	0.000	1.66	[1.44, 1.91]	0.000
Retired (ref: not retired)	0.90	[0.66, 1.24]	0.478	2.06	[1.82, 2.33]	0.000
N	22,065			19,191		

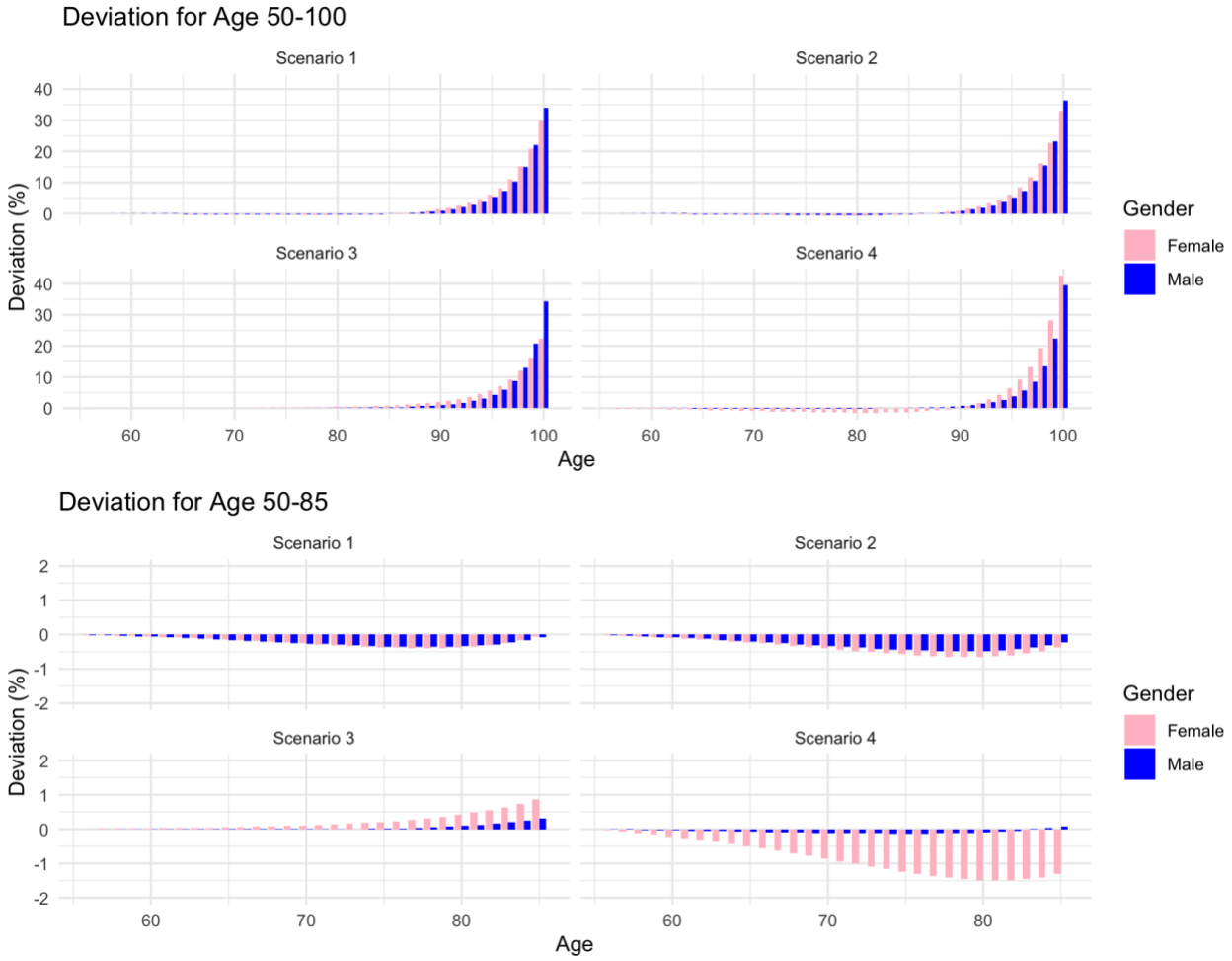
Note: Characteristics in this table were measured at the last observation available for each respondent. Sample attrition referred to respondents who were lost to follow-up without known survival status. Results were based on both male and female respondents.
†Household income quartile was a constructed variable within each sample, determined by the total household income.

Figure 1 Estimated Proportion Surviving between Ages 55 and 100, CHARLS (Waves 2011-2018) and CFPS (Waves 2010-2018)



Note: This figure plots the estimated proportion surviving between ages 55 and 100. The solid black line shows the proportions of survivors estimated using the WHO life tables (benchmark). The dashed blue line refers to the proportion of survivors estimated using the Chinese Health and Retirement Longitudinal Surveys (CHARLS) waves 2011-2018. The dashed red line refers to the proportion of survivors estimated using the Chinese Family Panel Studies (CFPS) waves 2010-2018. Results only show female respondents. The left panel presents estimates ignoring sample attrition in both surveys. The right panel presents estimates of a hypothetical scenario in which all attritors were assumed to have died in both surveys. This is noted as CHARLS* and CFPS* in the right panel. Ignoring panel attrition refers to the common practice of not making any adjustments or imputations beyond marking the respondent as missing, lost to follow-up, or censored.

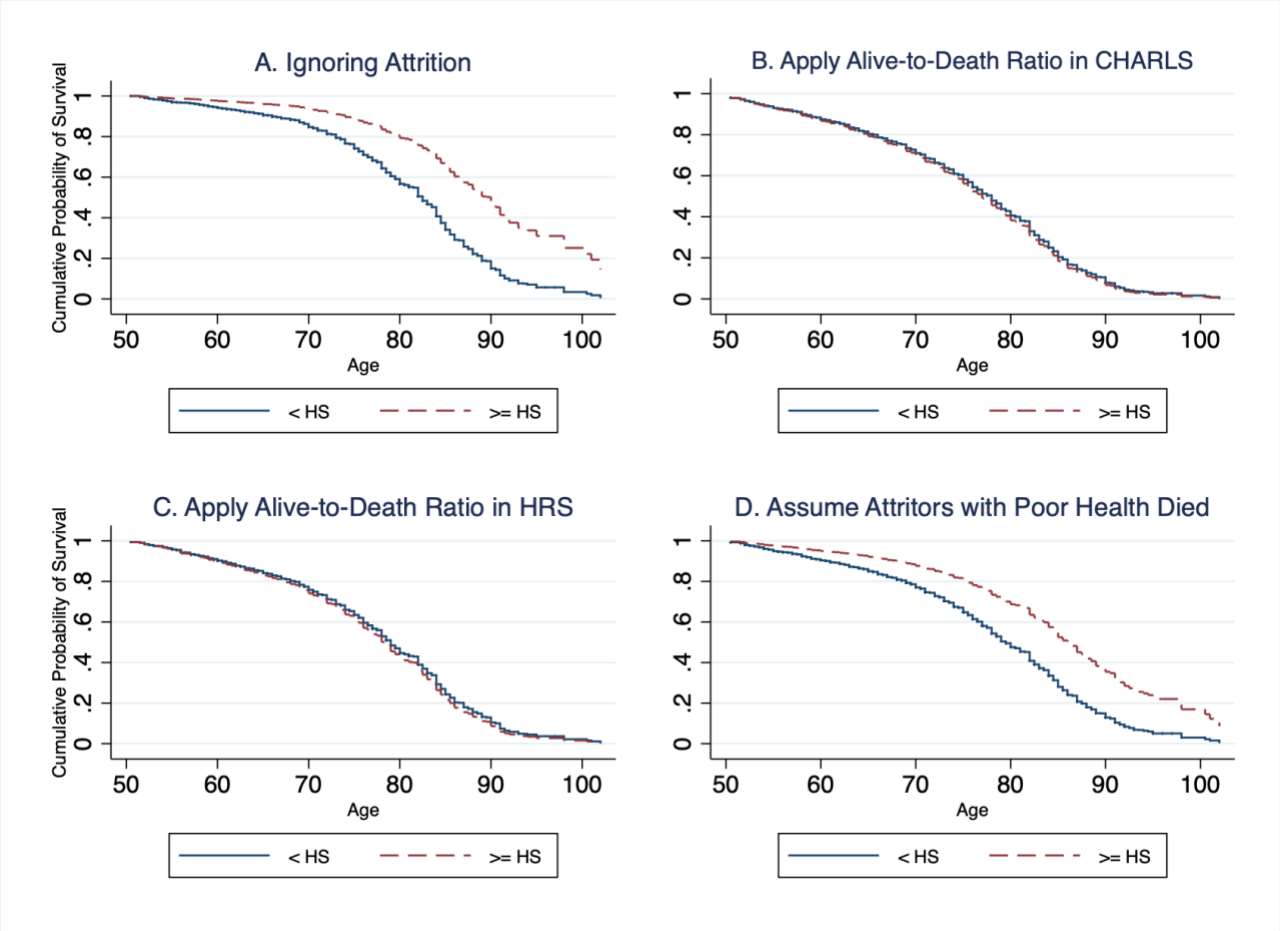
Figure 2. Age-Specific Percentage Deviation of Estimated Survival Proportion from the Benchmark, by Different Imputation Scenarios, Age and Gender



Note. This figure shows the age-specific deviation of estimated l_x from the benchmark, expressed as percentages. The upper panel shows the full age range (50-100), while the lower panel focuses on ages 50-85. Scenario 1 imputes a subset of attritors as deceased using the age-specific percentage of deaths among attritors observed in HRS. Scenario 2 imputes a subset of attritors as deceased based on the age-specific alive-to-death ratio directly observed in CHARLS. Scenario 3 imputes attritors as deceased if they reported

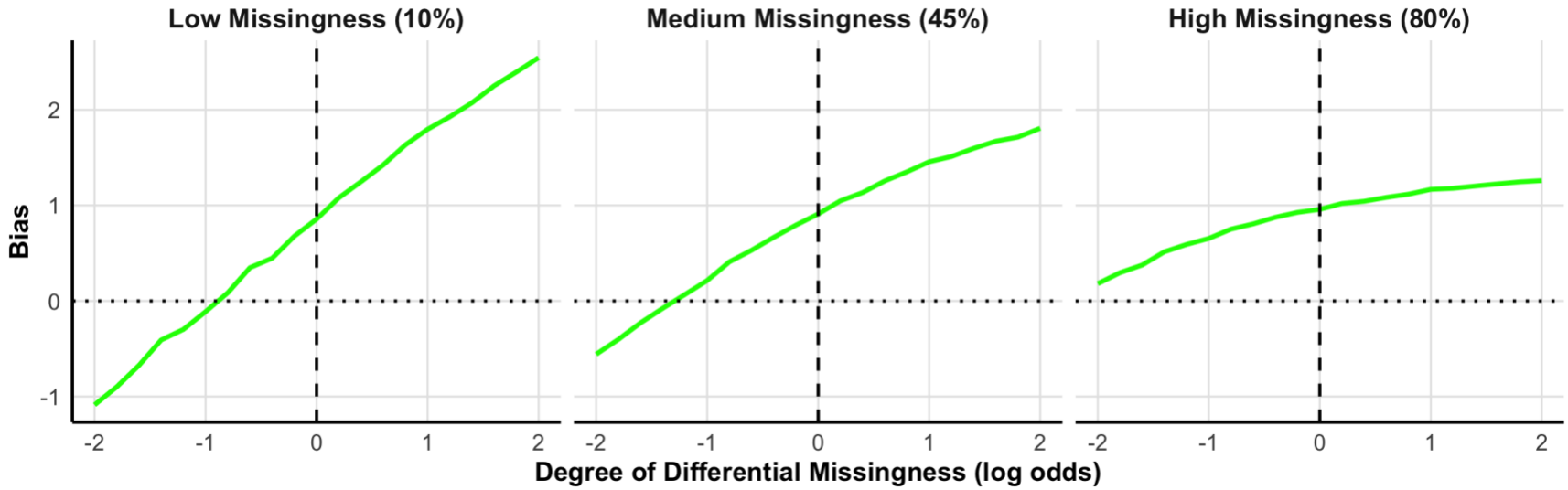
poor health status during their last observation. Scenario 4 imputes older family members as deceased if both an older and a younger family member are lost to follow-up in the same wave.

Figure 3. Estimated Education-Mortality Differential, CHARLS (Waves 2011-2018)



Note: This graph shows results using the CHARLS (waves 2011-2018) sample. Log-rank tests were performed and the difference between survival curves of the higher educated and lower educated was statistically significant at 0.05 (two-tailed test) in Panel A and D. <HS refers to respondents with less than high school education. >= HS refers to respondents with high school and beyond education. Results were based both male and female respondents. Baseline weights accounting for individual-level non-response were applied.

Figure 4. Bias in Estimated Relationship between an Individual Characteristic η and Odds of Deaths, by Different Levels of Death Underreporting



Note. Bias in estimated relationship between an individual-level characteristic η and odds of death (expressed in log odds), according to overall death underreporting prevalence and degree of differential reporting by characteristic η, estimated using Monte Carlo simulations. True log odds (β_1) are fixed at 1.

Appendix Table A1 Distribution of Demographic and Household Characteristics Among Attritors with Known Survival Status and Those with Unknown Survival Status, CHARLS (Waves 2011-2015).

	CHARLS 2011-2015						
	Lost-to-follow-up, alive	%	Lost-to-follow-up, don't know	%	Died	%	Total
Female	844	36.9%	998	43.7%	444	19.4%	2286
male	830	36.3%	980	42.9%	584	25.5%	2394
Age group							
50-60	739	32.3%	528	23.1%	120	5.2%	1387
60-70	438	19.2%	349	15.3%	247	10.8%	1034
70-80	165	7.2%	215	9.4%	304	13.3%	684
80+	40	1.7%	90	3.9%	226	9.9%	356
Educational attainment							
no formal	647	28.3%	803	35.1%	552	24.1%	2002
Elementary school	297	13.0%	322	14.1%	160	7.0%	779
Middle school	319	14.0%	313	13.7%	102	4.5%	734
High school and above	295	12.9%	378	16.5%	36	1.6%	709
Marital status							
married or partnered	1189	52.0%	1069	46.8%	620	27.1%	2878
Never married	14	0.6%	15	0.7%	14	0.6%	43
Divorced or separated	30	1.3%	25	1.1%	11	0.5%	66
Widowed	160	7.0%	203	8.9%	298	13.0%	661
Place of residence							
Urban	777	34.0%	1027	44.9%	339	14.8%	2143
rural	616	26.9%	292	12.8%	604	26.4%	1512
Hukou status							
Urban hukou	494	21.6%	733	32.1%	187	8.2%	1414
rural hukou	891	39.0%	567	24.8%	753	32.9%	2211

Self-rated health							
Very Good	113	4.9%	90	3.9%	26	1.1%	229
Good	230	10.1%	194	8.5%	80	3.5%	504
Fair	658	28.8%	573	25.1%	283	12.4%	1514
Poor	261	11.4%	247	10.8%	315	13.8%	823
Very Poor	60	2.6%	61	2.7%	143	6.3%	264
Living arrangement (ref: living with spouse only)							
Living alone	107	4.7%	145	6.3%	114	5.0%	366
Living with at least 2 family members	1286	56.3%	1174	51.4%	829	36.3%	3289
Currently working							
not working	597	26.1%	713	31.2%	682	29.8%	1992
working	680	29.7%	451	19.7%	227	9.9%	1358
Retirement							
retire	557	24.4%	680	29.7%	650	28.4%	1887
not retired	756	33.1%	484	21.2%	259	11.3%	1499
N	1674		1983		1028		4685

Note. CHARLS waves 2 and 3 marked a subset of attritors as 'non-response but alive,' but this information is not available in wave 4.

Appendix Table A2. Summary of Four Scenarios

Scenario	Description	Attrition Type	Survey
Scenario 1	Impute a subset of attritors as deceased using age-specific alive-to-death ratio directly observed in CHARLS.	Mortality-based attrition	CHARLS
Scenario 2	Impute a subset of attritors as deceased using age-specific percentage died among attritors observed in HRS.	Mortality-based attrition	CHARLS
Scenario 3	Impute attritors as deceased if they self-reported poor health status during their last observation.	Mortality-based attrition	CHARLS
Scenario 4	Impute older family members as deceased if both an older and a younger family member are lost-to-follow-up in the same wave.	Mobility-based attrition/Loss of death reporters	CFPS

Appendix Table A3 Odds Ratios from Logistic Regression Models of Family Member Attrition, CFPS (Waves 2010-2018).

	70 and above	*p*	Urban only	*p*	Rural Only	*p*
Attrition of family member aged 50-60†	1.39 [1.05, 1.86]	0.024	1.18 [0.80, 1.73]	0.398	1.97 [1.32, 2.95]	0.001
Household size ‡	0.93 [0.76, 1.14]	0.492	1.01 [0.78, 1.31]	0.922	0.92 [0.72, 1.19]	0.538
Urban (*ref: rural*)	1.22 [1.02, 1.44]	0.025				
Home ownership	0.66 [0.52, 0.82]	0.000	0.99 [0.73, 1.34]	0.934	0.47 [0.33, 0.67]	0.000
Living with spouse only§	0.58 [0.43, 0.79]	0.000	0.98 [0.61, 1.57]	0.921	0.58 [0.38, 0.86]	0.008
Living with children¶	0.96 [0.78, 1.17]	0.670	0.88 [0.66, 1.18]	0.390	1.18 [0.90, 1.55]	0.238
Max. age in the household	1.15 [1.14, 1.17]	0.000	1.15 [1.14, 1.17]	0.000	1.16 [1.15, 1.18]	0.000
Min. age in the household	1.04 [1.03, 1.05]	0.000	1.04 [1.02, 1.05]	0.000	1.03 [1.02, 1.05]	0.000
Household income quartile (*ref: bottom 25%)*						
2	0.77 [0.61, 0.97]	0.029	0.99 [0.68, 1.42]	0.936	0.84 [0.62, 1.14]	0.256
3	1.04 [0.83, 1.30]	0.712	0.99 [0.71, 1.38]	0.970	1.05 [0.77, 1.44]	0.745
4 (Top 25%)	0.85 [0.67, 1.07]	0.172	1.01 [0.73, 1.40]	0.953	0.73 [0.50, 1.06]	0.098
Constant	1.02E-06 [3.75E-07, 2.76E-06]	0.000	1.14E-06 [1.75E-07, 3.02E-06]	0.000	1.04E-06 [2.97E-07, 4.73E-06]	0.000

N	8,506	4,134	4,380

Note: The logistic regression models examined the likelihood of having at least one family members aged 70 and above lost-to-follow-up in the family. The unit of analysis was family. Families that only had one eligible respondent were excluded from this analysis. In each family, we excluded family members who were less than age 50.

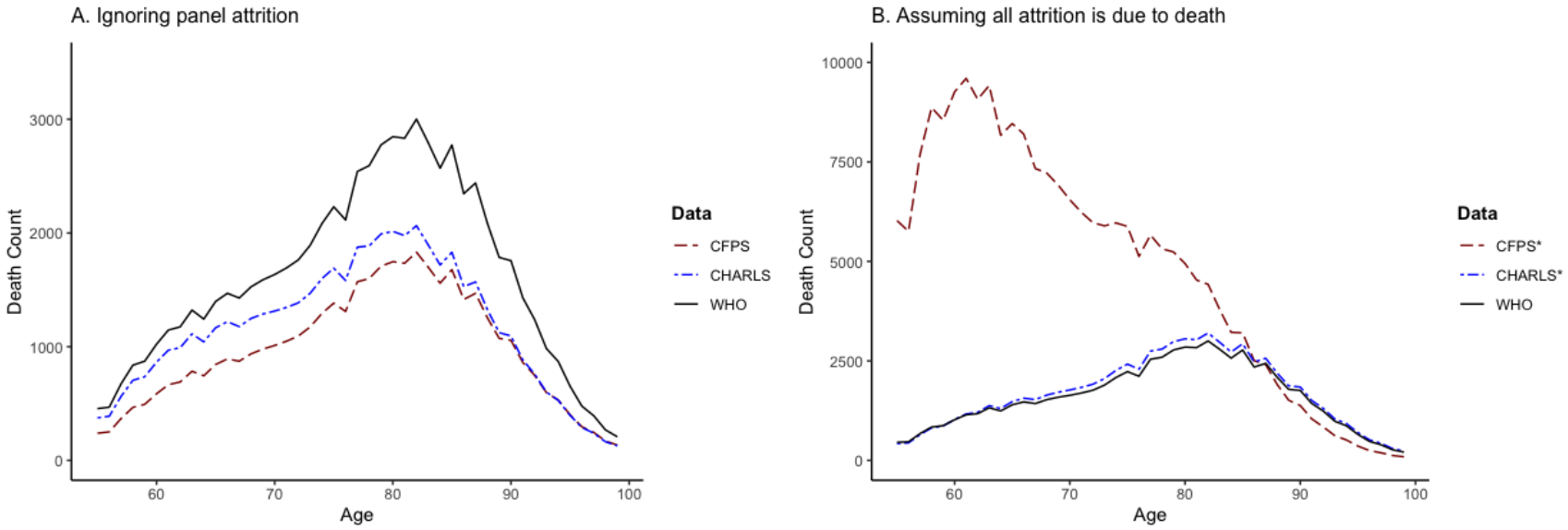
†Defined as having at least one family member aged 50-60 attrited.

‡Household size in the sample ranged from 2 to 6. The odd ratio should be interpreted as the odds of attrition of at least two family members with one additional person in the household.

§Reference category was not living with spouse.

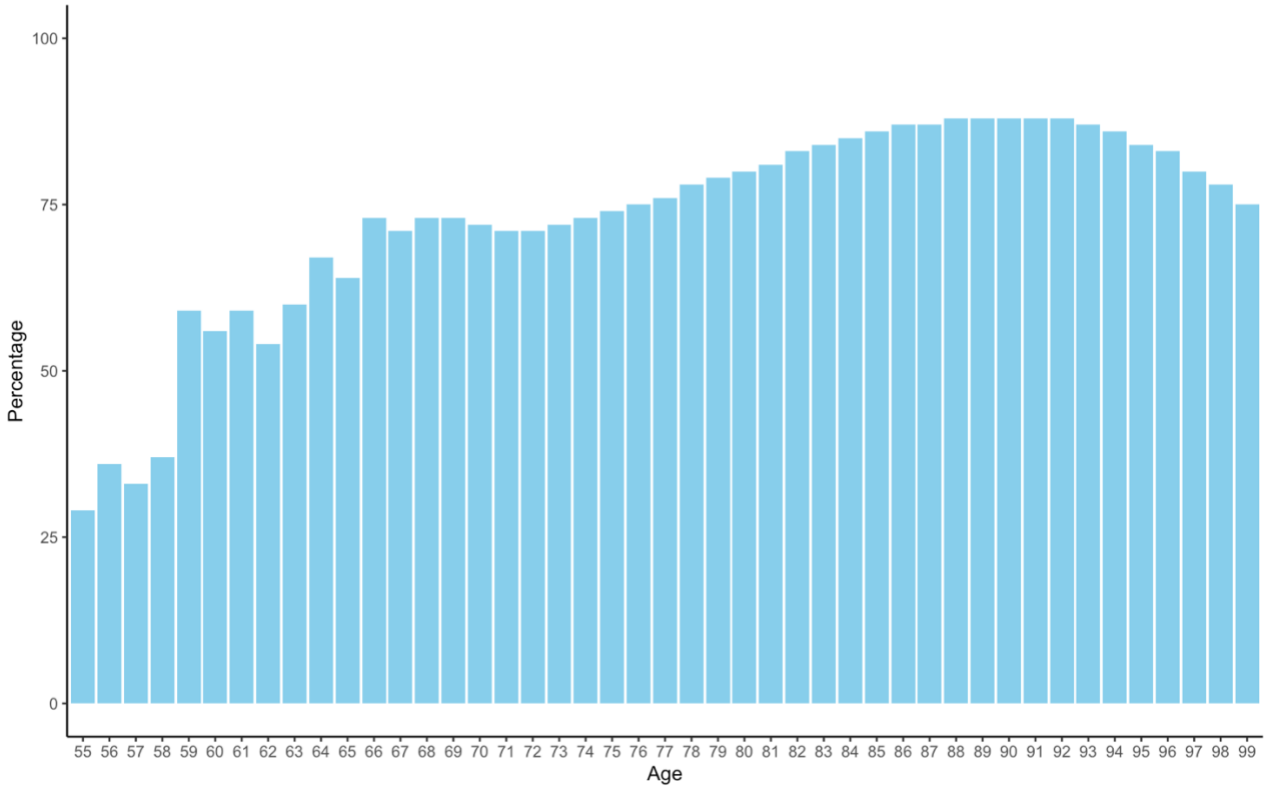
¶Reference category was not living with children.

