ABSTRACT

Title of dissertation: HOW STRATIFICATION SHAPES HEALTH IN THE FACE OF RAPID ECONOMIC, DEMOGRAPHIC, AND EPIDEMIOLOGICAL CHANGE: INSIGHTS FROM INDIA

Neerad Deshmukh, Doctor of Philosophy, 2026

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This dissertation examines how social stratification shape health and demographic outcomes in a context of rapid economic, demographic, and environmental change. Focusing on India, it asks how long-standing hierarchies of caste, class, gender, and place are reproduced, transformed, or reconfigured as the country undergoes sustained economic growth, widespread poverty transitions, population aging, and increasing exposure to climate-related stress. India offers a critical setting for this analysis. It is experiencing one of the world's largest and fastest demographic transitions, yet these changes are unfolding within deeply institutionalized systems of inequality that continue to shape access to resources, risks, and protection. Across three empirical chapters, the dissertation shows that aggregate development does not eliminate health inequality. Rather, social advantage and disadvantage are reorganized across new domains, from women's nutritional change to older adults' functional health and survival.

The first chapter examines the effect of India's long-term economic growth on women's nutritional status, as measured by body mass index (BMI). While economic expansion can improve nutrition by increasing access to food, healthcare, and education, rising inequality may offset these gains by concentrating resources among the affluent. Using four waves of the National Family

Health Survey (1998–2019), this study examines whether BMI has converged or diverged across socio-economic status and states for women aged 25–49. The results suggest that undernutrition declined across all economic groups, with the largest absolute declines among the poorest, narrowing the gap with the affluent. At the same time, overweight and obesity spread beyond the richest groups.

The second chapter examines how income mobility, particularly transition out of poverty, shapes survival in later life. Using three waves of the India Human Development Survey (2004