Appendix Figure A1 Expected Death Counts between Ages 55 and 100, CHARLS (Waves 2011-2018) and CFPS (Waves 2010-2018)



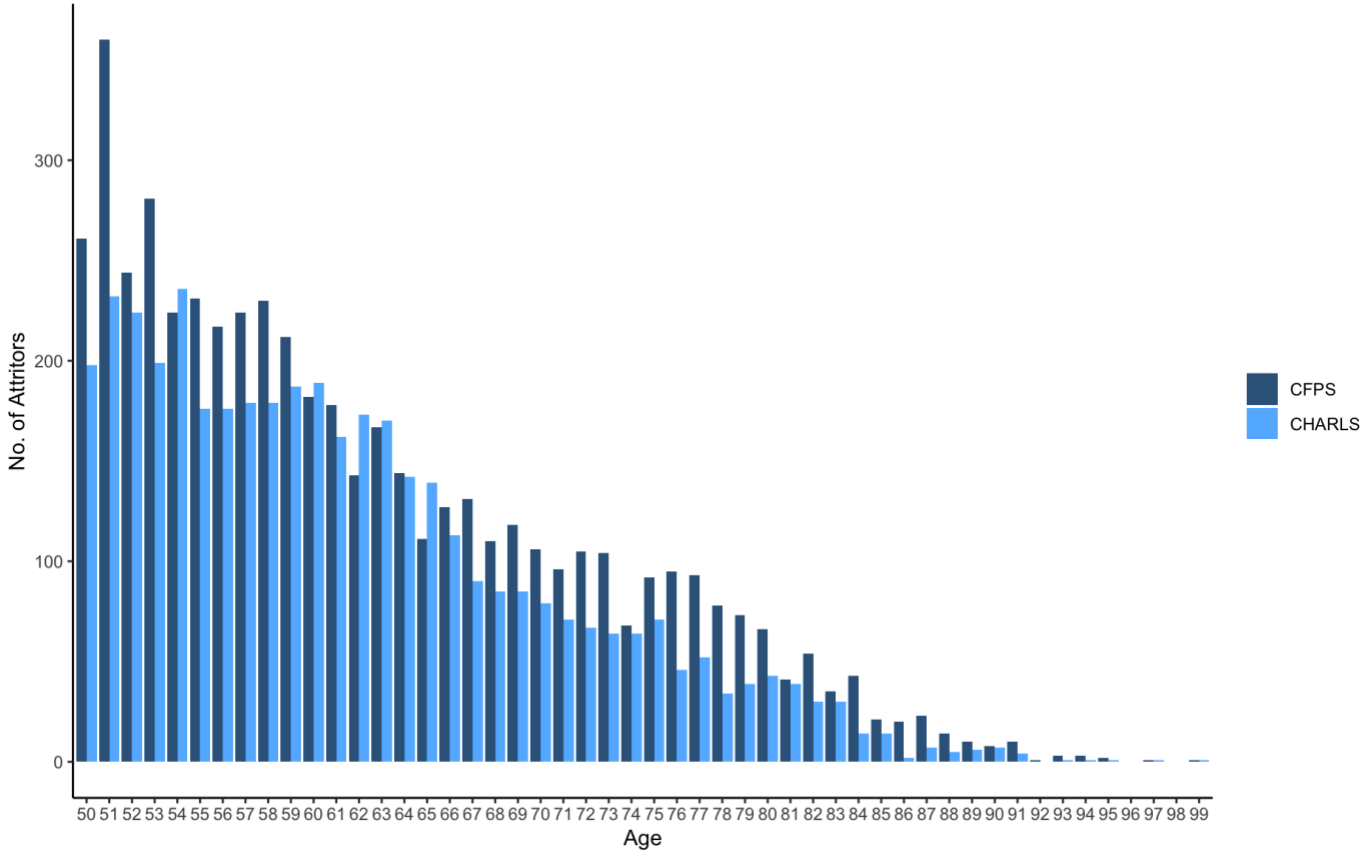
Note: This figure shows the expected death counts in the female Chinese population had the population been subject to death rates estimated from various data sources. The y-axis presents expected death count in thousands. The black solid line refers to the expected death counts using the WHO life tables (benchmark). The blue dot-dashed line refers to the expected death counts estimated using the Chinese Health and Retirement Longitudinal Surveys (CHARLS) waves 2011-2018. The red dashed line refers to the expected death counts estimated using the Chinese Family Panel Studies (CFPS) waves 2010-2018. Results only show female respondents.
The left panel presents estimates of standard practice; that is, ignoring sample attrition in both surveys. The right panel presents estimates of a hypothetical scenario in which all attritors were assumed to have died in both surveys. This is noted as CHARLS* and CFPS* in the right panel. Ignoring panel attrition refers to the common practice of not making any adjustments or imputations beyond marking the respondent as missing, lost to follow-up, or censored.

Appendix Figure A2. Percentage of Attritors Needed to be Dead for Survival Curves to Match WHO Benchmark, CHARLS (2011-2018)



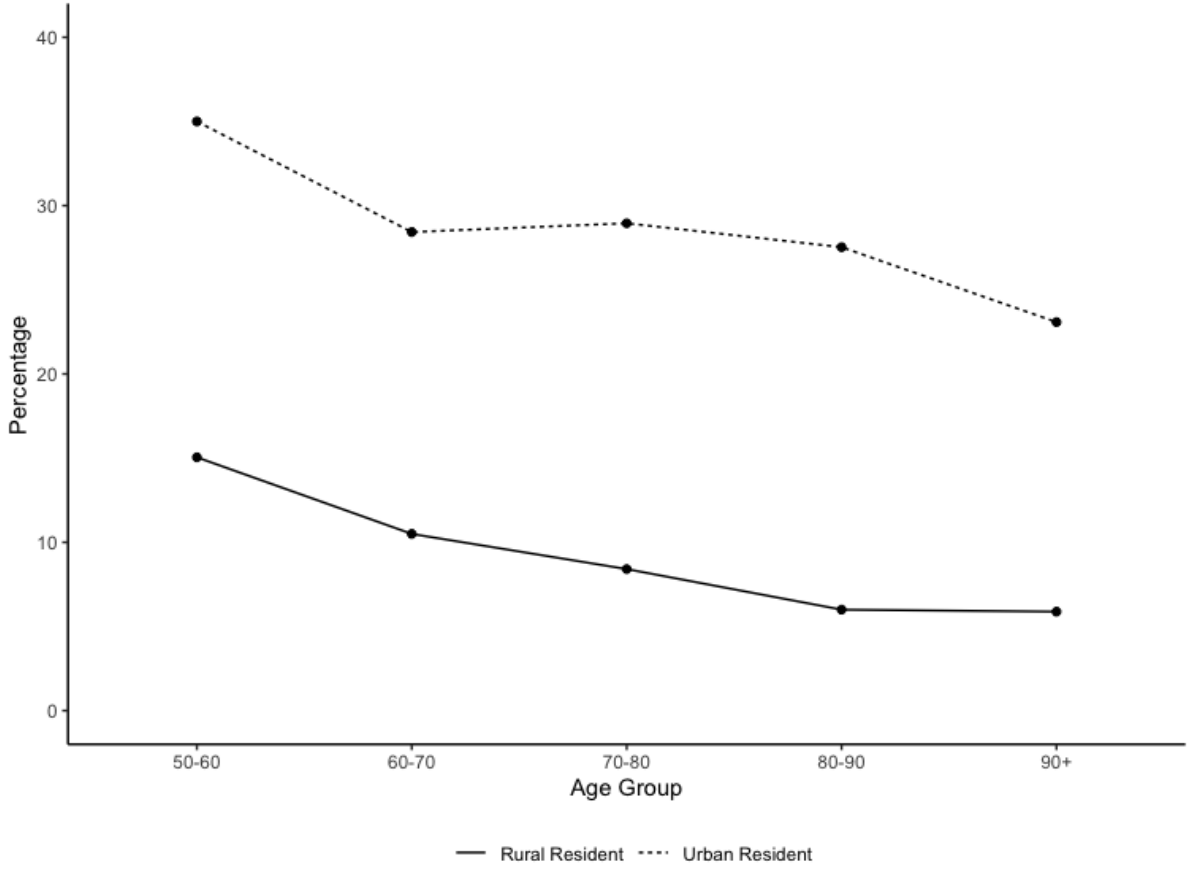
Note. Author's calculation.

Appendix Figure A3. Distribution of Attritors by Age, CHARLS (Waves 2011-2018) and CFPS (Waves 2010-2018)



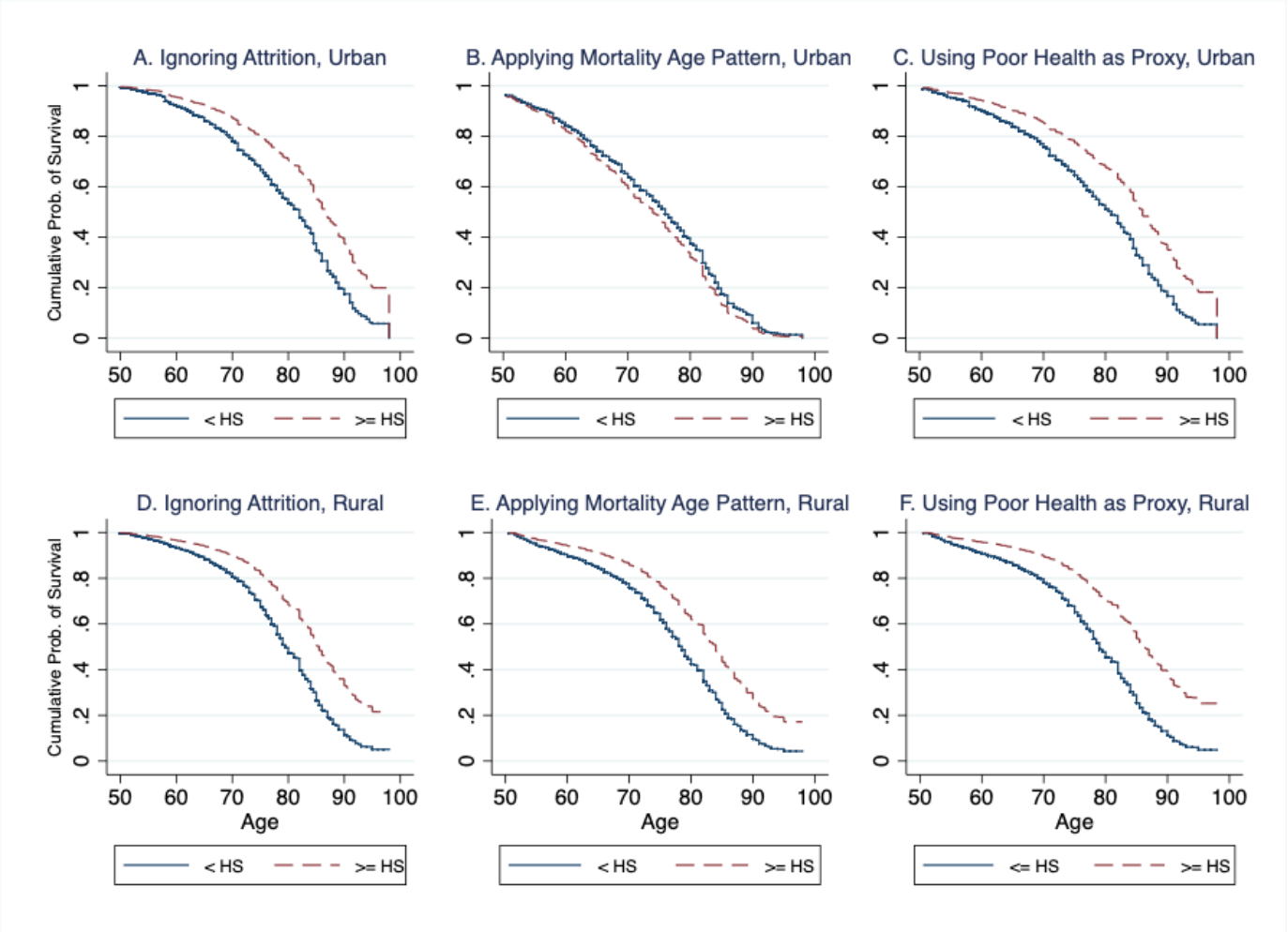
Note. Author's calculation.

Appendix Figure A4. Percentage of Attritors among Urban/Rural Respondents, CHARLS (Waves 2011-2018)



Note. Calculations from CHARLS (waves 2011-2018). Place of residence was based on respondents' self-report at each wave.

Appendix Figure A5. Sensitivity of Education-Mortality Differential, by Urban/Rural Residence, CHARLS (2011-2018)



Note. This graph shows results using the CHARLS (waves 2011-2018) sample. Results in panel B and E were calculated using CHARLS alive-to-death ratios. Log-rank tests were performed and the difference between survival curves of the higher educated and lower educated was statistically significant at 0.05 (two-tailed test) in Panel A, C, D, E and F. <HS refers to respondents with less than high school education. >= HS refers to respondents with high school and beyond education. Results were based both male and female respondents. Baseline weights accounting for individual-level non-response were applied.

Chapter 2: Migration and the Demography of Loneliness: How Internal Migration Shapes the Landscape of Late-Life Loneliness in China

Abstract

China's internal migration—the largest population movement in human history, with over 293 million working-age migrants—has left more than 67 million older parents "left behind". This demographic shift has weakened the social and emotional support that older adults traditionally receive from their children. Despite its scale, how internal migration shapes the national landscape of loneliness—its prevalence and distribution across the population—remains an open question. Using China Health and Retirement Longitudinal Study (2011–2018) and counterfactual analyses, this study demonstrates that internal migration is an important driver of rise in loneliness among aging parents, driven by an increase in complete family separation—where all children have migrated away—rather than partial separation, in which at least one child remains nearby. The implications for low-fertility China are profound: As parents of the one-child cohorts enter old age, current migration trends have the potential to further elevate loneliness prevalence, as a single migrating child leads to complete separation. These findings highlight how large-scale internal migration and persistently low fertility are reshaping the landscape of emotional well-being in aging populations, challenging policy assumptions that rely on families as primary sources of emotional care.

Key Words: Loneliness, internal migration, population aging, family separation, China

"While your parents are alive, do not travel far."

- Confucius, *The Analects*

Introduction

China is experiencing two unprecedented demographic shifts simultaneously: rapid population aging and massive internal migration. The proportion of China's population aged 65 and older is projected to more than double from 12.6% in 2020 to 30.9% by 2050, representing one of the most accelerated demographic aging globally (United Nations 2022). Meanwhile, internal migration has grown drastically over the past four decades — from 6.57 million migrants in 1982 to 293 million in 2022, representing the largest population movement in human history (UNICEF 2019). This massive movement of working-age adults has fundamentally reshaped family living arrangements, creating a phenomenon unprecedented in scale: approximately 67 million "left-behind" older parents—representing one-third of the country's older population—remain in rural hometowns or underdeveloped urban areas while their adult children work in distant cities (China Statistical Press 2012; Connelly and Maurer-Fazio 2016). The physical separation from their adult children reduces opportunities for social connection and emotional support, potentially increasing older adults' vulnerability to loneliness (Wang et al. 2017; Wu et al. 2010). Indeed, evidence shows that loneliness among the Chinese older population increased by 30% between 1995 and 2011(Yan et al. 2014), a period paralleling the rapid expansion of internal migration. This parallel rise raises a critical question: How does this unprecedented rise in internal migration influence the trends and patterns of loneliness among China's aging population?

While extensive research has documented individual-level associations between children's migration and parents' well-being (Antman 2010; Ao, Jiang and Zhao 2016; Kuhn, Everett and Silvey 2011), a critical gap remains in our understanding of how this unprecedented population

movement transforms patterns of loneliness at the national level. Population processes like migration are critical for understanding loneliness in aging societies because they shape both the opportunity structure (who is available for interaction and where) and societal expectations (how much support family members should provide) (de Jong Gierveld and Tesch-Romer 2012). Existing scholarship has established that parents with migrant children face increased risk of psychological distress, social isolation, and reduced support compared to those whose children remain nearby (Antman 2010; Connelly and Maurer-Fazio 2016; Evandrou et al. 2017; Scheffel and Zhang 2019). They have also identified factors that moderate these effects, including family size, communication frequency, and remittance patterns (Chen, Hicks and While 2014). However, these individual-level insights cannot reveal how migration systematically reshapes the prevalence and distribution of loneliness in China's aging population. For instance, whether rising loneliness prevalence stems primarily from an incidence effect (more families experiencing new separations) or a duration effect (the accumulated emotional impact of prolonged separation)—distinct demographic mechanisms with different implications for intervention. This study addresses this gap by aggregating individual-level data to examine population-level correspondence: by analyzing how the changing proportion of older adults with migrant children relates to shifting levels of loneliness in the population, we can better understand how China's massive internal migration reconfigures the national landscape of emotional well-being at older ages.

Understanding migration as a driver of the national landscape of loneliness is necessary as the field of demography of loneliness has only recently emerged, with researchers beginning to map national landscape of loneliness—their prevalence, distribution, duration, and links to social stratification—across populations in China and globally (Newmyer et al. 2021; Raymo and Wang 2022; Wang 2024). While these studies have established important descriptive patterns, the critical

next step is to identify and quantify the demographic forces shaping these patterns, particularly fundamental demographic processes such as migration and fertility. By quantifying how migration-induced family separation corresponds with population-level loneliness, this study reveals how structural demographic forces systematically shape emotional well-being—knowledge essential for anticipating future health burden in populations experiencing both rapid aging and large-scale migration. This approach extends the emerging literature on the demography of loneliness while addressing a fundamental research agenda in the broader field of the demography of aging (National Academies of Sciences 2018): understanding how large-scale demographic shifts shape the patterns of well-being at older ages.

China's historical and persistent low fertility makes it an interesting case study for examining how migration intersects with fertility to shape late-life loneliness. Evidence consistently shows that parents whose children have all migrated away—becoming "empty-nested"—experience the most severe declines in psychological well-being (Ao et al. 2016; Li 2024), suggesting that family size likely determines how migration drives loneliness. Currently, Chinese older adults have approximately 2.5 living children[1]—already fewer than countries like Mexico that face similar migration and aging challenges—making complete family separation through migration more potentially frequent and consequential. Furthermore, China's ultra-low fertility, achieved in just decades rather than the century-long transition seen in many high-income countries, means the current older population will soon be replaced by cohorts with historically small families, including a substantial proportion with only one child. This demographic convergence creates a structural vulnerability unique to China: as low-fertility cohorts age, complete family separation becomes virtually inevitable for many, as even a single child's

[1] Author's calculation based on the analytical sample.

migration leaves parents with no children nearby. What makes this intersection particularly significant is that cultural expectations of filial piety persist and national policies consistently emphasize family support as the fundamental safety net for aging adults, while few alternative sources of emotional support exist outside the family system. The collision between these enduring cultural expectations and the demographic realities potentially amplifies loneliness among China's older adults in ways unseen elsewhere.

The maturity of China's one-child cohort represents a critical demographic milestone that warrants further examination. The cohort born between 1960-1970—the first whose reproductive years fully coincided with the One-Child Policy window—will comprise a sizable proportion of China's elderly population by 2030. While previous generations navigated aging with diminished but still multi-child family structures, this cohort faces unprecedented challenges with approximately 150 million one-child families structured in the "4-2-1" pattern (four grandparents, two parents, one child) (Wang, Cai and Gu 2013), replaced extended family networks where multiple children shared elderly care responsibilities. Their situation represents not merely a reduction in family size but a shift of family support dynamics. One immediate consequence is that when the only child moves away, parents lose all family support nearby.

Demographers have extensively documented the unintended consequences of the One Child Policy, primarily focusing on plummeting fertility rates, skewed sex ratios, accelerated population aging, and the resulting shrinking workforce and caregiving shortage (Bongaarts and Greenhalgh 1985; Cai and Feng 2021; Ebenstein 2010; Wang et al. 2013). However, we know little about how the one-child cohort parents navigate aging and their emotional experiences as they age with unprecedented family structures. Understanding this emotional vulnerability requires a methodological perspective that can anticipate population-level patterns before they

fully emerge. This study addresses this gap by applying a demographic framework that extrapolates observed relationships between migration and loneliness to future cohorts. In addition to quantifying how loneliness corresponds with migration at the population level, this study also projects cohort-specific loneliness prevalence by assuming that current migration patterns will apply to the adult children of future aging parents and that the observed migration-loneliness relationship will persist when one-child cohort parents reach old age. This projection exercise provides preliminary estimates of the emotional vulnerability these cohorts may face, offering a glimpse into the plausible future confronting China's aging population in coming decades.

Drawing on nationally representative data from 2011-2018, this study addresses two questions about the demography of loneliness in China: (1) to what extent can changes in loneliness prevalence be attributed to changing patterns of family separation—particularly the distinction between partial separation (some children migrated) and complete separation (all children migrated)? (2) What are the projected implications for future loneliness burden as the one-child cohorts enter old age, where any child migration necessarily results in complete family separation? Throughout the analysis, this study pays particular attention to how these patterns differ across key demographic dimensions that shape family structures and emotional well-being, including urban/rural residence and gender. Collectively, results from this study seek to demonstrate how the intersection of ultra-low fertility and internal migration collectively shape the emotional well-being of China's current and future cohorts of older adults.

Background

The Demography of Loneliness

Loneliness, defined as the perception of insufficient or inadequate social ties in terms of either scope or quality of connections (Hawkley and Cacioppo 2010; Hawkley et al. 2008), has

emerged as a critical public health challenge in recent decades. Unlike social isolation, which measures objective social disconnection, loneliness captures the subjective experience of perceived social disconnection and inadequate integration into social networks (de Jong Gierveld and Tesch-Romer 2012). This subjective dimension is particularly significant in contexts where family ties form the foundation of intergenerational support (de Jong Gierveld and Tesch-Romer 2012), and that intergenerational social support networks are among the strongest predictors of health and survival in later life in developing countries (DaVanzo and Chan 1994). At the individual level, vulnerability to loneliness is shaped by multiple intersecting factors: socioeconomic resources that enable social participation, health conditions that may constrain social engagement, personality traits that influence interaction patterns, and importantly, the availability and quality of family relationships (see Hawkley et al. 2008).

Loneliness operates not only as an individual experience but as a population-level phenomenon shaped by demographic processes. An emerging field—the demography of loneliness—describes the burden of loneliness at the aggregate level, examines how loneliness is distributed in and across populations, with studies tracking these patterns across time, space, and cohort (see Luhmann, Buecker and Rusberg 2023). Another strand of research demonstrates that the population burden falls unevenly across demographic groups. In the United States, Raymo and Wang (2022) demonstrate that Americans' expected lifetime spent feeling lonely systematically varies by sex, race/ethnicity, and education—revealing how social disparities in emotional well-being contribute to broader health inequalities. Wang (2024) documents similar patterns in China, where adults after age 55 can expect to spend one-third of their remaining lifetime feeling lonely, indicating a substantial national burden of loneliness, though with notable geographic stratification: Rural elders, particularly women, face the most severe burden, while urban residents experience

lower but still substantial burden of loneliness. These patterns of stratification across different societies highlight loneliness as a structural phenomenon shaped by fundamental demographic and social forces.

Researchers are now transitioning from mapping loneliness patterns to uncovering the demographic mechanisms that drive these distributions. This shift toward explanation represents a meaningful step toward understanding how population processes systematically shape loneliness prevalence and patterns. Population aging has emerged as the first well-documented demographic driver of loneliness burden. Newmyer et al. (2022) demonstrated that population aging will significantly increase global loneliness burden, with the number of lonely adults aged 50 and above projected to nearly triple—from 104.9 million in 1990 to 333.5 million in 2050—as demographic distributions shift toward age groups more vulnerable to loneliness.

While population aging is projected to increase global loneliness burden, it cannot fully account for the uneven distribution of loneliness across demographic groups and geographic regions. This points to additional demographic mechanisms at work, with internal migration emerging as a compelling explanatory factor, especially in China. The geographic distribution of loneliness initially suggests migration's influence—rural areas consistently show both higher outmigration rates and higher loneliness prevalence (Wang 2024). However, migration's impact extends beyond this simple geographic divide. Recent patterns show substantial population movement affecting both urban and rural areas, with urban-to-urban migration nearly doubling in recent years, rising from approximately 20.9% to 37.9% of total migration flows (UNICEF 2019). This shift in migration patterns suggests that population mobility is elevating loneliness throughout the country, positioning migration as a demographic driver of China's overall loneliness burden rather than merely creating geographic disparities. Yet, no study has formally quantified

migration's contribution to the nationwide emotional vulnerability. Understanding how internal migration systematically shapes the national landscape of loneliness thus represents a next step and may explain why China's older population collectively experiences such high burden of loneliness.

Migration may shape population-level loneliness through two distinct mechanisms. First, migration of adult children creates an incidence effect by expanding the population experiencing disrupted kinship ties. This separation reduces social support and increases loneliness (Cong and Silverstein 2008; Song 2017b), with effects particularly pronounced in low-income rural areas (Song, Wang and Burr 2022). As the number of migrant children increases, a larger proportion of older adults likely experience family separation, possibly elevating the prevalence of loneliness in the population. Second, prolonged separation generates a duration effect that may deepen emotional impact over time. Evidence from Anhui, China shows older adults whose children remained migrants for longer periods experienced steeper increases in depressive symptoms as they aged (Lin and Tang 2023), with similar evidence showing long-term migration exacting a heavier toll on parental health than short-term migration (Li 2024; Song 2017a). At the population level, this mechanism works by increasing the proportion of separated parents who cross the threshold into experiencing loneliness as time since separation extends. While parents may initially adapt to children's migration, prolonged separation can erode coping resources, causing more parents to transition from non-lonely to lonely states over time.

Children's Migration and Parents Well-being

At the individual level, substantial evidence documents how children's migration negatively affects older parents' psychological well-being, particularly in societies where intergenerational proximity is culturally normative (Angel, Vega and Lopez-Ortega 2017; Antman

2010; Ao et al. 2016; Yahirun and Arenas 2018; Zhong and Zhao 2020). Parents with migrant children consistently report higher levels of social isolation and emotional distress compared to those whose children remain nearby (Abas et al. 2013; Bridges and Liu 2022; King and Vullnetari 2006; Kumar 2021; Li et al. 2020; Yahirun and Arenas 2018; Zhong and Zhao 2020). While remittances and modern communication technologies provide some material benefits and facilitate long-distance contact, evidence in China suggests these advantages rarely compensate for the absence of in-person family support, particularly for parents needing substantial care (Bridges and Liu 2022; Li et al. 2020).

The emotional impact of children's migration on elderly parents varies based on the number of children who migrate. In families with multiple children in rural China, non-migrant children typically serve as buffers against psychological distress (Giles, Wang and Zhao 2010; Guo, Aranda and Silverstein 2009; Song 2017b). Parental well-being deteriorates progressively with each additional migrant child—Ao et al. (2016) found each additional migrant child increases poor health likelihood by approximately 8%. The most severe impacts occur in families with an only child who migrates, where parents face acute emotional challenges due to complete absence of local children (Ao et al. 2016; Li 2024). Understanding migration's population-level impact thus requires careful attention to both partial separation (some children migrated) and complete separation (all children migrated), as these distinct configurations may differently shape loneliness prevalence.

The Case of China: the Urban/Rural Distinction

Urban and rural contexts represent distinct demographic and social environments that may likely differ in how migration drives loneliness at the aggregate level.

Urban and rural areas differ in their demographic vulnerability to family separation through migration. Rural areas generally maintain stronger traditional family values and more explicit filial expectations (Giles et al. 2010), creating potentially larger gaps between expected and received support when children migrate. However, urban areas face unique structural constraints due to lower fertility rates—a direct consequence of both socioeconomic conditions and stricter enforcement of the One-Child Policy in cities. With urban fertility averaging just 1.3 children per woman compared to 2.4 in rural areas (National Bureau of Statistics, 2020), urban parents have a much higher likelihood of experiencing complete family separation when migration occurs. This demographic feature creates a structural vulnerability where any child's migration almost certainly results in complete family separation, potentially overwhelming any protective effects of urban advantages like better service access and healthcare infrastructure.

The importance of distinguishing between urban and rural experiences has grown as China's total migrant flow shifts towards greater proportion of urban-to-urban migration (UNICEF 2019). This increase reflects the heterogeneity within urban China that traditional rural-focused migration narratives often overlook: the urban part of China is highly unequal in terms of economic development, job prospects, living conditions, such that parents in less developed cities increasingly experience family separation as their adult children migrate to mega-cities for economic opportunities, yet they remain understudied in migration literature despite potentially facing emotional challenge (Ao et al. 2016; Giles et al. 2010; Song et al. 2022; Wang et al. 2017; Xiang, Jiang and Zhong 2016). Ignoring this growing segment of urban parents with migrant children will lead to an incomplete understanding of migration's impact on emotional well-being and could result in interventions that miss the unique family constraints facing urban residents.

Although this study focuses primarily on migration as a driver of increasing loneliness, several other demographic shifts likely contribute to both current prevalence and future trends. First, population aging mechanically increases the absolute number of potentially lonely adults by shifting the age distribution toward groups more vulnerable to loneliness (Newmyer et al. 2022). Second, changes in family structures, such as the rise of single-generation households and solo living, may increase loneliness prevalence by reducing opportunities for daily intergenerational interaction that traditionally buffered against social isolation. Third, rising educational attainment among younger cohorts may provide protective resources through expanded social networks (Yang and Victor 2011). Fourth, changes in the proportion married may closely linked to the proportion feeling lonely, as marriage is generally associated with lower loneliness risk while widowhood often leads to reduced social networks and increased risk of isolation, particularly when other family support is limited (Yang and Gu 2021). Additionally, health composition—particularly the rising prevalence of chronic conditions and functional limitations—constrains social engagement opportunities and increases dependency, potentially amplifying loneliness when family support is disrupted through migration (Cohen-Mansfield et al. 2016; Yang and Gu 2020).

Data and Measures

This analysis draws on data from the China Health and Retirement Longitudinal Study (CHARLS) from 2011 to 2018. In each wave, a replenishment sample was added to maintain overall national representativeness (Zhao et al. 2013). This study focused on participants with at least one living child, who comprised 96.4% of the original sample. After excluding 924 respondents without living children from the initial 25,586 participants, the final sample consisted of 24,662 individuals, contributing 60,258 person-wave observations. These respondents averaged 56.74 years of age and

had 2.5 living children (see Table 1). The most recent CHARLS wave (2020) was not included due to the omission of questions regarding the residence of children.

Additional exclusions were made for respondents with missing data: 419 observations with missing age, 17 observations with missing or unclear education, 793 respondents with missing information on loneliness, and 1,806 respondents who used a proxy during the interview and thus had no data on loneliness. An additional 501 respondents with missing information on children's migration status were excluded as well. Among the remaining respondents, 81% came from the original baseline sample, while the remaining 19% were part of a refreshment sample added at later waves. Of the final sample, approximately 93% of respondents had data for at least three waves of observation.

Measures

Loneliness: CHARLS measured loneliness by asking respondents how frequently they experienced loneliness during the week prior to the interview, with response options ranging from "not at all" to "most of the time." The analysis employed a dichotomous measure of loneliness, classifying respondents as lonely if they reported experiencing loneliness for at least a moderate amount of time. This dichotomization approach aligned with common practice in existing research (see Luo and Ye 2014), particularly given that the distribution of responses was highly skewed toward reporting no loneliness.

Children migration Children's migration status was determined from respondents' reports of each child's residence location in the household roster. Following standard definitions of internal migration (UNICEF 2019), a child was classified as "migrated" if they had not lived with or near the respondent for at least 6 months. Children were considered living "nearby" if they resided in the same village, county, or residential complex as the respondent, similar to how UNICEF

distinguishes local mobility from migration by excluding moves within the same township or district. A respondent was considered to have a non-migrated child if at least one child resided in the same household or lived nearby. This measurement approach, which conceptualizes migration as a family-level phenomenon, aligns with established research examining migration's consequences for older parents' well-being in developing countries (Kuhn et al. 2011; Song et al. 2022).

On average, respondents reported having 2.5 living children, with approximately 80% having more than one child. For respondents with multiple children, previous research suggests that migration's impact varies by factors such as the number and gender of migrant children (Lin and Tang 2023; Song 2017a). Given that children often migrate sequentially rather than simultaneously, the analysis developed two measures to capture different patterns of family separation through migration. The first measure, *at least one child migrated*, indicated whether a respondent had at least one migrant child, but not all, by wave *t*. The second measure, *all children migrated*, identified cases where all children had migrated by wave *t*. Together, these measures captured the progression of family separation—from having all children nearby, to partial separation through migration, to complete family separation. At baseline, among respondents with multiple children, 30% had at least one migrated child, while 10% reported all children had migrated.

Analytical Strategy

Aim 1: How much of the increase in loneliness is due to increases in children's migration?

To estimate how changes in children's migration contributed to rising loneliness, the analysis proceeded in two steps. First, separate logistic regression models were estimated for wave 1 (year 2011) and wave4 (year 2018). The individual-level model was specified as:

$$logit(l_{i,p,t}) = \beta_0 + \gamma M_i + X_{i,t}\theta + \delta t + P_p + \varepsilon_{i,t} \ (1)$$

Where $logit(l_{i,s,t})$ is the log-odds of loneliness for individual i in province p at time t; M_i is an indicator for the migration status of children (either having at least one child migrated or all children migrated away). $\boldsymbol{X}$ is a vector of other individual characteristics, t is a control for time, and $\boldsymbol{P}_p$represents a vector of province fixed effects[2].

The second step uses the coefficients from equation (1) to estimate children migration's contribution to rising loneliness between 2011 and 2018, assuming only the proportion of children's migration changed over this period. Specifically, I replace the 2013 proportions of children having at least one child migrated and having all children migrated with the corresponding proportions from 2018. The resulting change in predicted loneliness prevalence quantified how shifts in children's migration patterns contributed to the population-level increase in loneliness. If children's migration is positively associated with loneliness, as hypothesized, the predicted increase in loneliness prevalence will provide an estimate of the effect of changes in children's migration status, while holding other factors constant.

As a robustness check, I also conducted a non-linear extension of the Oaxaca-Blinder decomposition to examine children's migration's contribution to changing loneliness prevalence while accounting for other potential drivers of rising loneliness at the population level. These factors include: age structure, proportion of individuals with good self-reported health, proportion of individuals living alone, proportion of married individuals, proportion of individuals with at least one living sibling, and proportion of individuals having higher education.

While the Oaxaca-Blinder decomposition provides a comprehensive accounting of all factors contributing to rising loneliness, the counterfactual approach offers two distinct advantages:

[2] Results using linear probability models show similar estimates and are available upon request.

it generates intuitive, policy-relevant estimates by isolating migration's direct impact on loneliness prevalence, and it provides a framework for projecting future vulnerability as one-child cohorts age.

Aim 2: Understanding the implication for low-fertility China

The second aim focuses on projecting loneliness prevalence for parents born between 1960 and 1970—the cohort most affected by China's one-child policy—when they reach age 65. The analysis proceeds in three steps. First, an age-cohort analysis examined patterns of complete child migration using the 2011-2018 waves. Assuming minimal period effects over this timeframe, the analysis modeled the probability of having all children migrated as a function of age groups (in 5-year intervals), birth cohorts, and number of children, while controlling for key parent characteristics and province fixed effects. The model is specified as follows:

$$M_i = \alpha_0 + \beta\, Age_i + \gamma Cohort_i + \theta Child_i + \lambda(Cohort \times Child)_i + X_i'\sigma + P_p + \eta_i \quad (2)$$

where M_i is an indicator for children's migration, Age_i represents age group indicators (5-year age group), $Cohort_i$ represents birth cohort, $Child_i$ represents number of children, X_i represents other parent characteristics, P_p represents province fixed effects, and $\eta_{i,t}$ is the error term. The model included interactions between birth cohort and number of children to account for how fertility-migration relationships might vary across cohorts [3].

To validate this approach, I use data from 2011-2015 to predict migration outcomes in 2018, comparing predicted probabilities with actual outcomes across different age groups and

[3] The model includes interaction terms between birth cohort and number of children to examine how the relationship between family size and migration patterns varies across birth cohorts. This interaction is included because the probability of having all children migrate may depend not only on how many children a parent has, but also on when those parents were born. For example, among parents with two children, those born in 1960 may face different probabilities of having all children migrate compared to those born in 1970, even though they have the same family size. These cohort differences could reflect broader societal changes across generations, including changing social norms around family obligations, expanding economic opportunities in urban areas, and rising education levels among younger cohorts.

family sizes. Results show that the predicted proportion of having all children migrated closely matches with the actual proportion observed in 2018, as shown in Appendix Figure A1.

Next, I project the likelihood of complete child migration when this cohort reaches age 65-75, accounting for their fertility patterns and cohort characteristics. Following the methodology described in Munnell, Sanzenbacher and Zulkarnain (2020), I classify respondents as future parents of having all children migrated if their predicted probability exceeded a random draw from a uniform [0,1] distribution[4]. Finally, the predicted proportion of parents experiencing complete family separation through migration were combined with coefficients from equation (1) to estimate loneliness prevalence for this cohort when they reach age 65-75.

All analyses are estimated using the weights provided by CHARLS to adjust for household-level nonresponse and differential propensity to select into the sample.

Results

Table 1 presents descriptive statistics comparing sample characteristics in 2011 and 2018. While key demographic characteristics—gender composition, education level, and urban/rural residence—remained stable, significant changes emerged in family arrangements and migration patterns. By 2018, respondents reported having fewer living children but more living siblings compared to 2011 (both $p<0.001$), alongside a slight decline in the proportion married (from 88.68% to 87.15%, $p<0.001$). There was also a slight increase in the proportion of respondents reporting good self-reported health (from 18.97% to 19.29%, $p<0.001$).

[Table 1 About Here]

[4] A sensitivity analysis using a simpler 0.5 probability threshold yielded similar results.

The most pronounced changes during this period occurred in children's migration patterns and loneliness prevalence. The proportion of respondents experiencing complete family separation (where all children migrated) rose from 11.62% to 22.40%, while those experiencing partial family separation (where at least one child migrated) increased from 35.26% to 48.15% (both $p<0.001$). Figure 1 shows that the prevalence of complete family separation rose across all population groups. Both urban and rural areas experienced this upward trend, though rural parents showed higher prevalence, with complete separation increasing from 13% to 28% compared to urban areas' increase from 9% to 15%. Similarly, partial family separation revealed urban-rural differences: rural areas experienced a substantial increase from 39% to 59%, while urban areas showed a more modest rise from 29% to 33%. While partial separation remained more common throughout the period, the increase in complete separation warrants particular attention: as previous research suggests, the absence of all children removes an important buffer against social isolation, potentially creating a more direct pathway to loneliness than when at least one child remains nearby.

[Figure 1 About Here]

Meanwhile, the proportion of respondents reporting feelings of loneliness increased from 19.25% to 29.11% ($p<0.001$). To put this increase into perspective, given China's population aged 45 and above of approximately 500 million in 2018, this 10 percentage point increase translates to roughly 50 million additional middle-aged and older adults reporting feelings of loneliness. Loneliness prevalence showed consistent differences across gender and urban/rural residence. Women consistently experienced higher loneliness levels than men in both age groups. Rural residents reported higher loneliness prevalence compared to urban residents (detailed estimates in Appendix Table A1). When examining the intersection of gender and residence, a clear pattern

emerges: rural women reported the highest loneliness levels, while urban men showed the lowest prevalence among all gender/residence combinations (See Appendix Figure A2).

Migration's Contribution to Rising Loneliness

Table 2 presents odds ratios from logistic regressions analyzing how children's migration status relates to parents' likelihood of experiencing loneliness. Model 1 shows that having at least one migrated child but not all (versus no migrated children) is associated with a 9% higher likelihood of feeling lonely (OR=1.09, 95% CI=[1.05, 1.13]), after adjusting for year, gender, urban/rural residence, education, marital status, number of children, poor self-rated health, and presence of living siblings. Model 2 reveals a stronger relationship: having all children migrated (versus having at least one child present) is associated with a 31% higher likelihood of feeling lonely (OR=1.31, 95% CI=[1.25, 1.37]), controlling for the same factors. These findings indicate that while having one child migrate increases the risk of loneliness, it is the migration of all children that more strongly elevates parents' likelihood of feeling lonely.

[Table 2 About Here]

The regression models show significant associations between children's migration and parental loneliness, though much of the individual-level variation in loneliness remains unexplained by the measured characteristics (r-square ~ 12%). However, prior research examining similar demographic trends suggests that modest individual-level explanatory power need not preclude meaningful insights about aggregate patterns. For example, in their analysis of declining poverty among American widows, Munnell et al. (2020) found that while their model explained only 17% of individual-level variance, it effectively captured changes in average poverty rates

across time periods[5]. Similarly, while this study's regression model may not fully predict any given individual's experience of loneliness, it can still provide insights into changes in population-level loneliness rates between 2011 and 2018, especially considering that many unmeasured factors likely remained relatively stable during this period.

Figure 2 compares actual loneliness prevalence with counterfactual estimates. The black bars display observed prevalence in 2011 and 2018, while blue patterned bars represent counterfactual estimates of what 2018 loneliness levels would be if only migration patterns changed from 2011 levels while holding all other factors constant. The changing proportion of partial family separation (having at least one child migrated but not all) explains only about 3% of the increase in loneliness (calculated as [19.33-19]/[29.31-19]=0.33/10.31=3.2%), while changes in complete family separation (having all children migrated) account for approximately 30% of the rise (calculated as [22.1-19]/[29.31-19]=3.1/10.31=30.1%). This analysis reveals that complete family separation is a primary driver of increased loneliness at the population level, while partial separation contributes minimally. As shown in Appendix Figure A5, the emotional impact of newly occurring complete family separations (incidence effect), rather than the accumulated strain of long-term separation (duration effect), is the primary mechanism driving this relationship (see Appendix II for detailed methodology).

[Figure 2 About Here]

Table 3 shows the results from the non-linear extension of the Kitagawa-Oaxaca-Blinder decomposition, distinguishing between changes in the distribution of measured characteristics

[5] It successfully predicted the substantial decline in widows' average poverty rates between time periods—from 20% in the 1990s to 13% in the 2000s—demonstrating its utility for understanding population-level changes even when individual outcomes were harder to predict.

(composition effects) versus changes in how these characteristics relate to loneliness (coefficient effects). Complete separation emerges as the single largest positive compositional factor contributing to increased loneliness, explaining 22.45% of the total increase, which confirms the results from Figure 2. Additionally, the small and non-significant coefficient effect of complete separation confirms that children's migration influenced loneliness during 2011-2018 primarily through new transitions rather than accumulated strain.

[Table 3 About Here]

Changes in children's migration patterns contribute differently to rising loneliness in urban and rural areas. Appendix Figure A3 shows that migration patterns account for approximately 35% of the increase in loneliness among urban residents, where prevalence rose from 18% to 25%. In contrast, among rural residents, where loneliness increased more sharply from 25% to 34%, migration patterns explain only about 15% of this rise. These estimates are further confirmed by decomposition analysis (Table 3), which attributes 30.79% of urban loneliness increases to migration compared to just 11.55% in rural areas. Interestingly, urban loneliness increases are more explainable through measured characteristics (20.5% vs. 7.7% composition effects in Table 3) and more strongly driven by migration. Rural loneliness increases, in contrast, are less explainable through measured factors and show a much larger constant term (170.45% vs. 124.87%), suggesting unmeasured social or cultural changes play a more significant role in rural emotional well-being.

Despite the rise of complete separation explaining a substantial proportion of rise in loneliness, a larger part remains unexplained. Beyond children's migration, most of the loneliness increase (80-92%) stems from changing relationships between social factors and loneliness, rather than changing distribution of those factors in the population (Table 3). During 2011-2018, two

relationships emerge as particularly important: the weakening protective association of marriage and changes in how health relates to loneliness. Changes in the marriage-loneliness relationship account for 104.52% of the overall increase in loneliness, indicating that marriage became significantly less protective against loneliness over time—married individuals were more likely to report loneliness in 2018 than in 2011, even with similar demographic profiles and family separation patterns. If not counterbalanced by other factors—particularly the changing relationship between health and loneliness (which worked against the trend by 160-175%)—this shift would have produced an even larger increase in loneliness than observed. The negative coefficient for health indicates that poor self-reported health became less strongly associated with loneliness during this period; individuals with poor health in 2018 were less likely to report loneliness compared to those with similar health status in 2011, potentially reflecting changing expectations about health and social integration in later life.

The implication for low-fertility China

The finding that complete family separation—rather than partial separation—drives rising loneliness reveals a structural vulnerability in China's demographic future. As one-child parents enter old age, their smaller family size creates a structural constraint where any child migration necessarily results in complete separation—precisely the condition most strongly associated with loneliness. Table 4 quantifies this vulnerability, showing that parents born after 1960—the first generation whose prime reproductive ages fully overlapped by the fertility restriction window—face higher odds of complete family separation (OR=12.89, 95% CI=[9.45, 17.59]) compared to the pre-1950 cohort, even after controlling for key demographic characteristics. Having only one child nearly triples the odds of experiencing complete family separation (OR=2.90, 95% CI=[2.05, 4.11]) compared to having multiple children.

[Table 4 About Here]

Using coefficients from Table 4, I project the proportions of complete separation for when these cohorts reach age 65. Figure 3 compares these projections between the post-1960 cohort and the 1950-1960 cohort, with the left panel showing age trajectories for both cohorts and the right panel isolating the trends of complete family separation. Both panels reveal a substantially steeper rise in complete separation among the post-1960 cohort (from 15.8% to 57.4%) compared to the 1950-1960 cohort (31.2% to 49.4%). By age 65, the post-1960 cohort is projected to have 8 percentage points higher complete separation than the 1950-1960 birth cohort. When examining these projections across demographic subgroups, Table 5 reveals remarkably similar vulnerability patterns despite traditional urban-rural distinctions—urban parents (56%), rural parents (59%), men (58%), and women (57%) all face comparable risks of complete family separation by age 65. This demographic convergence suggests that urban areas are rapidly catching up to rural areas in vulnerability to migration-driven family separation, primarily because urban parents have significantly smaller average family sizes.

[Figure 3 About Here]

These demographic projections translate directly into anticipated loneliness burden as one-child cohorts age. When the post-1960 cohort reaches age 65, our model projects their loneliness prevalence will increase to 33%—a 17.9% increase from 2018 levels—driven specifically by rising prevalence of complete family separation. This burden will distribute unevenly across demographic groups despite similar rates of complete separation: urban parents face the largest projected increase in loneliness (19.9%) compared to rural parents' more moderate increases (12.5%, or just 4.8% using conservative estimates). These projections reveal a previously overlooked consequence of the One Child Policy: as parents with historically small families enter

old age, the interaction between ultra-low fertility and internal migration creates a structural vulnerability to loneliness that increasingly transcends traditional urban-rural divides. This vulnerability will progressively manifest as cohort succession unfolds over the coming decades.

[Table 5 About Here]

Discussion

This study examines how China's massive internal migration—the largest population movement in human history—shapes the national landscape of loneliness among middle-aged and older adults. Three key findings emerge with implications for China's demographic future: First, loneliness prevalence increased substantially from 19% to 29% between 2011-2018, with complete family separation (all children migrated) explaining approximately 22-30% of this rise, while partial separation contributed minimally despite being more common. Second, children's migration contributes more strongly to loneliness increases in urban areas than rural areas, reflecting urban parents' average smaller family size and challenging conventional narratives that focus primarily on rural vulnerability. Third, parents from one-child cohorts face heightened vulnerability to loneliness as they age: projections indicate nearly 60% will experience complete family separation by age 65, potentially increasing their loneliness prevalence by 18% beyond current levels. Collectively, these findings demonstrate how the convergence of internal migration with historically low fertility creates systematic challenges for emotional well-being that will increasingly characterize China's future.

This study extends the emerging field of the demography of loneliness by identifying migration as a significant demographic driver of emotional well-being at older ages. This finding has important implications for projecting the future global burden of loneliness, which may be substantially higher than current estimates suggest. While previous research established that

population aging alone will dramatically increase loneliness by applying currently observed age-specific loneliness profiles to future age structures (Newmyer et al., 2022), these projections likely underestimate the full burden by overlooking migration's independent effects. The finding that internal migration contributes approximately 30% to increasing loneliness prevalence indicates that current global projections may significantly undercount future loneliness in regions experiencing substantial population movements. This quantified relationship has implications beyond China for numerous countries undergoing similar demographic transitions. Populations with strong familial traditions like Vietnam, Indonesia, and Thailand—where extensive internal migration coincides with rapid population aging and fertility declines—may face comparable challenges to emotional well-being as family separation through migration becomes increasingly prevalent.

In addition, this study highlights migration as a critical demographic process shaping the landscape of old-age well-being. While the demography of aging literature has extensively examined how changing patterns in fertility, mortality, marriage and partnership reshape social contexts for older adults (National Academies of Sciences 2018), the role of migration remains relatively unexplored despite mounting individual-level evidence linking children's migration to older parents' health outcomes. This study demonstrates that migration is not merely an individual life event but a substantial population process with measurable impacts on emotional well-being at the aggregate level, with implications for understanding the kin availability in rapidly aging developing countries where large-scale migration is extensive. For example, recent studies using formal kinship models to project kin availability in developing populations has primarily relied on mortality and fertility profiles without incorporating migration patterns (see discussion in Matos-Moreno et al. 2025)—potentially overlooking how migration disrupts kinship networks and

complicates care arrangements. Thus, their estimates of kin and care availability may be conservative. Furthermore, the findings also reveal how fertility and migration interact across successive cohorts to create distinct vulnerability profiles—as China transitions from older cohorts with multiple children to younger one-child cohorts entering old age, the demographic consequences is likely to be amplified by lowest-low fertility, a demographic vulnerability embedded in the population structure that will unfold as cohort succession progresses. Note that migration influences old-age well-being not only through family changes but also by reshaping community social capital in both sending and receiving regions—depleting social resources in origin communities (e.g., see Song et al. 2022) while potentially creating new support networks in destination areas (e.g., through paid caregiving). The substantial heterogeneity of migration patterns, particularly regarding distance, frequency of return visits, and communication technologies, likely moderates these outcomes and merits further investigation to fully understand how population movement reconfigures the emotional landscape of aging societies.

The key theme in understanding the consequences of children's migration and wellbeing of the "left-behind" older adults, particularly in China, has traditionally emphasized rural parents' vulnerability to adult children, portraying rural areas as disproportionately affected by out-migration and subsequent family separation. However, this study reveals a significant but overlooked vulnerability among parents living in underdeveloped cities. Children's migration plays a stronger role in driving loneliness among these parents than rural, directly linked to their smaller family sizes resulting from a blend of both a history of faster fertility decline and stricter enforcement of fertility policies in urban areas compared to rural regions. While rural parents currently experience higher absolute loneliness levels, the projections indicate that urban loneliness will increase at an accelerated rate, potentially narrowing the rural-urban gap as the one-

child cohort parents enter old age, highlighting a demographic vulnerability created by the intersection of persistent migration patterns and historically low fertility in urban areas. As economic opportunities continue to draw children to megacities, urban parents with fewer children face a structural disadvantage that increases their risk of complete family separation and subsequent loneliness. Nevertheless, this does not diminish the significant challenges facing rural China's left-behind elders. An unexpected finding from Table 3 reveals substantially larger unexplained components in the rise of rural loneliness, suggesting factors beyond our measured demographic variables—perhaps cultural, social, or community-level changes—play more significant roles in rural emotional well-being than in urban areas and warrant further investigation.

Limitation

Several methodological caveats warrant discussion. First, this decomposition analysis examines population-level associations between migration patterns and loneliness prevalence, rather than establishing direct causal relationships. Migration could affect loneliness through multiple pathways—including remittances, improved living standards, and changes in family dynamics—which the analysis cannot fully disentangle. Parents whose children migrate may differ systematically from those whose children remain nearby in ways that affect their propensity for loneliness. For instance, if children are more likely to migrate when their parents are more resilient or have stronger social networks (positive selection), the analysis might underestimate migration's association with loneliness. Conversely, if children are more likely to migrate when parents are already socially isolated (negative selection), the estimates might overstate migration's contribution to loneliness prevalence.

However, as Munnell et al. (2020) demonstrate in their analyses of widows' poverty trends, demographic decomposition methods can provide good insights about population-level changes

even when individual-level relationships are complex. While their model explained only 17% of individual-level variance in poverty status, it effectively captured changes in average poverty rates over time. Similarly, the goal of this study is not to isolate the causal effect of migration on individual experiences of loneliness, but rather to understand how changing migration patterns correspond to the observed increase in loneliness prevalence among China's older population. Selection concerns warrant caution in interpretation but do not negate the value of identifying migration as a significant demographic driver of changes in loneliness prevalence, particularly given this study's focus on broad demographic shifts rather than individual-level causal effects.

Second, the data cannot distinguish between international and internal migration. While international migration represents a small proportion of total migration in China during this period and is largely concentrated in urban areas (UNICEF 2019), this distinction may be meaningful. Research from Mexico, for instance, suggests that parents whose children emigrated internationally experience similar levels of emotional well-being compared to parents of non-migrants (Yahirun and Arenas 2018), indicating that different types of migration might have distinct emotional impacts.

Third, the measure of loneliness, while consistent with previous research (Luo and Waite 2014), captures only the frequency of feeling lonely in the past week. More nuanced measures might reveal different patterns or mechanisms. Additionally, the data lack detailed data about the frequency of contact or quality of relationships between migrants and parents. High non-response rates for survey items about weekly contact and grandparent caregiving prevented from examining how these factors might mediate the relationship between migration and loneliness—an important area for future research.

The projected burden of loneliness likely underestimates the full impact of demographic change on future cohorts' emotional well-being. While nearly all current older adults (99%) in CHARLS 2011-2018 had at least one child, future cohorts will include increasing numbers of childless adults due to lifelong singlehood or voluntary childlessness. The projections showing a roughly 18% increase in loneliness prevalence as one-child cohorts enter old age are conservative for several reasons: they only capture migration effects while holding other social factors constant; they don't fully account for one-child parents' lack of the protective buffer that multiple children provide (Giles et al. 2010); and they cannot incorporate how these future cohorts' different expectations about family support might shape their emotional responses to separation—potentially intensifying loneliness if higher quality-of-life expectations create disappointment when support is unavailable, or possibly moderating it if reduced filial expectations lead to better psychological adaptation to separation.

Despite these limitations, this study highlights an intergenerational emotional cost of fertility restriction that has remained largely unexplored in assessments of the policy's long-term consequences. The projected increase in loneliness prevalence as one-child cohorts reach old age represents a looming challenge that extends beyond more frequently discussed concerns about caregiving shortages, healthcare delivery, and pension sustainability. While current policy frameworks primarily emphasize material solutions like expanding nursing facilities (Qiao 2001), they overlook emotional well-being—a dimension the World Health Organization identifies as fundamental to healthy aging (Kim et al. 2021). This study calls for reconceptualizing China's approach to population aging by integrating emotional health alongside practical needs. The urgency of this shift becomes particularly apparent given loneliness's strong association with cognitive decline (Read, Comas-Herrera and Grundy 2019; Yu, Westrick and Kobayashi 2023),

suggesting that understanding these demographic drivers can help policymakers anticipate and address emerging challenges in cognitive health before they manifest as major public health burdens.

References

Abas, M., Tangchonlatip, K., Punpuing, S., Jirapramukpitak, T., Darawuttimaprakorn, N., Prince, M., and Flach, C. (2013). Migration of children and impact on depression in older parents in rural Thailand, southeast Asia. *JAMA Psychiatry*, *70*(2), 226-234. https://doi.org/10.1001/jamapsychiatry.2013.271

Angel, J.L., Vega, W., and Lopez-Ortega, M. (2017). Aging in Mexico: Population Trends and Emerging Issues. *Gerontologist*, *57*(2), 153-162. https://doi.org/10.1093/geront/gnw136

Antman, F.M. (2010). Adult Child Migration and the Health of Elderly Parents Left behind in Mexico. *American Economic Review*, *100*(2), 205-208. https://doi.org/10.1257/aer.100.2.205

Ao, X., Jiang, D., and Zhao, Z. (2016). The impact of rural–urban migration on the health of the left-behind parents. *China Economic Review*, *37*, 126-139. https://doi.org/https://doi.org/10.1016/j.chieco.2015.09.007

Bongaarts, J.and Greenhalgh, S. (1985). An alternative to the one-child policy in China. *Population and Development Review*, 585-617.

Bridges, S.and Liu, L. (2022). The impact of child migration on the health and well-being of parents left behind. *Journal of International Development*, *34*(6), 1145-1164.

Cai, Y.and Feng, W. (2021). The social and sociological consequences of China's one-child policy. *Annual Review of Sociology*, *47*(1), 587-606.

Chen, Y., Hicks, A., and While, A.E. (2014). Loneliness and social support of older people in China: a systematic literature review. *Health & Social Care in the Community*, *22*(2), 113-123. https://doi.org/https://doi.org/10.1111/hsc.12051

China Statistical Press. (2012). *Tabulation on the 2010 population census of the People's Republic of China*. China Statistics Press.

Cohen-Mansfield, J., Hazan, H., Lerman, Y., and Shalom, V. (2016). Correlates and predictors of loneliness in older-adults: a review of quantitative results informed by qualitative insights. *International psychogeriatrics*, *28*(4), 557-576.

Cong, Z.and Silverstein, M. (2008). Intergenerational Support and Depression Among Elders in Rural China: Do Daughters-In-Law Matter? *Journal of Marriage and Family*, *70*(3), 599-612. https://doi.org/https://doi.org/10.1111/j.1741-3737.2008.00508.x

Connelly, R.and Maurer-Fazio, M. (2016). Left behind, at-risk, and vulnerable elders in rural China. *China Economic Review*, *37*, 140-153. https://doi.org/https://doi.org/10.1016/j.chieco.2015.10.005

DaVanzo, J.and Chan, A. (1994). Living arrangements of older Malaysians: Who coresides with their adult children? *Demography*, *31*(1), 95-113.

de Jong Gierveld, J.and Tesch-Romer, C. (2012). Loneliness in old age in Eastern and Western European societies: theoretical perspectives. *Eur J Ageing*, *9*(4), 285-295. https://doi.org/10.1007/s10433-012-0248-2

Ebenstein, A. (2010). The "missing girls" of China and the unintended consequences of the one child policy. *Journal of Human resources*, *45*(1), 87-115.

Evandrou, M., Falkingham, J., Qin, M., and Vlachantoni, A. (2017). Children's migration and chronic illness among older parents 'left behind' in China. *SSM Popul Health*, *3*, 803-807. https://doi.org/10.1016/j.ssmph.2017.10.002

Giles, J., Wang, D., and Zhao, C. (2010). Can China's Rural Elderly Count on Support from Adult Children? Implications of Rural-to-Urban Migration. *Journal of Population Ageing*, *3*(3), 183-204. https://doi.org/10.1007/s12062-011-9036-6

Guo, M.A.N., Aranda, M.P., and Silverstein, M. (2009). The impact of out-migration on the inter-generational support and psychological wellbeing of older adults in rural China. *Ageing and Society*, *29*(7), 1085-1104. https://doi.org/10.1017/S0144686X0900871X

Hawkley, L.C.and Cacioppo, J.T. (2010). Loneliness matters: a theoretical and empirical review of consequences and mechanisms. *Ann Behav Med*, *40*(2), 218-227. https://doi.org/10.1007/s12160-010-9210-8

Hawkley, L.C., Hughes, M.E., Waite, L.J., Masi, C.M., Thisted, R.A., and Cacioppo, J.T. (2008). From social structural factors to perceptions of relationship quality and loneliness: the Chicago health, aging, and social relations study. *The Journals of Gerontology: Series B*, *63*(6), S375-384. https://doi.org/10.1093/geronb/63.6.s375

Kim, E.S., Tkatch, R., Martin, D., MacLeod, S., Sandy, L., and Yeh, C. (2021). Resilient aging: Psychological well-being and social well-being as targets for the promotion of healthy aging. *Gerontology and geriatric medicine*, *7*, 23337214211002951.

King, R.and Vullnetari, J. (2006). Orphan pensioners and migrating grandparents: the impact of mass migration on older people in rural Albania. *Ageing and Society*, *26*(5), 783-816. https://doi.org/10.1017/S0144686X06005125

Kuhn, R., Everett, B., and Silvey, R. (2011). The effects of children's migration on elderly kin's health: a counterfactual approach. *Demography*, *48*(1), 183-209. https://doi.org/10.1007/s13524-010-0002-3

Kumar, S. (2021). Offspring's labor migration and its implications for elderly parents' emotional wellbeing in Indonesia. *Social Science & Medicine*, *276*, 113832.

Li, A. (2024). The effects of adult child migration and migration duration on the emotional health of rural elders in China. *Ageing & Society*, *44*(4), 939-962.

Li, T., Wu, B., Yi, F., Wang, B., and Balezentis, T. (2020). What Happens to the Health of Elderly Parents When Adult Child Migration Splits Households? Evidence from Rural China. *Int J Environ Res Public Health*, *17*(5). https://doi.org/10.3390/ijerph17051609

Lin, Z.and Tang, D. (2023). Separated kin: location of multiple children and mental health trajectories of older parents in rural China. *Aging Ment Health*, *27*(2), 425-433. https://doi.org/10.1080/13607863.2021.2019191

Luhmann, M., Buecker, S., and Rusberg, M. (2023). Loneliness across time and space. *Nat Rev Psychol*, *2*(1), 9-23. https://doi.org/10.1038/s44159-022-00124-1

Luo, Y.and Waite, L.J. (2014). Loneliness and mortality among older adults in China. *The Journals of Gerontology: Series B*, *69*(4), 633-645. https://doi.org/10.1093/geronb/gbu007

Matos-Moreno, A., Alburez-Gutierrez, D., Williams, I., Verdery, A.M., Fernández Soto, M., and Santos-Lozada, A. (2025). Kinship Structures for Left Behind Older Adults in High Outmigration Contexts: Evidence from Puerto Rico. *The Journals of Gerontology: Series B*. https://doi.org/10.1093/geronb/gbaf052

Munnell, A.H., Sanzenbacher, G., and Zulkarnain, A. (2020). What Factors Explain the Decline in Widowed Women's Poverty? *Demography*, *57*(5), 1881-1902. https://doi.org/10.1007/s13524-020-00915-2

National Academies of Sciences, E., and Medicine. (2018). In M.K. Majmundar and M.D. Hayward (Eds.), *Future Directions for the Demography of Aging: Proceedings of a Workshop*. https://doi.org/10.17226/25064

Newmyer, L., Verdery, A.M., Margolis, R., and Pessin, L. (2021). Measuring Older Adult Loneliness Across Countries. *J Gerontol B Psychol Sci Soc Sci*, *76*(7), 1408-1414. https://doi.org/10.1093/geronb/gbaa109

Newmyer, L., Verdery, A.M., Wang, H., and Margolis, R. (2022). Population Aging, Demographic Metabolism, and the Rising Tide of Late Middle Age to Older Adult Loneliness Around the World. *Population and Development Review*, *48*(3), 829-862. https://doi.org/https://doi.org/10.1111/padr.12506

Qiao, X. (2001). Aging issues and policy choices in rural China. International Union for the Scientific Study of Population's XXIVth General Population Conference, Salvador, Brazil,

Raymo, J.M.and Wang, J. (2022). Loneliness at Older Ages in the United States: Lonely Life Expectancy and the Role of Loneliness in Health Disparities. *Demography*, *59*(3), 921-947. https://doi.org/10.1215/00703370-9937606

Read, S., Comas-Herrera, A., and Grundy, E. (2019). Social Isolation and Memory Decline in Later-life. *The Journals of Gerontology: Series B*, *75*(2), 367-376. https://doi.org/10.1093/geronb/gbz152

Scheffel, J.and Zhang, Y. (2019). How does internal migration affect the emotional health of elderly parents left-behind? *Journal of Population Economics*, *32*(3), 953-980. https://doi.org/10.1007/s00148-018-0715-y

Song, Q. (2017a). Aging and separation from children: The health implications of adult migration for elderly parents in rural China. *Demogr Res*, *37*, 1761-1792. https://doi.org/10.4054/DemRes.2017.37.55

—. (2017b). Facing "Double Jeopardy"? Depressive Symptoms in Left-Behind Elderly in Rural China. *J Aging Health*, *29*(7), 1182-1213. https://doi.org/10.1177/0898264316659964

Song, Q., Wang, H., and Burr, J.A. (2022). Depressive Symptoms Among Rural "Left-Behind" Older Adults: A Test of the High Outmigration Penalty Hypothesis. *The Journals of Gerontology: Series B*, *77*(3), 592-603. https://doi.org/10.1093/geronb/gbab040

UNICEF. (2019). Domestic migrants in China (2018): trends, challenges and recommendations. *Dostępne na: https://china. unfpa. org/sites/default/files/pub-pdf/中国的流动人口 (2018)-EN-final. pdf [data dostępu: 26.08. 2021]*.

United Nations, D.o.E.a.S.A., Population Division. (2022). World Population Prospects 2022. https://population.un.org/wpp/DataQuery/.

Wang, F., Cai, Y., and Gu, B. (2013). Population, Policy, and Politics: How Will History Judge China's One-Child Policy? *Population and Development Review*, *38*(s1), 115-129. https://doi.org/https://doi.org/10.1111/j.1728-4457.2013.00555.x

Wang, G., Hu, M., Xiao, S.Y., and Zhou, L. (2017). Loneliness and depression among rural empty-nest elderly adults in Liuyang, China: a cross-sectional study. *BMJ Open*, *7*(10), e016091. https://doi.org/10.1136/bmjopen-2017-016091

Wang, X. (2024). Towards a National Profile of Loneliness in Old-Age China: Prevalence and Lonely Life Expectancy. *The Journals of Gerontology: Series B*. https://doi.org/10.1093/geronb/gbae187

Wu, Z.Q., Sun, L., Sun, Y.H., Zhang, X.J., Tao, F.B., and Cui, G.H. (2010). Correlation between loneliness and social relationship among empty nest elderly in Anhui rural area, China. *Aging Ment Health*, *14*(1), 108-112. https://doi.org/10.1080/13607860903228796

Xiang, A., Jiang, D., and Zhong, Z. (2016). The impact of rural–urban migration on the health of the left-behind parents. *China Economic Review*, *37*, 126-139.

Yahirun, J.J.and Arenas, E. (2018). Offspring Migration and Parents' Emotional and Psychological Well-being in Mexico. *J Marriage Fam*, *80*(4), 975-991. https://doi.org/10.1111/jomf.12479

Yan, Z., Yang, X., Wang, L., Zhao, Y., and Yu, L. (2014). Social change and birth cohort increase in loneliness among Chinese older adults: a cross-temporal meta-analysis, 1995-2011. *Int Psychogeriatr*, *26*(11), 1773-1781. https://doi.org/10.1017/S1041610214000921

Yang, F.and Gu, D. (2020). Predictors of loneliness incidence in Chinese older adults from a life course perspective: a national longitudinal study. *Aging & Mental Health*, *24*(6), 879-888. https://doi.org/10.1080/13607863.2018.1558174

—. (2021). Widowhood, widowhood duration, and loneliness among older adults in China. *Social Science & Medicine*, *283*, 114179. https://doi.org/https://doi.org/10.1016/j.socscimed.2021.114179

Yang, K.and Victor, C. (2011). Age and loneliness in 25 European nations. *Ageing & Society*, *31*(8), 1368-1388.

Yu, X., Westrick, A.C., and Kobayashi, L.C. (2023). Cumulative loneliness and subsequent memory function and rate of decline among adults aged >/=50 in the United States, 1996 to 2016. *Alzheimers Dement*, *19*(2), 578-588. https://doi.org/10.1002/alz.12734

Zhao, Y., Strauss, J., Yang, G., Giles, J., Hu, P., Hu, Y., Lei, X., Park, A., Smith, J.P., and Wang, Y. (2013). China health and retirement longitudinal study–2011–2012 national baseline users' guide. *Beijing: National School of Development, Peking University*, *2*, 1-56.

Zhong, H.and Zhao, J. (2020). The impact of adult child migration on the health of elderly parents left behind in China. *Canadian Studies in Population*, *47*(3), 151-168.

Tables and Figures

Table 1. Descriptive statistics of CHARLS respondents in 2011 and 2018

Characteristics	Entire Sample		2011		2018		
	Mean/N	(SD)%	Mean/N	(SD)%	Mean/N	(SD)%	
Men	24,139	47.28%	7,390	46.97%	8,003	47.21%	
Women	26,918	52.72%	8,344	53.03%	8,949	52.79%	
Age	59.59 (9.92)		59.12 (9.69)		60.84 (9.72)		*p<0.001*
45-50	9,136	17.89%	3,021	19.20%	2,170	12.80%	
50-60	17,169	33.63%	5,535	34.18%	5,751	33.93%	
60-70	16,050	31.44%	4,718	29.99%	5,737	33.84%	
70-80	7,113	13.93%	2,028	12.89%	2,659	15.69%	
80+	1,589	3.11%	432	2.75%	635	3.74%	
Education							
Illiterate	12,107	23.71%	3,974	25.26%	3,765	22.21%	
Elementary or less	10,136	44.56%	6,369	40.48%	7,898	46.60%	
Middle School	10,235	20.05%	3,383	21.50%	3,331	19.65%	
High school and beyond	5,962	11.67%	2,008	12.77%	1,958	11.54%	
Urban/rural							
Urban	20,333	39.82%	6,175	39.25%	6,825	40.26%	
Rural	30,724	60.18%	9,559	60.75%	10,127	59.74%	
No. of living siblings	3.44 (1.85)		3.20 (1.90)		3.60 (1.90)		*p<0.001*
No. of living children							*p<0.001*
1	8,985	17.60%	2,778	17.66%	3,089	18.22%	
2	19,706	38.60%	5,726	36.39%	6,864	40.49%	
3+	22,366	43.81%	7,230	45.95%	6,999	41.29%	
Child migration status							
Complete family separation	9,267	18.15%	1,828	11.62%	3,797	22.40%	*p<0.001*
Partial family separation	23,154	45.35%	5,548	35.26%	8,162	48.15%	*p<0.001*
Married	45,011	88.16%	13,953	88.68%	14,774	87.15%	*p<0.001*

Self-reported good health	9,823	19.07%	2,969	18.87%	3,270	19.29%	*p<0.001*
Lonely	13,284	26.02%	3,029	19.25%	4,935	29.11%	*p<0.001*
N	51,057		15,734		16,952		

Note: Data from CHARLS 2011-2018 (N=51,057 person-wave observations). Statistical comparisons between 2011 and 2018 use chi-square tests for categorical variables and t-tests for continuous variables. Significant changes ($p<0.001$) were observed in age composition, number of siblings, number of living children, children's migration status, marital status, and loneliness, while gender composition, education level, and urban/rural residence remained stable. "Lonely" indicates respondents who reported feeling lonely at least a moderate amount of time in the past week.

Table 2. Odds ratios from logistic regression of loneliness, by two measures of children migration status

	Model 1		Model 2	
	Odds Ratio	95% CI	Odds Ratio	95% CI
Migration Status				
Partial separation (>=1 migrate, not all)	1.09**	[1.05, 1.13]		
Complete separation (all migrate)			1.31***	[1.25, 1.37]
Time Period				
Year 2018 (ref: 2011)	1.40***	[1.34, 1.46]	1.28***	[1.23, 1.33]
Demographic Characteristics				
Age	1.00*	[1.00, 1.00]	0.99**	[0.99, 1.00]
Male (ref: female)	0.89***	[0.86, 0.92]	0.90***	[0.84, 0.97]
Rural residence (ref: urban)	1.35***	[1.27, 1.43]	1.30***	[1.17, 1.45]
Rural hukou (ref: urban hukou)	1.15***	[1.08, 1.22]	1.18**	[1.05, 1.33]
Socioeconomic Status				
Education (ref: illiteracy)				
Elementary or less	0.96	[0.92, 1.00]	0.96	[0.92, 1.00]
Middle school	0.88*	[0.82, 0.94]	0.81**	[0.71, 0.92]
High school and beyond	0.83*	[0.71, 0.96]	0.82**	[0.70, 0.95]
Family Structure				
Married (ref: not married)	0.36***	[0.32, 0.39]	0.35***	[0.32, 0.39]
Number of children (ref: one)				
Two	0.98	[0.93, 1.03]	1.02	[0.97, 1.07]
Three and above	1.04	[0.98, 1.10]	1.18**	[1.05, 1.32]
Having living sibling(s)	0.98	[0.89, 1.07]	0.97	[0.88, 1.06]
Health				
Self-rated poor health (ref: good)	2.00***	[1.83, 2.19]	2.00***	[1.83, 2.19]
Constant	0.52	[0.34, 0.80]	0.51	[0.33, 0.78]
Observations	44,228		44,228	
Pseudo R2	0.12		0.12	
AIC	48344.41		48316.72	
Province fixed effects	Yes		Yes	

Note. *** p<0.001, ** p<0.01, * p<0.05. Model 1 examines the effect of partial family separation (having at least one child migrated while some remain nearby), while Model 2 examines the effect of complete family separation (having all children migrated away, including those who had only one child). Province fixed effects are included but not shown. All models are estimated using survey weights to account for complex survey design. Additional analyses testing time × rural interactions showed no significant effects.

Table 3. Nonlinear decomposition of loneliness prevalence between 2011 and 2018 into changes in composition versus changes in coefficients

	Complete Separation		
	All	Urban	Rural
A. Total Decomposition			
Loneliness prevalence 2011	19.25***	17.71***	25.41***
Loneliness prevalence 2018	29.11***	25.10***	33.56***
Difference (percentage point)	9.86 ***	7.39***	8.15***
Decomposed to:			
Composition	1.36	1.52	0.63
Coefficient	8.5***	5.88***	7.52***
Expressed in percentage			
% due to composition difference	13.77%	20.50	7.70
% due to coefficient difference	86.23%	79.50	92.30
B. Detailed Decomposition			
B1. Percentage due to compositional changes in:			
Complete separation	22.45***	30.79***	11.55*
Age	-10.79*	-14.71**	-4.46
Self-reported good health	-4.39***	-5.12***	-2.89***
Living alone	7.90**	10.82*	4.66**
Married	2.14***	1.68†	2.34***
Living siblings	-2.04	-0.53	-3.18†
Higher education	1.16*	1.15	0.06
No. of children	-2.65***	-3.59**	-0.39
B2. Percentage due to coefficient changes in:			
Complete separation	-3.23	-3.36	-2.66
Age	-8.15	-28.48	25.80
Self-reported good health	-170.95***	-174.49***	-160.41***
Living alone	3.11	4.64	0.96

Married	104.52***	115.20**	83.88**
Living siblings	-17.77	-15.95	-20.23
Higher education	5.80	10.71	1.03
No. of children	28.86**	46.36**	-6.52
Constant	144.05†	124.87	170.45†

Notes: Results from nonlinear decomposition. Percentages in panels B1 and B2 indicate each factor's contribution to the total difference in loneliness prevalence between 2011 and 2018. Negative values indicate the factor contributed to reducing the loneliness gap (i.e., without changes in this factor, the difference would have been larger). † $p < .10$; * $p < .05$; ** $p < .01$; *** $p < .001$

Table 4. Odds ratios from logistic regression predicting complete family separation through children's migration

Variables	OR	95% CI
Family Structure		
Multiple children (ref)	1.0	-
One child	2.90***	[2.05, 4.11]
Birth Cohort		
Pre-1950 cohort (ref)	1.0	-
1950-1960 cohort	5.41***	[4.41, 6.65]
Post-1960 cohort	12.89***	[9.45, 17.59]
Family Structure x Birth Cohort		
One child × 1950-1960 cohort	0.65*	[0.44, 0.96]
One child × Post-1960 cohort	0.65*	[0.44, 0.95]
Demographic characteristics		
Age	1.10***	[1.09, 1.12]
Male (ref: female)	1.07*	[1.03, 1.12]
Rural residence (ref: urban)	1.28***	[1.09, 1.50]
High school or above (ref: less than high school)	1.24**	[1.11, 1.39]
Married (ref: not married)	1.60***	[1.38, 1.84]
No living siblings (ref: has siblings)	0.42***	[0.35, 0.49]
Model Statistics		
Observations	64,812	
F(15, 226)	48.5	
Province fixed effects	Yes	

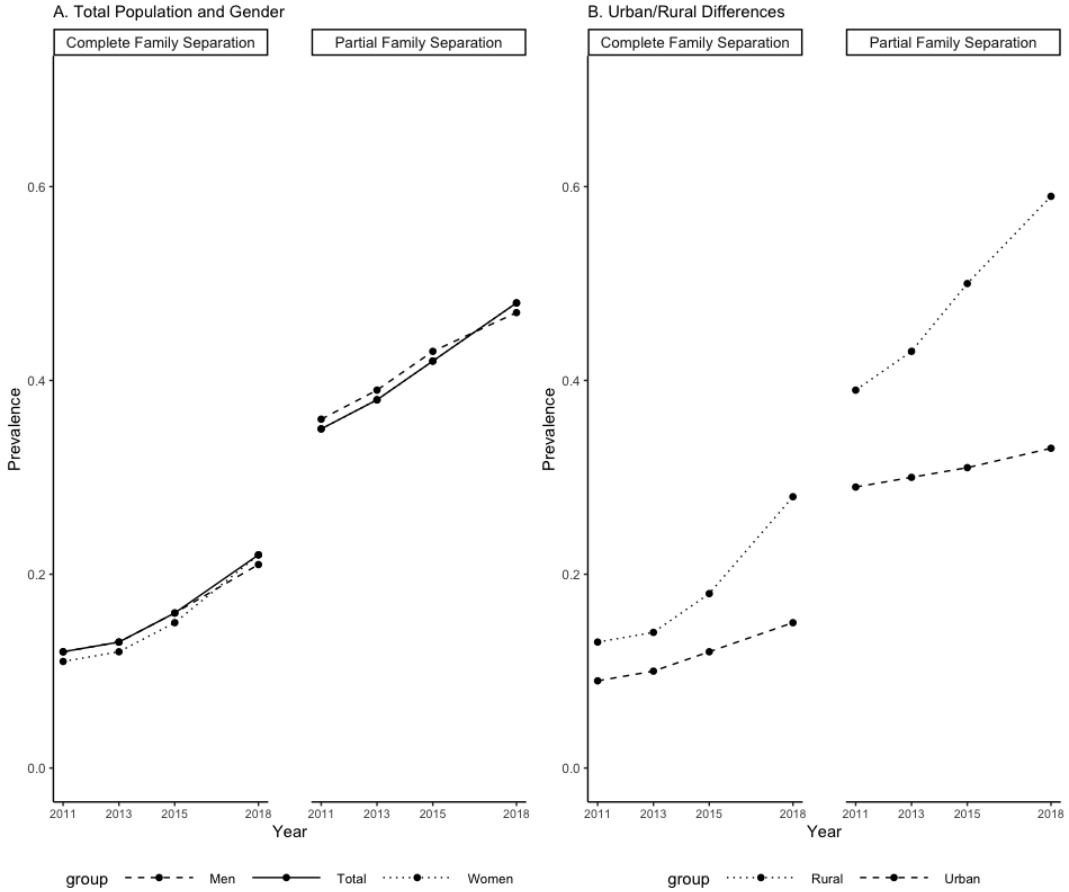
Note. *** p<0.001, ** p<0.01, * p<0.05, † p<0.10. Based on survey-weighted estimates from CHARLS 2011-2018. Birth cohorts: earliest (pre-1950), middle (1950-1960), recent (post-1960). Complete family separation indicates all children have migrated away from parents.

Table 5. Prevalence of loneliness among parents who aged 40-55 in 2013, and the predicted loneliness if only proportion of having all children migrated changed

		Complete Family Separation			Loneliness				
	Average Number of Children	2011	2018	2035†	2011	2018	2035† Projections		% change compared to 2018
							Counterfactual	Nonlinear	
		Age 41-51	Age 48-58	Age 65-74	Age 41-50	Age 48-57	Age 65-74	Age 65-74	
Total	1.96	0.16	0.39	0.57	0.20	0.28	0.33	0.312	17.86% (12.5%*)
By Residence									
Urban	1.78	0.15	0.36	0.56	0.17	0.24	0.29	0.29	19.90% (19.9%*)
Rural	2.14	0.17	0.41	0.59	0.23	0.32	0.36	0.33	12.50% (4.8%*)
By Gender									
Men	1.97	0.15	0.38	0.58	0.23	0.3	0.32	0.31	7.7% (5.0%*)
Women	1.95	0.16	0.39	0.57	0.16	0.25	0.26	0.25	3.3% (3.0%*)

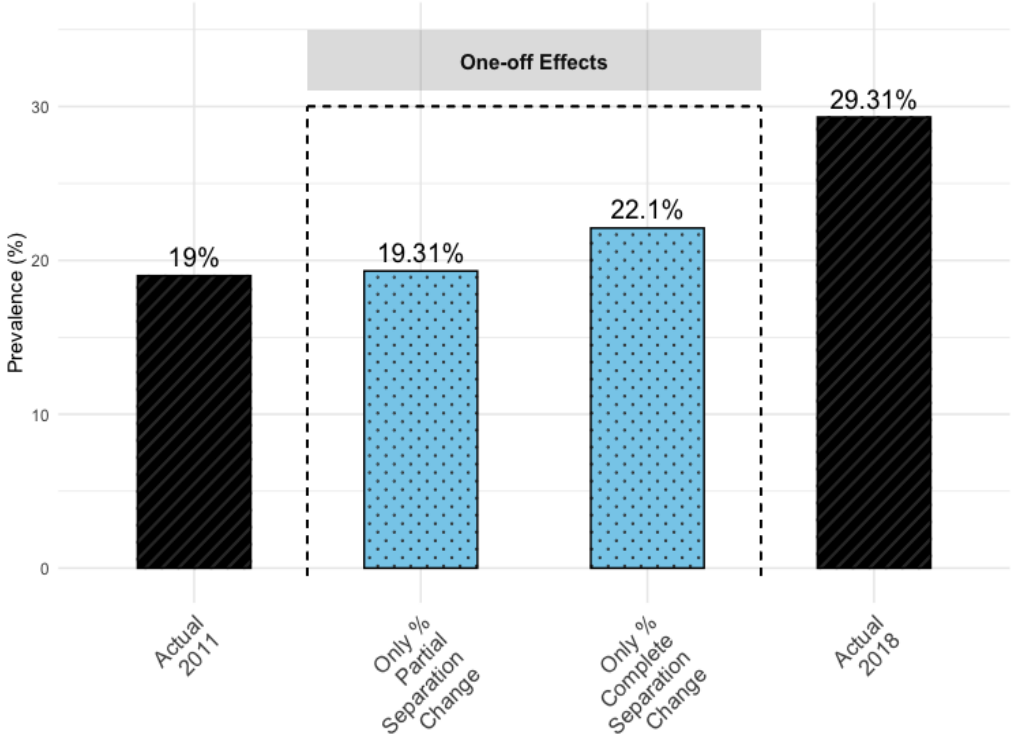
Note: This table tracks one cohort (parents aged 41-51 in 2011) over time. Average number of children reflects completed fertility for this cohort. Complete family separation shows the observed proportion (2011, 2018) and projected proportion (2035†) of parents with all children migrated away. Loneliness estimates show observed prevalence (2011, 2018) with two projection approaches for 2035†: original estimates from the counterfactual approach and conservative estimates based on decomposition analysis. Conservative estimates (marked with *) were derived by calculating the ratio between migration's contribution to loneliness in the nonlinear decomposition versus counterfactual approach, then applying these group-specific ratios scale in the projected increase. † indicates projections for when these parents reach age 65-75.

Figure 1. Prevalence of Family Separation Through Migration, 2011-2018



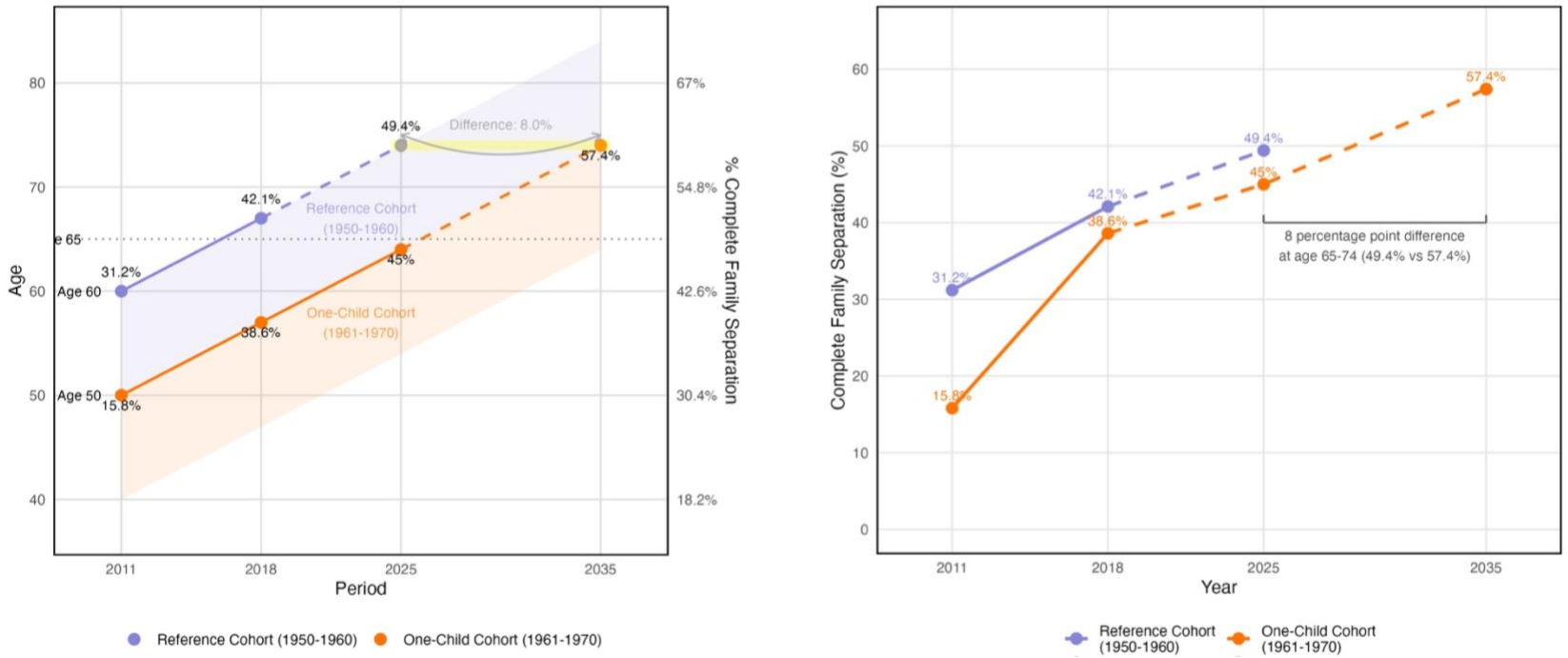
Note: Complete family separation indicates that all children have migrated away from parents, while partial family separation indicates at least one child has migrated. Data weighted using CHARLS survey weights.

Figure 2. Actual and predicted loneliness prevalence: the contribution of children's migration, 2011-2018



Note. This figure compares actual loneliness prevalence (black bars) with counterfactual predictions (blue patterned bars) showing migration's contribution to increasing loneliness. The 2011 and 2018 black bars show observed prevalence, while blue bars represent what 2018 loneliness levels would be if only migration patterns changed from 2011 levels while holding all other factors constant. While partial family separation (having at least one child migrate) explains only about 3% of the increase in loneliness (calculated as [19.33-19]/[29.31-19]=0.33/10.31=3.2%), changes in complete family separation (having all children migrate) account for approximately 30% of the rise (calculated as [22.1-19]/[29.31-19]=3.1/10.31=30.1%). The "One-off Effects" label indicates these are single-factor counterfactual projections rather than cumulative effects.

Figure 3. Age trajectories and complete family separation by birth cohort



Note: This figure compares two birth cohorts: the reference cohort (born 1950-1960) and the one-child cohort (born 1961-1970). Panel A shows the age progression (shaded areas) and complete family separation (percentages) for both cohorts. Panel B isolates the trajectories of complete family separation, highlighting the 8 percentage point difference when both cohorts reach age 65(49.4% vs 57.4%). Solid lines represent observed data (2011-2018); dashed lines indicate projected values. Complete family separation occurs when all children have migrated away from parents.

Appendix I

Table A1. Prevalence of loneliness and children migration status in the population and by population subgroups, 2011 and 2018

Panel A: Loneliness Prevalence

Population Group	2011	2018
Overall population	0.19	0.29
45-64	0.17	0.28
65+	0.21	0.31
Urban	0.18	0.25
Rural	0.25	0.34
Father	0.16	0.27
Mother	0.21	0.32

Panel B: Child Migration Prevalence

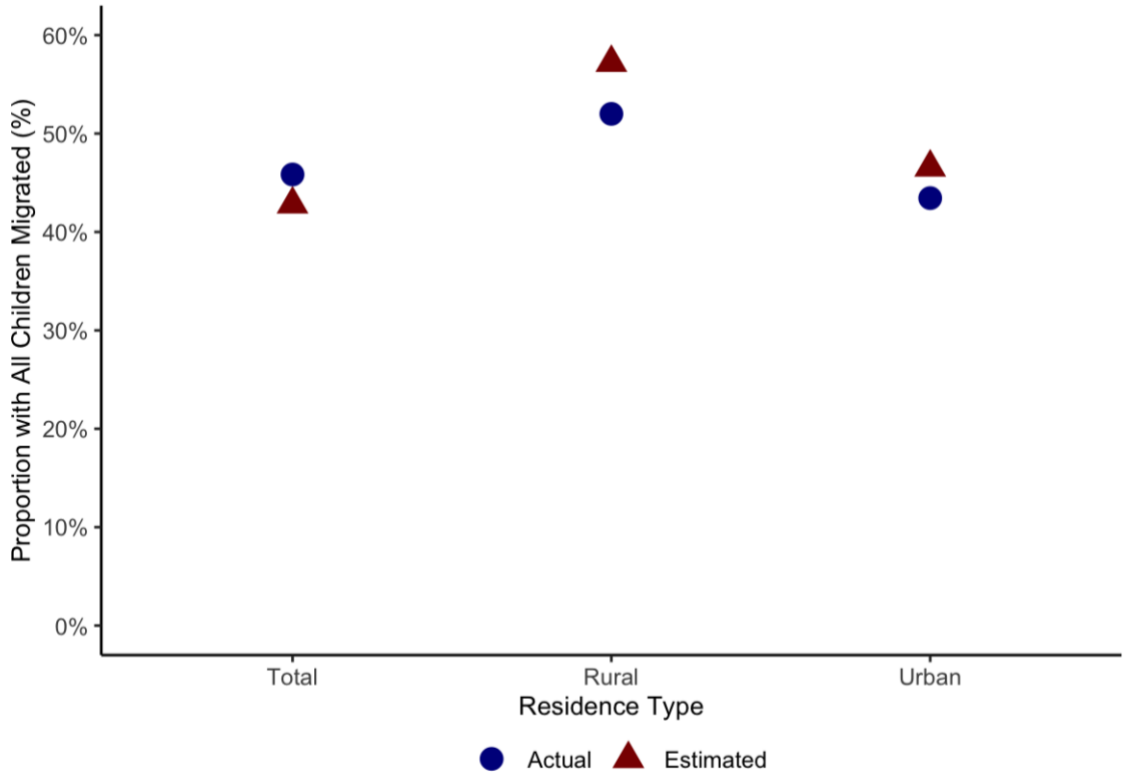
	Partial family separation (≥1 child migrated)		Complete family separation (all children migrated)	
Population Group	2011	2018	2011	2018
Overall population	0.35	0.48	0.12	0.22
45-64	0.34	0.45	0.14	0.26
65+	0.40	0.52	0.10	0.24
Urban	0.29	0.33	0.09	0.15
Rural	0.39	0.59	0.13	0.28
Father	0.36	0.47	0.12	0.21
Mother	0.35	0.48	0.11	0.22

Note. Estimates were weighted.

Table A3. Characteristics by Birth Cohort , CHARLS 2011-2018

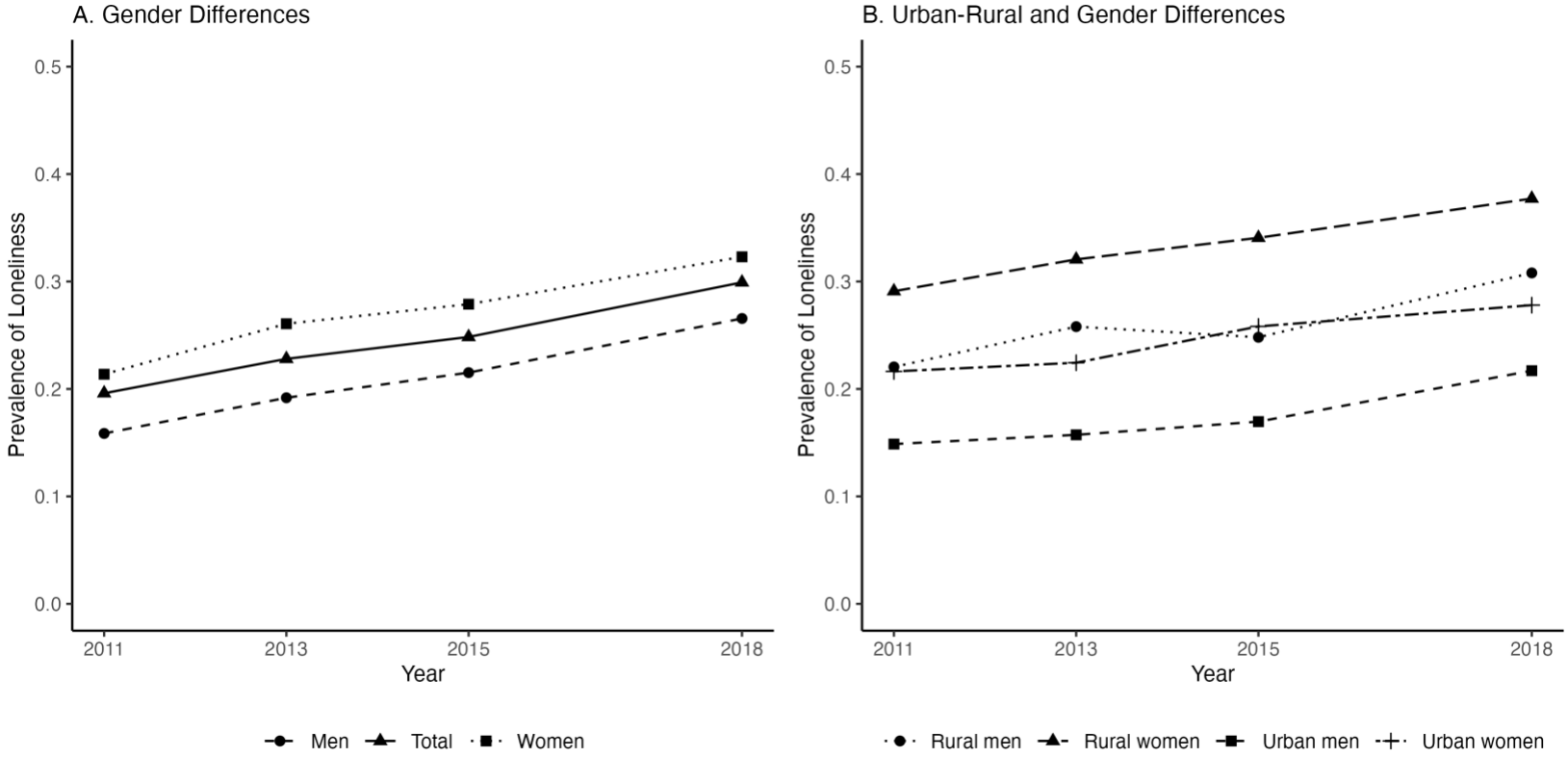
	Pre-1940	1940-1950	1950-1960	1960+
Number of Children (mean)	4.15(1.65)	3.25 (1.38)	2.40 (1.09)	1.96 (0.88)
Number of children (urban)	3.81 (1.61)	2.90 (1.33)	2.10 (1.07)	1.78 (0.89)
Number of children (rural)	4.41(1.64)	3.46 (1.37)	2.60 (1.06)	2.14 (0.86)
% With at least one migrant children	0.46 (0.50)	0.46 (0.50)	0.44 (0.50)	0.38 (0.49)
% With all children migrated	0.1(0.29)	0.16 (0.37)	0.22 (0.42)	0.23 (0.42)
Proportion lonely (%)	0.32 (0.46)	0.29 (0.46)	0.26 (0.44)	0.24 (0.43)

Figure A1. Comparison of Estimated and Predicted Proportion of Having All Children Migrated in 2018



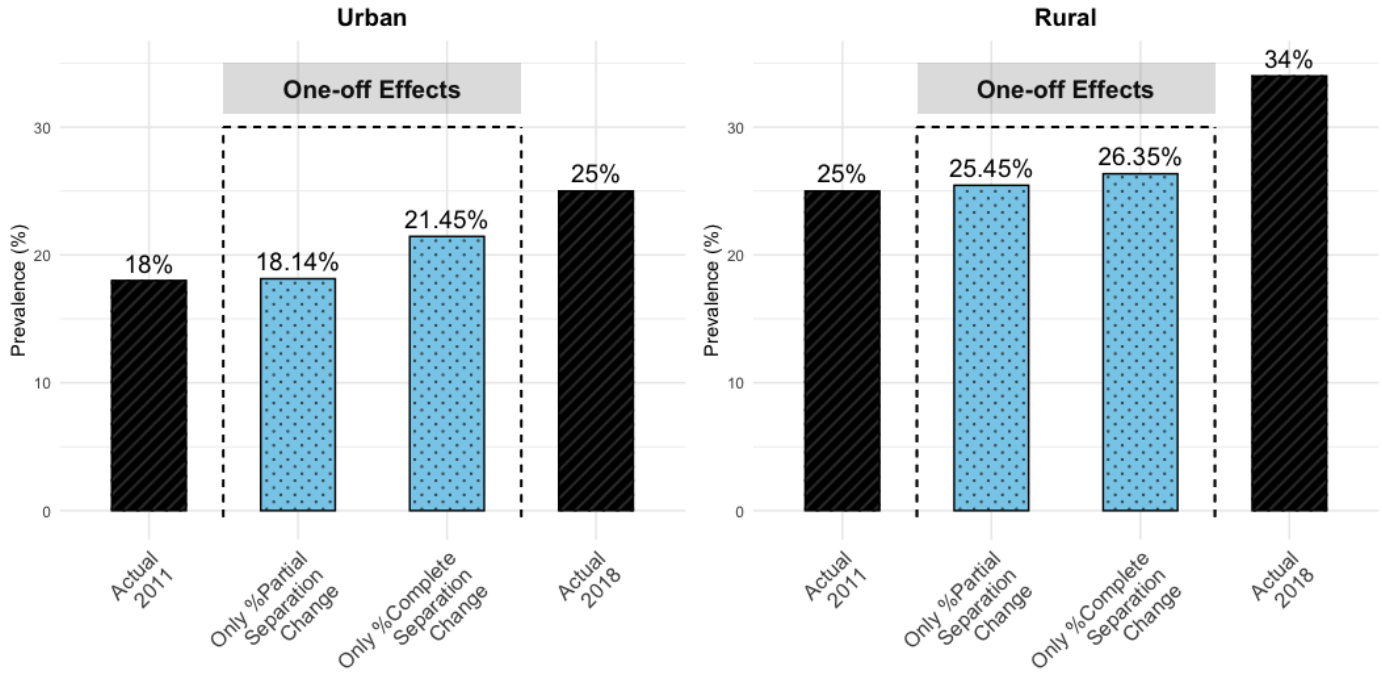
Note. This figure plots the estimated and actual proportions of older adults who had all children migrated in 2018. The estimated values are derived from a model using 2011-2015 data to predict 2018 outcomes, while actual values represent observed data from 2018. Estimates are shown separately for the total sample and by urban-rural residence status.

Figure A2. Trends in Loneliness Prevalence Among Chinese Adults Aged 45 and Above, 2011-2018



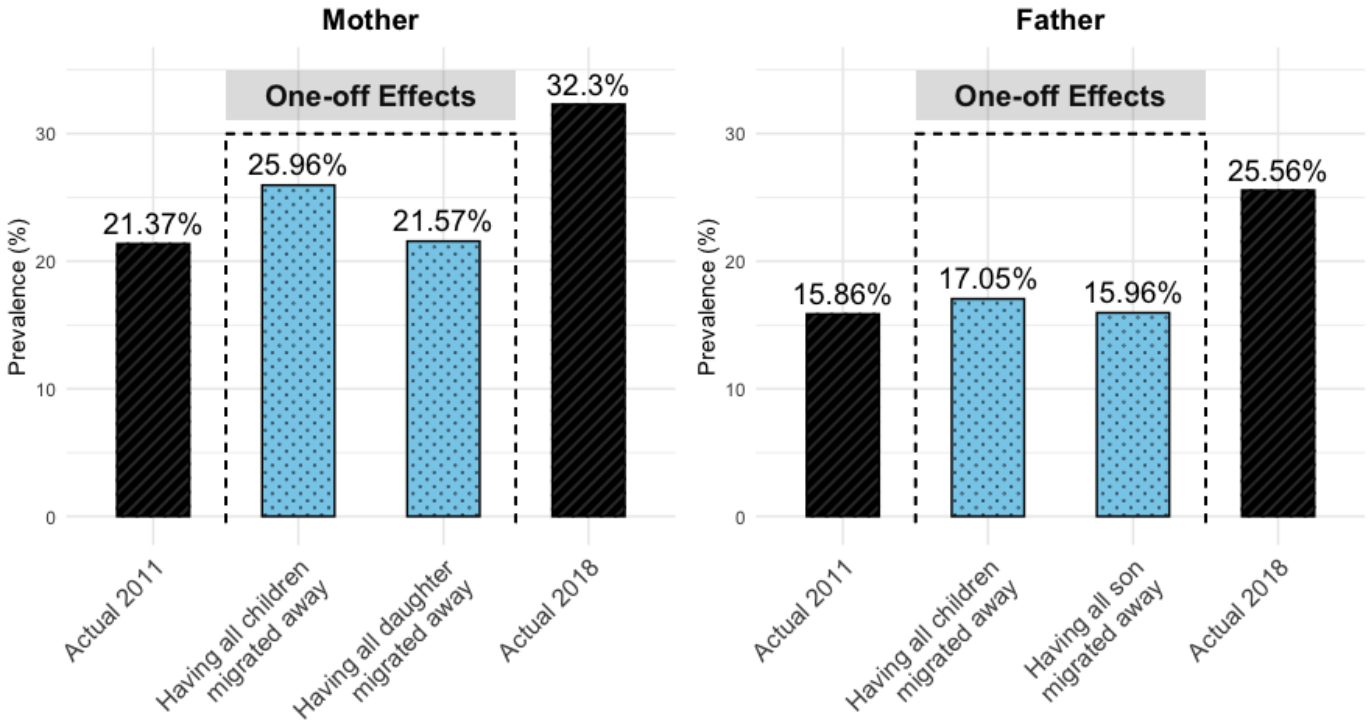
Note: The figure shows trends in loneliness prevalence from 2011 to 2018. Panel A displays the overall trend and trends by gender. Panel B shows trends by urban-rural residence and gender. The prevalence of loneliness refers to the proportion of respondents who reported feeling lonely at least a moderate amount of time in the past week. All estimates were weighted to be nationally representative.

Figure A3. Actual and predicted prevalence of loneliness by urban and rural residence, 2011 and 2018



Note. This figure compares actual loneliness prevalence (black bars) with predicted values based on migration patterns (blue patterned bars) for urban and rural populations. The 2011 and 2018 black bars show observed loneliness prevalence, while the blue patterned bars represent counterfactual estimates showing what 2018 loneliness prevalence would be if only children's migration patterns changed from 2011 levels while holding all other factors constant. In urban areas, changes in migration patterns explain approximately 35% of the increase in loneliness (from 18% to 25%), while in rural areas, where loneliness increased more substantially (from 25% to 34%), migration patterns explain about 15% of the rise. The "One-off Effects" label indicates these are single-factor counterfactual projections rather than cumulative effects.

Figure A4. Actual and predicted prevalence of loneliness by parent and children gender, 2011 and 2018



Note. This figure compares actual loneliness prevalence (black bars) with predicted values based on migration patterns (blue patterned bars) for mothers and fathers. The 2011 and 2018 black bars show observed loneliness prevalence, while the blue patterned bars represent counterfactual estimates showing what 2018 loneliness prevalence would be if only children's migration patterns changed from 2011 levels while holding all other factors constant. Among mothers, changes in migration patterns explain approximately 33% of the increase in loneliness (from 21.37% to 32.3%), while for fathers, whose loneliness increased from 15.86% to 25.56%, migration patterns explain only about 10% of this rise. The "One-off Effects" label indicates these are single-factor counterfactual projections rather than cumulative effects.

Appendix II Disentangling Incidence vs. Duration Contribution

In this Appendix, I investigate whether the observed relationship between aggregate level migration and loneliness operates primarily through new instances of separation (incidence effect) or through the accumulated impact of prolonged separation (duration effect). This distinction is important because it helps identify whether loneliness increases are driven by the shock of initial separation or by the cumulative strain of extended family separation. Using data from 2011 to 2018, I track complete separation patterns across families, categorizing them into four groups, shown in Appendix Table A2: those who never experienced complete separation (53.87%), those newly experiencing complete separation between 2011-2018 (37.68%), those consistently experiencing complete separation throughout the period (6.02%), and those with mixed patterns (2.42%). The substantially higher proportion of new separations compared to persistent separations (37.68% vs 6.02%) indicates that the rise in loneliness during this period may primarily reflect the emotional impact of recent transitions to complete family separation, rather than the accumulated effect of long-term separation. Indeed, Appendix Figure A5 confirms that the rise in loneliness during this period primarily reflects the emotional impact of initial transitions to family separation rather than the accumulated strain of prolonged separation (please see Appendix II for detailed methodology).

To disentangle whether the rise in loneliness primarily reflects new instances of family separation (incidence effect) or the accumulated impact of prolonged separation (duration effect), I firstly categorized separation states based on duration: no separation (reference group), new separation (occurred within the past year), short-duration separation (1-2 years), long-duration separation (3+ years), and consistently separated. Then, I estimate how different separation states relate to loneliness using the following model:

$$Loneliness_{i,t} = \beta_0 + \beta_1 NewSep_{i,t} + \beta_2 ShortDur_{i,t} + \beta_3 Long_{i,t} + \beta_4 ConsisSep_{i,t} + \gamma X_{i,t} + \varepsilon_{i,t}$$

where X represents individual-level controls including age, education, marital status, urban/rural residence, and province fixed effects. The coefficients (β_1 through β_4) capture how different separation durations associate with loneliness relative to having no separation.

Using these estimates, I decompose the total change in loneliness between 2011 and 2018 into two components:

$$\Delta\, Lonelineses = \sum [\beta_{state} \times \Delta(\text{proportion in state})] + \sum [\Delta\beta_{state} \times proportion_{2011}]$$

The first term captures changes due to shifts in the distribution of separation states (incidence effect), while the second term reflects changes in how duration affects loneliness (duration effect).

While ideally I would examine the full period from 2011 to 2018, the classification of separation duration states in 2011 is limited by left-censoring—I cannot observe separation history before the first wave. However, examining the raw transition patterns between 2011-2018 provides initial evidence: among adults experiencing complete family separation, 37.68% represented new

transitions during this period, while only 6.02% remained consistently separated throughout, suggesting the dominance of new separations over prolonged ones.

For a formal test of this pattern, I focused the decomposition analysis on 2015-2018, where I have sufficient history to properly classify all separation states. Figure A5 (below) reveals that new separations account for approximately 91.6% of the increase in loneliness during this period, while short-duration (19.1%) and long-duration separations (10.4%) play smaller roles. Notably, consistently separated families show a negative contribution (-21.1%) to the change in loneliness, suggesting possible adaptation to separation over time.

These findings provide strong evidence that the rise in loneliness during this period primarily reflects the emotional impact of initial transitions to family separation rather than the accumulated strain of prolonged separation.

Table A2 Tabulation of Different Separation States, 2011-2018

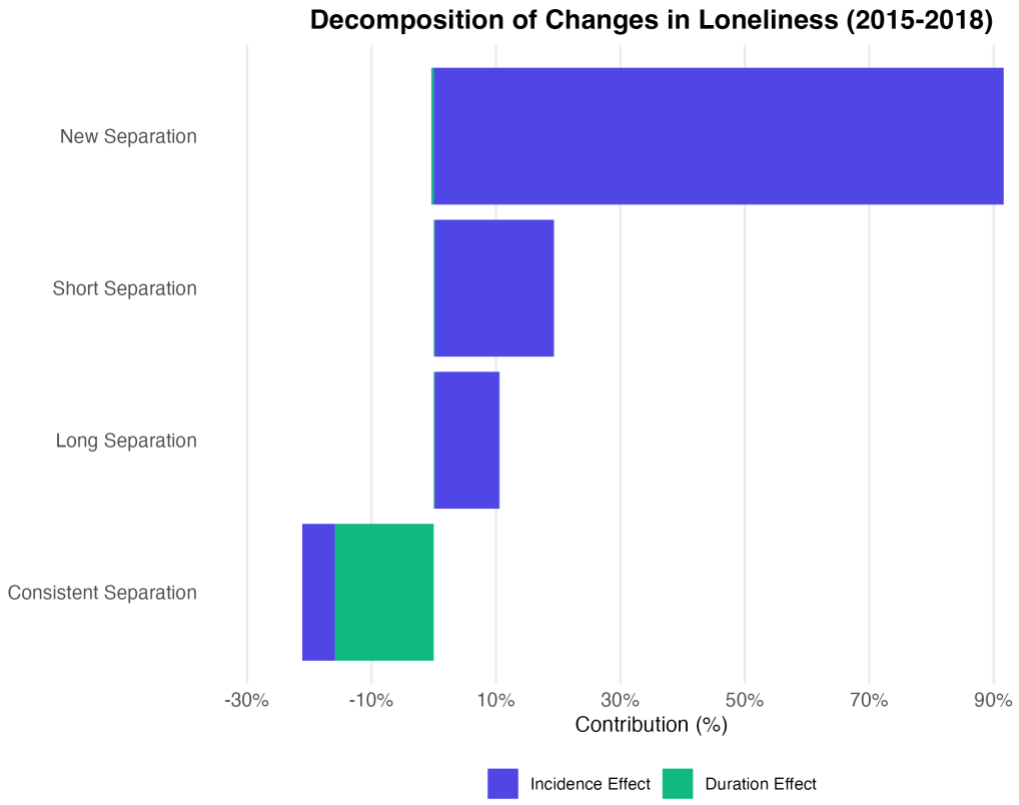
	Freq.	Percent(%)
Newly experiencing complete separation	19,655	37.68
Consistently experiencing complete separation	3,142	6.02
Never experienced complete separation	28,096	53.87
Mixed patterns	1,264	2.42
Total	52,157	100

Table A4. Odds ratios from Logistic Regression Examining Different Separation States on Loneliness, 2015-2018

State (*ref:* no separation)	(1) Incidence/Duration
New Separation	1.24***
	(0.04)
Short Separation	1.31***
	(0.10)
Long Separation	1.15
	(0.10)
Consistent Separation	1.11*
	(0.07)
Constant	0.29***
	(0.03)
Observations	59,143

Note. Models included same controls, not shown. *** p<0.01, ** p<0.05, * p<0.1. "New separation" means separation happened in last wave, "Short Separation" means separation happened in two waves before. "Long separation" means separation happened in three waves before. Consistent separation means respondents were separated in all waves observed.

Figure A5. Decomposition of Changes in Loneliness from 2015 to 2018, by different states of separation



Chapter 3: Beyond Lifelong Marriage and Spousal Coresidence: A Research Note on Racial and Ethnic Differences in Late-Life Family and Living Arrangements

Abstract

We use an innovative Bayesian Multi-State Life Table approach to examine how race, ethnicity, and sex shape marital status and living arrangements in later life. Using the Health and Retirement Study (1992–2018), we estimate expected years spent in various marital and living arrangements after age 50. Our findings reveal stark disparities: White adults largely follow traditional patterns, spending most of their later years married and living with a spouse. In contrast, Black adults experience the shortest durations of marriage and spousal co-residence, spending much of later life alone or with non-spouse family members. Hispanic adults occupy an intermediate position, maintaining substantial years in marriage while also spending extended time in multigenerational households. These patterns are further stratified by sex, with minority women experiencing significantly fewer years married and living with a spouse than men, amplifying their reliance on alternative family support structures. These findings underscore how the intersection of race, ethnicity, and sex shapes later-life social and economic security, emphasizing the need for policies that account for diverse family structures in aging populations.

Key words: Marital status, Living arrangement, Racial and ethnic disparities, Life Expectancies, Gray divorce.

Introduction

In recent decades, family life among American older adults has become increasingly diverse. Rising rates of late-life divorce, non-marital partnerships, and lifelong singlehood have reshaped traditional marriage patterns (Brown and Lin 2012; Brown et al. 2018, 2019; Carr and Utz 2020). Meanwhile, living arrangements have also shifted: while co-residing with a spouse was once the norm (Pew Research Center 2015), more older adults now live alone (Ausubel 2020) or in multigenerational households due to economic pressures (Cohn and Passel 2018). Examining patterns in both marriage and living arrangements is essential, as these trends reflect broader changes in how older Americans navigate family life, social support and housing choices.

Racial and ethnic differences in late-life marital and living arrangements remain understudied compared to earlier life stages. While much research has focused on marriage formation and dissolution in adulthood (Bulanda and Brown 2007; Cherlin 2010; Raley and Sweeney 2009), emerging evidence—typically relying on cross-sectional analyses of marital status or event-history models of single, one-way transitions—shows that older White adults are most likely to be married and living with a spouse (Carr and Utz 2020; Harawa et al. 2011; Liu, Umberson and Xu 2020), while Black adults experience higher rates of divorce, widowhood, and singlehood, with Hispanic adults falling in between (Bulanda and Brown 2007; Lichter, Qian and Leannam 2006; McNamee and Raley 2011). Living arrangements also vary significantly by race and ethnicity, with White older adults more likely to live alone or with a spouse only, whereas Black and Hispanic older adults more often reside in multigenerational or extended-family households (Kamo 2000; Landale, Oropesa and Bradatan 2006; Pew Research Center 2010; Raymo, Pike and Liang 2019).

Although rarely examined explicitly, an intersectional perspective suggests that race, ethnicity, and sex jointly shape access to marriage, relationship stability, and living arrangements in later life. Structural barriers such as economic insecurity, mass incarceration, and systemic racism contribute to lower marriage rates and higher divorce rates among racial and ethnic minorities, particularly Black adults (Western and Wildeman 2009). These disadvantages persist into later life, with divorced and widowed minority adults less likely to remarry (Lichter et al. 2006; McNamee and Raley 2011; Song 2022). Sex disparities further compound these patterns: women live longer than men and are more likely to spend extended periods without a spouse. This is especially true for Black and Hispanic women, who may be more likely to live alone or in extended-family households due to a mix of cultural norms and economic constraints (Carr and Utz 2020; Kamo 2000; Landale et al. 2006).

A major gap in the literature is the lack of studies that systematically examine long-term transitions in marital status and living arrangements or estimate the number of years older adults spend in each state by race, ethnicity, and sex. Marital- and living arrangement-specific life expectancies offer insights beyond marriage and divorce rates, shedding light on the time spent in different family structures, caregiving needs, and access to spousal or familial support. Life table approaches are required for such estimates, yet only two studies have applied them—both focused solely on living arrangements. Raymo et al. (2019) used a multistate life table to classify co-residence patterns and found that White older adults spent less time living with adult children and more time living farther away compared to Black and Hispanic counterparts. Raymo et al. (2022) used Sullivan's method to estimate life expectancies by living arrangement for older adults with and without children, showing that childless White women and Black men spent the most time living alone. While informative, these studies omit marital transitions, which directly affect living

arrangements and social and financial support (Liang et al. 2005). For example, losing a spouse can lead to living alone, moving in with family, or entering institutional care—trajectories shaped by race, ethnicity, and sex. These studies also overlook traditional arrangements like living alone, with a spouse only, with non-spousal others, or in institutions, all of which are key to understanding support structures in later life (Cornwell, Laumann and Schumm 2008; Fiori, Antonucci and Cortina 2006). Finally, neither study quantifies uncertainty in life expectancy estimates or in the proportion of remaining life spent in each state, limiting valid cross-group comparisons. A joint analysis of marital and living arrangements using life table methods—while incorporating uncertainty—would yield a fuller understanding of how older adults navigate family life across racial, ethnic, and sex groups.

A key challenge in estimating marital- and living arrangement-specific life expectancies is accurately quantifying uncertainty to support valid comparisons across racial and ethnic groups. Because overall life expectancy differs by group, reporting only the expected number of years spent in each state can obscure disparities; proportional estimates and confidence intervals are essential for meaningful cross-group comparisons. However, traditional life table approaches using longitudinal panel data—such as bootstrapping or estimating embedded Markov chains—often rely on asymptotic approximations like the delta method and assume normality in the sampling distribution of estimates, which may not accurately capture uncertainty in complex, high-dimensional settings (Lynch and Zang 2022). These methods also struggle with structural zeros—states that cannot be revisited once exited, such as the "never-married" status after first marriage—and are only effective in small state spaces. As the number of marital and living arrangement states increases, the resulting high-dimensional transition matrix poses additional computational challenges. Updated Bayesian approaches, including extensions of methods developed by Lynch

and Brown (2005), provide a more robust framework for addressing these issues, enabling precise uncertainty quantification across a wide range of outcomes.

To address these gaps, we apply an innovative Bayesian Multi-State Life Table (MSLT) approach (Lynch and Zang 2022) to estimate marital- and living arrangement-specific life expectancies and the proportion of remaining life to be spent in each state at age 50, stratified by sex, race, and ethnicity, using data from the Health and Retirement Study (HRS). This method effectively handles high-dimensional transition matrices, making it well-suited for modeling complex marital and living arrangement transitions over time. It provides precise uncertainty estimates for various quantities, including proportions and racial gaps, through credible intervals, enabling statistically valid comparisons across racial and ethnic groups. Additionally, the Bayesian framework properly accounts for structural zeros, ensuring more accurate modeling of transitions that cannot be revisited (Lynch and Zang 2022). In doing so, this study advances prior research not only by applying a novel methodological framework, but more importantly by asking new and meaningful questions—such as how much time older adults spend in different marital and living arrangement states, and how these durations differ by race, ethnicity, and sex. Prior research has not provided this life-course perspective, nor the uncertainty estimates necessary for valid cross-group comparisons. Our approach enables statistically rigorous evaluations of racial and gender disparities that were previously only suggestive.

Method

Our data came from the HRS 1992-2018. The HRS is a nationally representative longitudinal survey of U.S. adults aged 50 and above. Since 1992, the HRS has been collecting economic, demographic, and health information from non-institutionalized U.S. adults over age 50 biennially, using a multi-stage probability sample of households (RAND Center for the Study of Aging 2019).

In each round of the interviews, respondents report their current marital status and living arrangements.[1] Our units of analysis were transitions between marital statuses or living arrangements. A transition is defined as the change in marital status or living arrangements between survey wave *t* and wave *t+1*.

[Figure 1 About Here]

We considered the full range of marital statuses, including married (married, remarried, or partnered), divorced (divorced or separated), widowed, and never-married. In HRS, partnered refers to individuals living with a partner but is not legally married (RAND Center for the Study of Aging 2019). We considered the following living arrangements: living with a spouse, living with non-spouses only, living alone, and living in a nursing home. Living with a spouse was defined as residing in a household with a marital or partnered companion, while living with non-spouses only applied to individuals who did not live in such a couple household but had at least one co-resident who was not their spouse or partner. Adult children make up the majority of non-spouse co-residents across all racial and ethnic groups—81.3% for White, 73.8% for Black, and 81.4% for Hispanic. The remainder include siblings, other relatives, or friends (see Appendix Table A1 for details). Death was the absorbing state. All possible transitions are shown in Figure 1.

After removing individuals missing information on marital status in any wave (N = 159) and those missing information on race and ethnicity (N = 101) and covariates (N = 11), our final sample for the analyses on marital statuses included 26,387 individuals and 132,385 transitions. Among those whose information on living arrangements was available in HRS (N = 21,638), 22

[1] Since the 1996 wave represented the first year that nursing home information was systematically recorded, our analysis of the living arrangement sample started from 1996 and extended through to 2018.

individuals were missing information on race and ethnicity and 35 individuals were missing covariates. After excluding these missing values, our final sample for the analyses on living arrangements included 21,581 individuals and 111,312 transitions. A tabulation of all transitions is shown in Table 1.

[Table 1 About Here]

Using the Bayesian MSLT method, we first estimated a Bayesian multinomial logit model via Gibbs sampling, controlling for race and ethnicity, sex, and birth cohorts. We stratified all analyses by sex in addition to race and ethnicity. Using estimates from the multinomial logit model, we constructed age-specific transition matrices and generated 1,000 life tables for each combination to compute state expectancies. To quantify uncertainty, we used 84% credible intervals. If two 84% confidence intervals do not overlap, the difference between estimates is statistically significant at the 5% level (Albert and Chib 1993).

We examined the following racial and ethnic groups: non-Hispanic White, non-Hispanic Black, and Hispanic. The covariates included age (continuous), sex (male, female), birth year (categorical), current region (Northeast, South, West, Midwest), and nativity status (U.S.-born, foreign-born). In the HRS, race and ethnicity, sex, and birth cohort are used to construct sampling weights (Hauser and Willis 2004; Ofstedal et al. 2011). Controlling for these characteristics in our model helps maintain the representativeness of the sample (Lynch and Brown 2010; Lynch and Zang 2022; Si, Pillai and Gelman 2015). Table 2 presents descriptive statistics for the full samples.

Our main analysis estimates marital status- and living arrangement-specific life expectancy—the expected years spent in each marital status and living arrangement at age 50. Additionally, we conduct two auxiliary analyses: (1) assessing racial and ethnic disparities in these measures, using non-Hispanic White adults as the reference group, and (2) estimating the

proportion of remaining life to be spent in each marital status and living arrangement to account for differences in overall life expectancy across racial, ethnic, and sex groups.

Results

Figures 2–3 show the expected years to be spent in each marital status and living arrangement at age 50 across racial, ethnic, and sex groups. Appendix Table A2-A4 provides detailed estimates, racial disparities, and proportions, with corresponding figures in the Appendix (A2-A4).

Marital Status

As shown in Figure 2, at age 50, White older adults were expected to spend the most years married: 25.47 years for men (CI: 25.14, 25.82) and 18.05 years for women (CI: 17.72, 18.40). Hispanic men and women followed closely, with 23.37 years (CI: 22.60, 24.18) and 15.52 years (CI: 14.86, 16.22), respectively. The Hispanic-White gap was largely due to longer time expected divorced: Hispanic men were expected to spend 1.37 more years divorced than White men (CI: 0.91, 1.83), with a similar pattern among women (see Appendix Table A3).

[Figure 2 About Here]

Black adults had the shortest expected years married: 17.62 for men (CI: 17.09, 18.15) and 9.68 for women (CI: 9.30, 10.08), reflecting Black-White gaps of 7.85 (CI: -8.36, -7.29) and 8.37 years (CI: -8.77, -7.95), respectively. Most of these gaps were explained by longer time expected divorced: 5.99 years for Black men (CI: 5.57, 6.40) vs. 2.73 for White men, and 12.56 years for Black women (CI: 11.96, 13.15) vs. 7.28 for White women. Black adults also had the longest time expected never married—1.31 years for men (CI: 1.16, 1.46) and 1.82 years for women (CI: 1.64, 2.01)—compared to 0.59 and 1.06 years for White men and women.

Proportional estimates confirm these differences (Appendix Table A4). White men were expected to spend the largest share of their remaining life married (81.77%, CI: 81.15, 82.42), followed by Hispanic men (76.43%, CI: 74.81, 78.07) and Black men (64.61%, CI: 63.02, 66.18). Among women, the gaps were starker: White women 52.33% (CI: 51.39, 53.28), Hispanic women 44.77% (CI: 42.75, 46.79), and Black women only 30.99% (CI: 29.79, 32.23).

Across all groups, women were expected to spend fewer years married than men, and more years divorced or widowed. Divorce-related racial gaps were especially large among women. While Black women are more likely to become widowed (Preston, Lim and Morgan 1992; Ruggles 1994), their shorter life expectancy means they were expected to spend less time widowed than White women.

Living Arrangements

As shown in Figure 3, White adults were expected to spend the most years living with a spouse—25.12 years for men (CI: 24.79, 25.47) and 18.05 for women (CI: 17.63, 18.45)—followed by Hispanic men (23.76 years, CI: 22.91, 24.58) and women (14.94 years, CI: 14.21, 15.68). Black adults had the lowest spousal co-residence life expectancies: 18.52 years for men (CI: 17.95, 19.08) and 8.92 for women (CI: 8.50, 9.37), representing gaps of 6.60 and 9.13 years, respectively, compared to Whites. The Hispanic-White gap was largely due to more years expected living with non-spouse family members: 1.46 more years for men (CI: 1.20, 1.74) and 5.24 more for women (CI: 4.51, 5.94), alongside slightly fewer years expected living alone. Black adults were expected to spend significantly more years both living alone and living with non-spouse family members. Compared to White men, Black men were expected to spend 1.35 more years living alone (CI:

1.05, 1.67) and 2.05 more with non-spouse others (CI: 1.84, 2.26). For women, these differences were 0.75 years (CI: 0.28, 1.22) and 5.96 years (CI: 5.22, 6.41), respectively.

[Figure 3 About Here]

Proportional estimates again reflected these disparities (Appendix Table A4). The proportion of remaining life spent living with a spouse was highest for White adults (81.35% for men, 52.49% for women), followed by Hispanics (78.07% for men, 43.18% for women), and lowest for Blacks (67.15% for men, 28.22% for women). Black adults, particularly women, also spent the highest share of life living alone (19.85% for men, 36.03% for women).

Across all groups, women were expected to spend more time living alone or with non-spouse family members than men. Racial disparities in these living arrangements were again more pronounced among women, especially in non-spouse family co-residence.

A Broad Picture: Composition of Life Expectancy at Age 50

Figure 4 highlights clear racial, ethnic, and sex differences in the composition of life expectancy at age 50, with each group following a distinct trajectory shaped by intersecting structural and cultural factors. Across all racial groups, women were expected to spend fewer years married and more years divorced, widowed, living alone, or in non-spouse family arrangements than men—reflecting the compounding effects of gendered life expectancy and partnership patterns. These differences were especially pronounced among women of color. Black women were expected to spend the fewest years married or living with a spouse and the most years unpartnered—whether divorced, never married, or living alone—reflecting cumulative social and health disadvantages over the life course. White adults, especially men, were expected to spend the greatest number of years in marriage and spousal co-residence, reflecting a more traditional

marital and household trajectory. In contrast, Hispanic adults followed a distinct path marked by moderately fewer years in marriage but more years in extended-family living arrangements. Hispanic women, in particular, were expected to spend fewer years alone and more years residing with non-spouse family members, suggesting strong cultural and economic norms around multigenerational support. Rather than falling between the Black and White patterns, the Hispanic trajectory reflects a qualitatively different approach to family and caregiving in later life.

[Figure 4 About Here]

Additional Analyses by Nativity

We also examined differences by nativity status, stratifying the sample into U.S.-born and foreign-born adults (see Appendix Figures A5–A6). Notable patterns emerged: U.S.-born adults generally spent fewer years married and divorced than their foreign-born counterparts, likely due to their shorter total life expectancy. For living arrangements, U.S.-born adults spent fewer years living with a spouse or non-spouse family members. Among women, U.S.-born individuals spent more years living alone and in nursing homes compared to foreign-born women. Despite these differences, the overall patterns of racial and ethnic disparities remained consistent within both nativity groups.

Discussion

Our study uses a Bayesian Multistate Life Table (MSLT) approach to examine racial and ethnic disparities in marital status and living arrangements in later life. This method handles complex, high-dimensional transitions, accounts for structural zeros, and provides credible uncertainty estimates—enabling statistically valid comparisons across groups. More than a methodological

advance, it allows us to answer previously unasked questions about the time older adults spend in different family states and to assess whether observed disparities are meaningful. Our findings reveal persistent racial and ethnic differences: White older adults are more likely to follow traditional patterns of stable marriage and spousal co-residence, while Black and Hispanic adults spend more years unmarried and are more likely to live with extended family, such as adult children.

Importantly, our findings highlight distinct patterns in how Black and Hispanic older adults spend their later years in family arrangements. While prior research has often focused on Black-White disparities (Goldscheider and Bures 2003; Morgan et al. 1993), our results underscore that Hispanic older adults follow unique trajectories distinct from both Black and White adults. Hispanic adults maintain relatively stable marriages with durations only slightly shorter than Whites, whereas Black adults are projected to spend the longest years in non-married states. At the same time, Black adults expect the most time living alone, while Hispanic adults expect the least, instead spending more time in extended-family households. These findings highlight the limitations of a Black-White comparative framework and emphasize the need to examine Hispanic family patterns as a distinct trajectory with its own implications for aging and support structures.

These patterns have important implications for social support and caregiving in later life. Black older adults, who expect fewer years with spouses, may rely more heavily on adult children, extended family, and community networks, potentially creating disproportionate caregiving burdens given structural disadvantages many Black communities face, including economic hardship and limited access to formal caregiving resources. Hispanic older adults, on the other hand, benefit from a more diversified support structure—they anticipate substantial years of spousal support due to their relatively stable marriages while also maintaining strong connections

with extended family. This combination may provide Hispanic older adults with more flexible caregiving arrangements, reinforcing the importance of familism as a protective factor in later life. However, while extended-family living arrangements may provide social and economic support, they also raise questions about caregiving equity and intergenerational transfers of resources. Older adults who live with non-spouse family members may receive informal care but may also be expected to contribute financially or provide caregiving to younger generations (Seltzer and Bianchi 2013; Silverstein and Giarrusso 2010). These complexities highlight the bidirectional nature of intergenerational support and the potential vulnerabilities older adults may face within multigenerational households.

Our results further illustrate how sex intersects with race and ethnicity to shape family life in later years. Despite longer life expectancy, women across all racial and ethnic groups expect fewer years married and living with spouses compared to men, instead spending more years divorced, widowed, and living alone or with non-spouses. However, these gendered patterns manifest differently across racial and ethnic groups. White women, while experiencing fewer married years than White men, still maintain relatively long periods of spousal co-residence. In contrast, Black women face compounded disadvantages—structural barriers to marriage formation, coupled with gendered remarriage patterns, result in the shortest expected years in marriage and spousal co-residence among all groups (Angel, Jiménez and Angel 2007). Hispanic women occupy a unique position where cultural traditions of familism may buffer some challenges of unmarried status through extended family living arrangements, even as they face similar gender-based constraints in marriage patterns. These intersecting disadvantages also shape living arrangements in old age. Black women expect not only the longest years living without spouses but also significant periods living alone—a pattern that contrasts with Hispanic women, who are more

likely to integrate into extended-family households when not married. These disparities have critical implications for social isolation, access to caregiving, and financial stability, particularly for Black women who lack both spousal support and consistent extended-family co-residence.

These disparities translate directly into economic insecurity. Data from the 2023 Current Population Survey reveal stark differences in poverty rates by marital status among women aged 65 and older: only 4.3% of married women live in poverty, compared to 13.6% of widowed women, 14.0% of divorced women, and 18.2% of never-married women (U.S. Census Bureau 2024). These vulnerabilities are even more pronounced by race and ethnicity, with nearly half of unmarried Black (46.4%) and Hispanic (47.2%) older women living below 200% of the poverty threshold.

This economic vulnerability stems largely from policies that favor traditional marriages, disproportionately disadvantaging minority women who experience shorter marriage durations. Social Security spousal benefits require marriages lasting at least ten years (Social Security Administration 2014), limiting access for women with fewer married years who must instead rely on their own earnings records—often lower due to racial and gender wage gaps. Furthermore, policy changes such as the elimination of the Retirement Earnings Test encourage older adults—especially unmarried women—to claim Social Security benefits earlier, resulting in permanently reduced monthly payments (Figinski and Neumark 2018). Since minority women spend substantial portions of later life unmarried, these policy structures systematically exclude them from key benefits, increasing their likelihood of poverty. These structural issues highlight how social safety nets fail to support the diverse family pathways that minorities women increasingly follow, reinforcing economic penalties for non-traditional family patterns.

Our study has several limitations. First, due to limited sample sizes, we were unable to include Asian American, Pacific Islander, and Indigenous older adults. Second, our life table

estimates for racial and ethnic minorities may be conservative due to sample attrition. Respondents with only a single observation—who were disproportionately racial and ethnic minorities (Appendix Table A5)—had to be excluded, potentially causing us to miss transitions out of marriage or exits from couple-headed households that occurred after attrition. Third, our data measured transitions using two-year intervals, potentially missing shorter-term marital and living arrangement changes occurring between survey waves. Finally, we grouped marital and partnered statuses together in our primary analyses; although sensitivity analyses in Appendix Figure A7 suggest this had minimal impact on our overall conclusions, future studies with larger samples could examine these statuses separately to better capture distinct partnership dynamics.

As the U.S. aging population becomes increasingly diverse in racial and ethnic composition (U.S. Census Bureau 2023), our findings imply that existing social policies built around lifelong marriage assumptions may systematically disadvantage minority, particularly older women. These disparities highlight the urgent need for policies that broaden eligibility criteria for spousal benefits, improve housing access for unmarried older adults, and develop interventions sensitive to cultural and community-based caregiving arrangements, with the purpose of recognizing the diverse pathways through which older adults experience family life. While this study is primarily descriptive, future research should investigate underlying factors shaping these disparities, particularly intersectional vulnerabilities of minority women, to improve economic security and well-being for an increasingly diverse aging population.

References

Albert, J.H.and Chib, S. (1993). Bayesian analysis of binary and polychotomous response data. *Journal of the American statistical Association*, *88*(422), 669-679.

Angel, J.L., Jiménez, M.A., and Angel, R.J. (2007). The Economic Consequences of Widowhood for Older Minority Women. *The Gerontologist*, *47*(2), 224-234. https://doi.org/10.1093/geront/47.2.224

Ausubel, J. (2020). *Older people are more likely to live alone in the U.S. than elsewhere in the world*.

Brown, S.L.and Lin, I.F. (2012). The gray divorce revolution: rising divorce among middle-aged and older adults, 1990-2010. *J Gerontol B Psychol Sci Soc Sci*, *67*(6), 731-741. https://doi.org/10.1093/geronb/gbs089

Brown, S.L., Lin, I.F., Hammersmith, A.M., and Wright, M.R. (2018). Later Life Marital Dissolution and Repartnership Status: A National Portrait. *Journals of Gerontology Series B-Psychological Sciences and Social Sciences*, *73*(6), 1032-1042. https://doi.org/10.1093/geronb/gbw051

—. (2019). Repartnering Following Gray Divorce: The Roles of Resources and Constraints for Women and Men. *Demography*, *56*(2), 503-523. https://doi.org/10.1007/s13524-018-0752-x

Bulanda, J.R.and Brown, S.L. (2007). Race-ethnic differences in marital quality and divorce. *Social Science Research*, *36*(3), 945-967.

Carr, D.and Utz, R.L. (2020). Families in Later Life: A Decade in Review. *Journal of Marriage and Family*, *82*(1), 346-363. https://doi.org/https://doi.org/10.1111/jomf.12609

Cherlin, A.J. (2010). *The Marriage-Go-Round: The State of Marriage and the Family in America Today*. Knopf Doubleday Publishing Group. https://books.google.com/books?id=LHvr6ySZ8FwC

Cohn, D.v.and Passel, J.S. (2018). *A record 64 million Americans live in multigenerational households*.

Cornwell, B., Laumann, E.O., and Schumm, L.P. (2008). The Social Connectedness of Older Adults: A National Profile*. *Am Sociol Rev*, *73*(2), 185-203. https://doi.org/10.1177/000312240807300201

de Vos, S.and Arias, E. (2003). A Note on the Living Arrangements of Elders 1970–2000, with Special Emphasis on Hispanic Subgroup Differentials. *Population Research and Policy Review*, *22*(1), 91-101. https://doi.org/10.1023/A:1023504322396

Figinski, T.and Neumark, D. (2018). Does Eliminating the Earnings Test Increase the Incidence of Low Income Among Older Women? *Res Aging*, *40*(1), 27-53. https://doi.org/10.1177/0164027516676877

Fiori, K.L., Antonucci, T.C., and Cortina, K.S. (2006). Social Network Typologies and Mental Health Among Older Adults. *The Journals of Gerontology: Series B*, *61*(1), P25-P32. https://doi.org/10.1093/geronb/61.1.P25

Goldscheider, F.K.and Bures, R.M. (2003). The racial crossover in family complexity in the United States. *Demography*, *40*(3), 569-587. https://doi.org/10.1353/dem.2003.0022

Harawa, N.T., Leng, M., Kim, J., and Cunningham, W.E. (2011). Racial/ethnic and gender differences among older adults in nonmonogamous partnerships, time spent single, and

human immunodeficiency virus testing. *Sex Transm Dis*, *38*(12), 1110-1117. https://doi.org/10.1097/OLQ.0b013e31822e614b

Hauser, R.M.and Willis, R.J. (2004). Survey design and methodology in the Health and Retirement Study and the Wisconsin Longitudinal Study. *Population and Development Review*, *30*, 209-235.

Himes, C.L., Hogan, D.P., and Eggebeen, D.J. (1996). Living arrangements of minority elders. *J Gerontol B Psychol Sci Soc Sci*, *51*(1), S42-48. https://doi.org/10.1093/geronb/51b.1.s42

Kamo, Y. (2000). Racial and Ethnic Differences in Extended Family Households. *Sociological Perspectives*, *43*(2), 211-229. https://doi.org/10.2307/1389794

Landale, N., Oropesa, R.S., and Bradatan, C. (2006). Hispanic Families in the United States: Family Structure and Process in an Era of Family Change. In M.F. Tienda M (Ed.), *Hispanics and the Future of America.* National Research Council (US) Panel on Hispanics in the United States.

Liang, J., Brown, J.W., Krause, N.M., Ofstedal, M.B., and Bennett, J. (2005). Health and living arrangements among older Americans: does marriage matter? *J Aging Health*, *17*(3), 305-335. https://doi.org/10.1177/0898264305276300

Lichter, D.T., Qian, Z., and Leannam, M.M. (2006). Marriage or Dissolution? Union Transitions among Poor Cohabiting Women. *Demography*, *43*(2), 223-240. http://www.jstor.org/stable/4137195

Liu, H., Umberson, D., and Xu, M. (2020). Widowhood and mortality: gender, race/ethnicity, and the role of economic resources. *Ann Epidemiol*, *45*, 69-75 e61. https://doi.org/10.1016/j.annepidem.2020.02.006

Lynch, S.M.and Brown, J.S. (2010). Obtaining multistate life table distributions for highly refined subpopulations from cross-sectional data: A bayesian extension of sullivan's method. *Demography*, *47*(4), 1053-1077. https://doi.org/10.1007/bf03213739

Lynch, S.M.and Zang, E. (2022). Bayesian Multistate Life Table Methods for Large and Complex State Spaces: Development and Illustration of a New Method. *Sociological Methodology*, *52*(2), 254-286. https://doi.org/10.1177/00811750221112398

McNamee, C.B.and Raley, R.K. (2011). A note on race, ethnicity and nativity differentials in remarriage in the United States. *Demographic Research*, *24*(13), 293-312. https://doi.org/10.4054/DemRes.2011.24.13

Morgan, S.P., McDaniel, A., Miller, A.T., and Preston, S.H. (1993). Racial Differences in Household and Family Structure at the Turn of the Century. *American Journal of Sociology*, *98*(4), 799-828. http://www.jstor.org/stable/2781236

Ofstedal, M.B., Weir, D.R., Chen, K.-T., and Wagner, J. (2011). Updates to HRS sample weights. *Ann Arbor: University of Michigan*.

Pew Research Center. (2010). *The Return of the Multi-Generational Family Household*.

—. (2015). *The America Family Today*. Pew Research Center.

Preston, S.H., Lim, S., and Morgan, S.P. (1992). African-American marriage in 1910: beneath the surface of census data. *Demography*, *29*(1), 1-15. https://www.ncbi.nlm.nih.gov/pubmed/1547897

Raley, R.K.and Sweeney, M.M. (2009). Explaining race and ethnic variation in marriage: Directions for future research. *Race and Social Problems*, *1*, 132-142.

RAND Center for the Study of Aging, R.C.f.t.S.o.A. (2019). Health and Retirement Study.

Raymo, J.M., Pike, I., and Liang, J. (2019). A New Look at the Living Arrangements of Older Americans Using Multistate Life Tables. *J Gerontol B Psychol Sci Soc Sci*, *74*(7), e84-e96. https://doi.org/10.1093/geronb/gby099

Raymo, J.M., Xu, X., Kim, B., Liang, J., and Ofstedal, M.B. (2022). Later-Life Living Arrangements of Americans With and Without Children: A Life Table Approach. *J Gerontol B Psychol Sci Soc Sci*, *77*(1), 181-190. https://doi.org/10.1093/geronb/gbab133

Ruggles, S. (1994). The origins of African-American family structure. *American Sociological Review*, 136-151.

Seltzer, J.A.and Bianchi, S.M. (2013). Demographic change and parent-child relationships in adulthood. *Annual review of sociology*, *39*(1), 275-290.

Si, Y.J., Pillai, N.S., and Gelman, A. (2015). Bayesian Nonparametric Weighted Sampling Inference. *Bayesian Analysis*, *10*(3), 605-625. https://doi.org/10.1214/14-Ba924

Silverstein, M.and Giarrusso, R. (2010). Aging and family life: A decade review. *Journal of Marriage and Family*, *72*(5), 1039-1058.

Social Security Administration. (2014). *Marriage Trends and Women's Benefits: Differences by Race-Ethnicity and Nativity*. https://www.ssa.gov/policy/docs/research-summaries/marriage-trends-race-ethnicity.html

Song, H.M. (2022). Women's Divergent Union Transitions After Marital Dissolution in the United States. *Population Research and Policy Review*, *41*(3), 953-980. https://doi.org/10.1007/s11113-021-09677-0

U.S. Census Bureau. (2023). *2023 National Population Projections Tables: Main Series*. https://www.census.gov/data/tables/2023/demo/popproj/2023-summary-tables.html

—. (2024). *Current Population Survey 2023 Annual Social and Economic (ASEC) Supplement* https://www2.census.gov/programs-surveys/cps/techdocs/cpsmar23.pdf

Western, B.and Wildeman, C. (2009). The black family and mass incarceration. *The ANNALS of the American Academy of Political and Social Science*, *621*(1), 221-242.

Tables

Table 1. Observed Transitions of Marital Statuses and Living Arrangements, the Health and Retirement Study (1992-2018)

Transition Start (Wave *t*)	Transition End (Wave *t+1*)					
Marital Status ↓	NM	M	D	W	Dead	Total
Never-married (NM)	6,059	102	0	0	398	6,559
Married (M)	0	66,937	1,355	2,623	3,593	74,508
Divorced (D)	0	1,149	21,588	0	1,342	24,079
Widowed (W)	0	505	0	22,896	3,838	27,239
Living Arrangement ↓	LA	LS	LNS	NH	Dead	Total
Live Alone (LA)	24,716	757	2,434	626	2,824	31,357
Live with Spouse (LS)	2,100	54,139	918	237	2,960	60,354
Live with Non-spouses Only (LNS)	2578	455	13238	196	1552	18,019
Nursing Home (NH)	90	35	31	710	716	1,582

Note: A total of 132,385 marital status transitions and 111,312 living arrangement transitions (including same-state transitions) are included. "Married" includes individuals who report being currently married, remarried, or partnered. "Divorced" includes those who are either divorced or separated. "Live with spouse" includes respondents residing with either a spouse or a partner. "Live with Non-spouses only" refers to respondents who do not live with a spouse or partner but have at least one co-resident, such as adult children, siblings, other relatives, or friends. Wave *t* and Wave *t+1* represent consecutive biennial survey waves from 1992 to 2018. Each row displays the distribution of transitions from a respondent's status at Wave *t* to their status at the next wave (Wave *t+1*), approximately two years later.

Table 2. Descriptive Statistics of Marital Status and Living Arrangement Samples, the Health and Retirement Study (1992-2018)

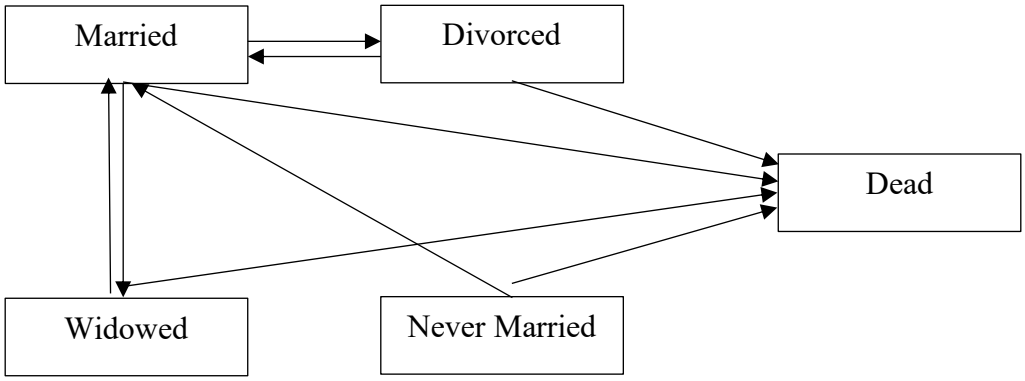
	Marital Status Sample	Living Arrangement Sample
Age at Baseline, Mean (SD)	61.4 (10.7)	63.5 (10.9)
Sex, n (%)		
Female	14,175 (53.7)	11,851 (54.9)
Male	12,212 (46.3)	97,30 (45.1)
Nativity Status, n (%)		
Foreign-born	3,513 (13.3)	2,681 (12.4)
US-born	22,874 (86.7)	18,900 (87.6)
Race/Ethnicity, n (%)		
Non-Hispanic White	16,691 (63.3)	14,304 (66.3)
Non-Hispanic Black	5,551 (21.0)	4,277 (19.8)
Hispanic	3,188 (12.1)	2,397 (11.1)
Other	957 (3.6)	603 (2.8)
Current Region, n (%)		
Northeast	4,601 (17.4)	3,798 (17.6)
Midwest	5,826 (22.1)	4,927 (22.8)
South	11,048 (41.9)	8,884 (41.2)
West	4,912 (18.6)	3,972 (18.4)
Number of Individuals	26,387	21,581
Number of Person-wave Observations	158,675	132,795

Note: Data is from the Health and Retirement Study (HRS) spanning from 1992 to 2018. The marital status sample includes all HRS waves from 1992 to 2018. The living arrangement sample is drawn from the HRS waves from 1996 to 2018, as the 1996 wave marked the initial year that nursing home information was systematically recorded.

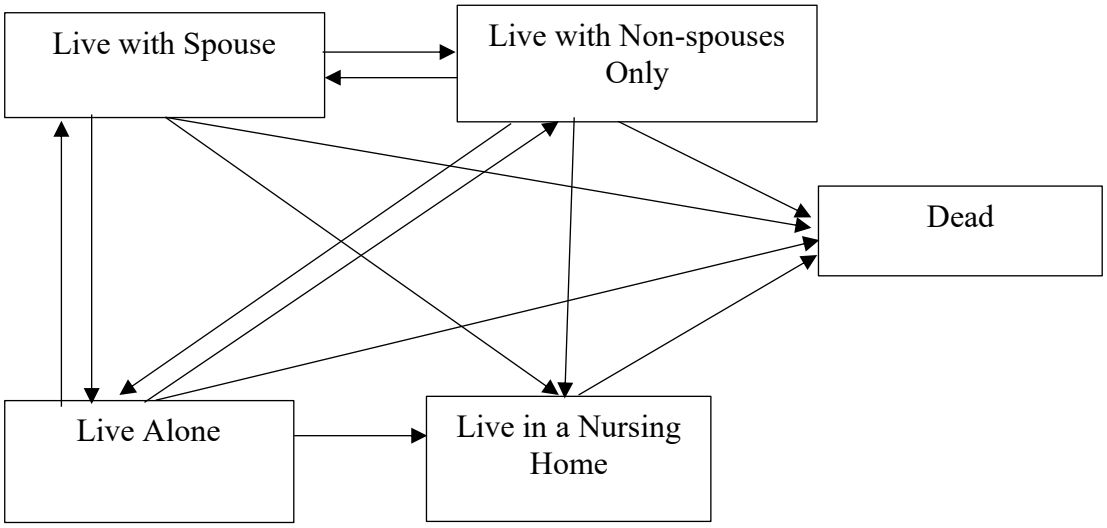
Figures

Figure 1. State Space Diagrams for Transitions in Marital Status and Living Arrangements

Panel A. Marital Status

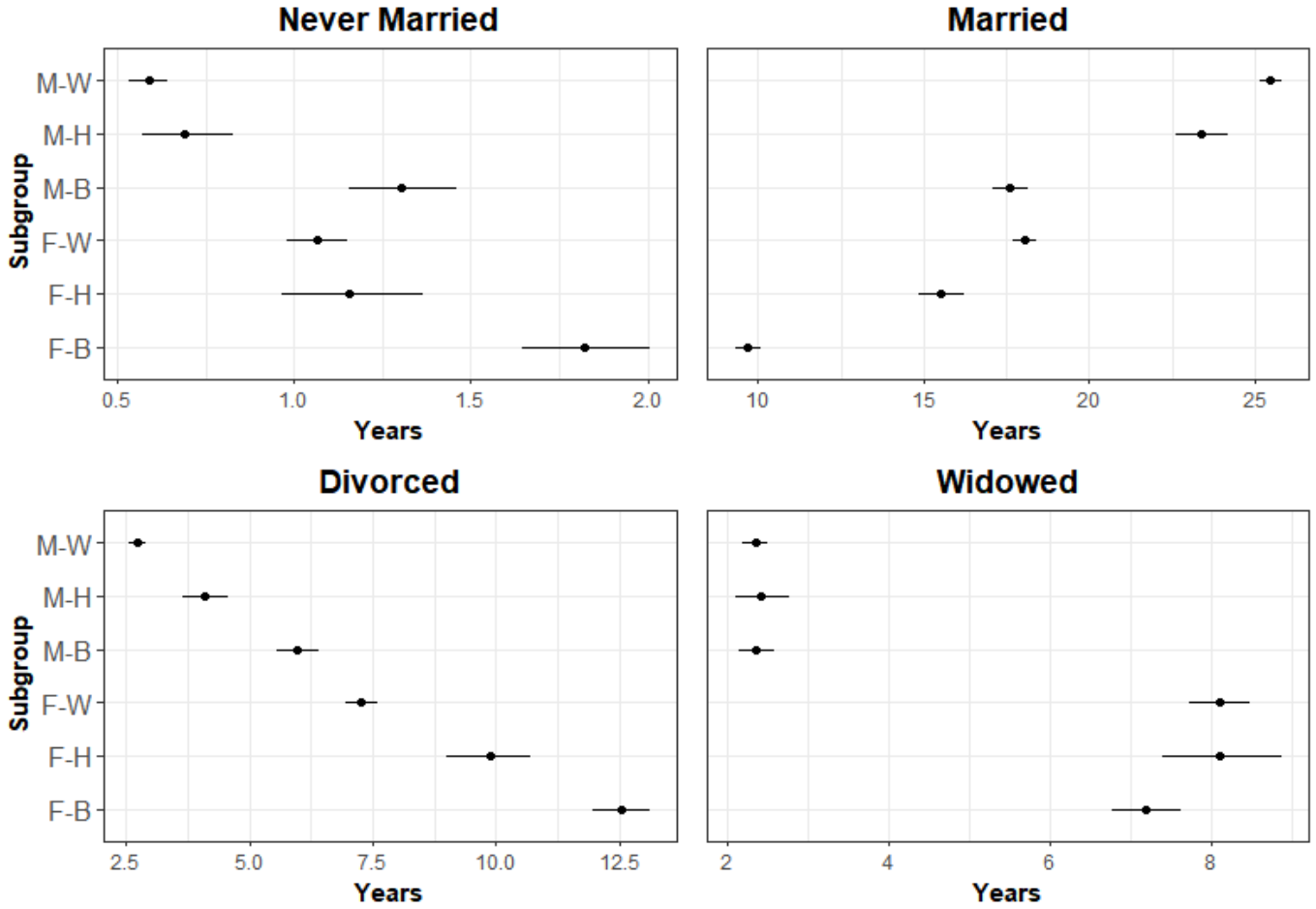


Panel B. Living Arrangements



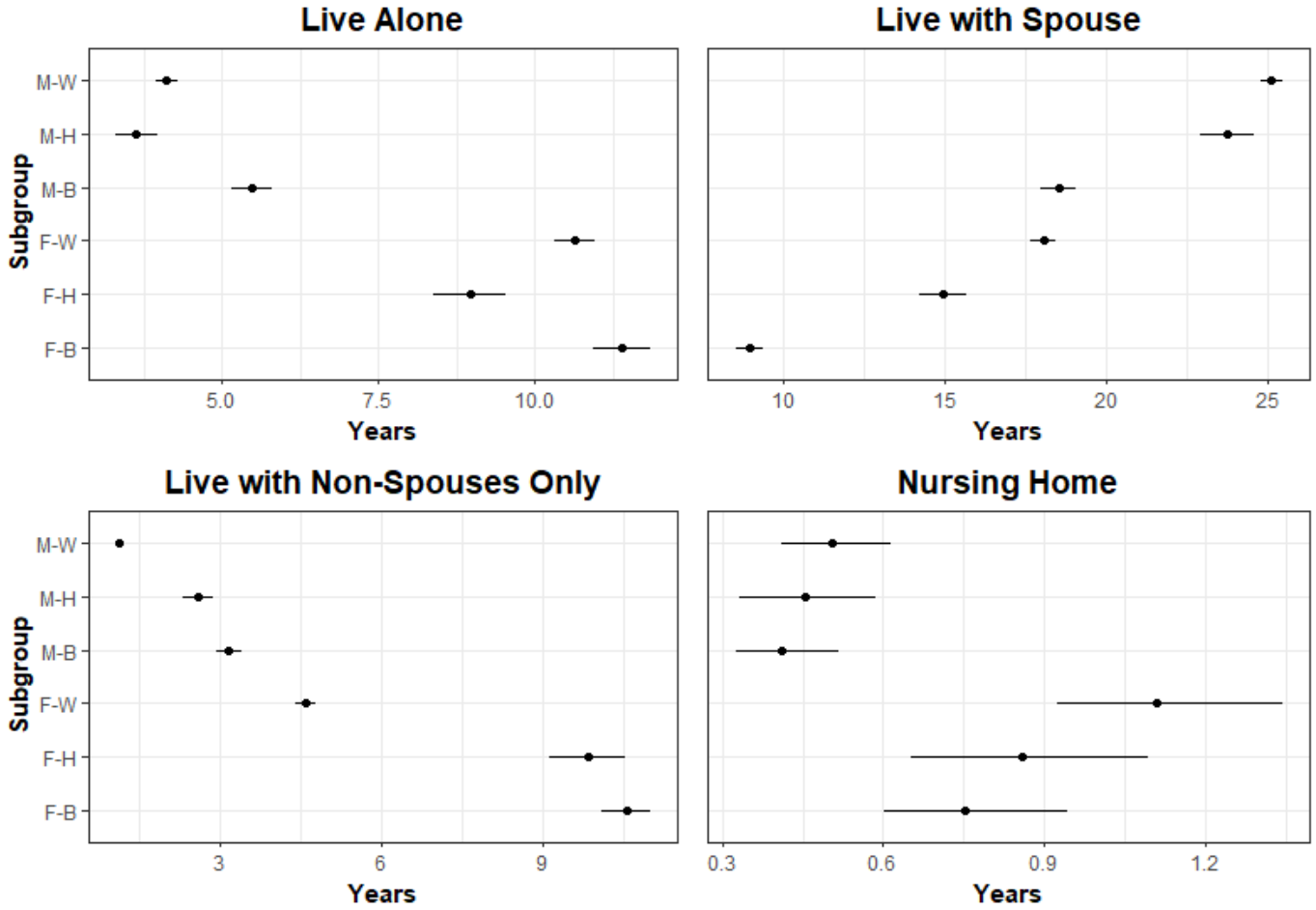
Note: "Married" includes individuals who report being currently married, remarried, or partnered. "Divorced" includes those who are either divorced or separated. "Live with spouse" includes respondents residing with either a spouse or a partner. "Live with Non-spouses only" refers to respondents who do not live with a spouse or partner but have at least one co-resident, such as adult children, siblings, other relatives, or friends. Very few individuals transition out of nursing homes unless they pass away. Therefore, we assume that individuals remain in a nursing home unless they experience a transition to death. These marital status and living arrangement transitions were observed across waves of the Health and Retirement Study from 1992 to 2018, with each wave occurring approximately every two years. At each wave *t*, respondents reported their marital status and living arrangement. Transitions are measured by comparing their status at wave *t* with their status at the subsequent wave *t+1*. The arrows in the figure represent the possible transitions that respondents could experience between two consecutive HRS waves.

Figure 2. Expected Years in Each Marital Status at Age 50 by Racial, Ethnic, and Sex Groups



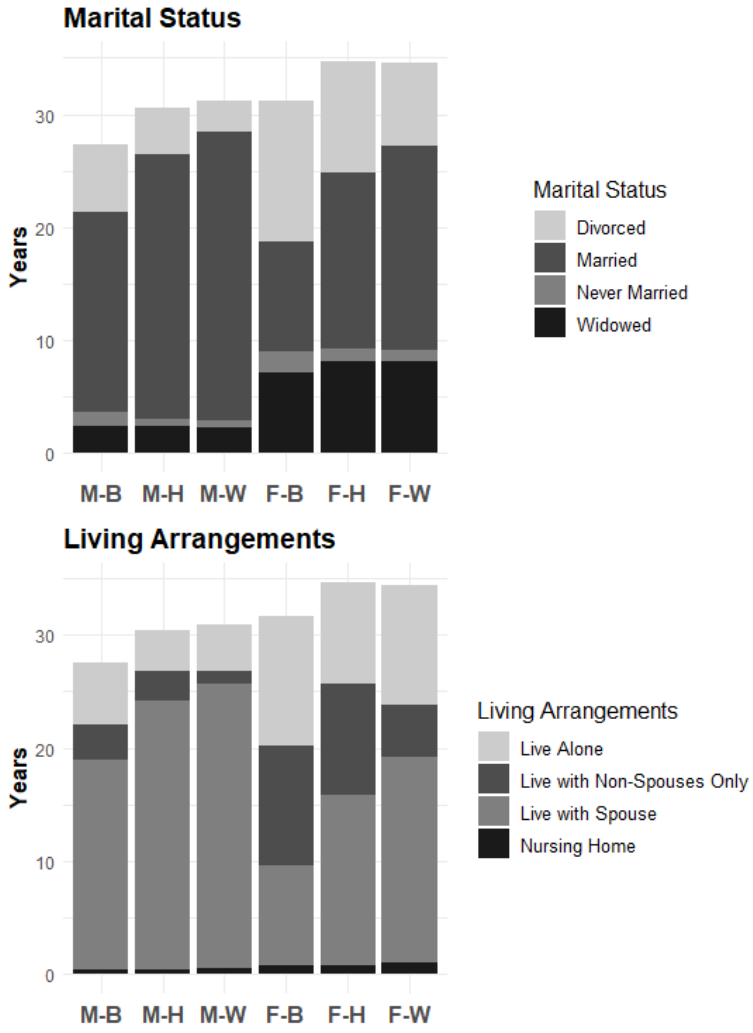
Note: "Married" includes those who report their current marital status as married, remarried, or partnered. "Divorced" includes those who are either divorced or separated. "M-W," "M-H," and "M-B" denote White, Hispanic, and Black males, respectively, while "F-W," "F-H," and "F-B" represent White, Hispanic, and Black females, respectively.

Figure 3. Expected Years in Each Living Arrangement at Age 50 by Racial, Ethnic, and Sex Groups



Note: "Live with spouse" includes respondents who reside with either a spouse or a partner. "Live with non-spouses only" refers to respondents who do not live with a spouse or partner but have at least one co-resident, such as adult children, siblings, other relatives, or friends. The abbreviations "M-W," "M-H," and "M-B" represent White, Hispanic, and Black males, respectively, while "F-W," "F-H," and "F-B" denote White, Hispanic, and Black females, respectively.

Figure 4. Composition of Life Expectancy at Age 50, by Marital Status and Living Arrangements



Note. "Married" includes those who report their current marital status as married, remarried, or partnered. "Divorced" includes those who are either divorced or separated. "Live with spouse" includes respondents who reside with either a spouse or a partner. "Live with non-spouses only" refers to respondents who do not live with a spouse or partner but have at least one co-resident, such as adult children, siblings, other relatives, or friends. "M-W," "M-H," and "M-B" denote White, Hispanic, and Black males, respectively, while "F-W," "F-H," and "F-B" represent White, Hispanic, and Black females, respectively.

Conclusion

This dissertation examined three interconnected dimensions of how demographic shifts affect older adults' life trajectories and well-being, addressing core areas in the National Academy of Sciences' research agenda for demography of aging: socioeconomic differentials in mortality, social connections and emotional well-being, and family structures and living arrangements.

Methodologically**,** this dissertation identifies critical problems with selective attrition in longitudinal surveys of aging populations and offers suggestive solutions. Chapter 1 demonstrates how attrition patterns correlate with socioeconomic status, systematically underestimating mortality rates and distorting measures of socioeconomic disparities. The imputation strategies explored—using alive-to-death ratios and family co-attrition patterns—provide guidance for researchers addressing data quality challenges in contexts where high-quality infrastructure is lacking.

Substantively, the findings highlight family change as an important demographic force shaping population health and well-being, with significant policy implications that vary by context. In China, family transitions primarily involve separation from adult children, creating widespread challenges for older adults' social and emotional well-being. This pattern becomes particularly pronounced as one-child cohort parents enter old age while cultural expectations of filial piety and policies emphasizing family-based care persist. With few alternative sources of emotional support available, these demographic shifts create new forms of vulnerability that require policy responses extending beyond traditional family-centered models.

In the United States, where gray divorce and repartnership are increasingly common, family changes involve union dissolution and new formation at later ages. Chapter 3 challenges conventional assumptions about stable, lifelong marriages as the normative experience, revealing

instead that contemporary cohorts follow increasingly diverse family trajectories. However, existing social policies built on lifelong marriage assumptions systematically disadvantage those with non-traditional pathways, particularly minority women. Social Security spousal benefits, for example, require marriages lasting at least ten years, forcing women with shorter unions to rely solely on earnings records often diminished by persistent wage gaps. This framework creates economic penalties for diverse family patterns, contributing to a situation where nearly half of unmarried Black and Hispanic older women live below 200% of the poverty threshold. These structural inequities highlight the urgent need for policies that broaden eligibility criteria and recognize diverse family pathways for later-life support.

Collectively, these findings demonstrate how demographic transformation creates new vulnerabilities while exposing critical gaps in both research methodology and policy frameworks. The research underscores the urgent need for methodological innovations and adaptive policy solutions that can accommodate the growing heterogeneity of aging experiences in the 21st century.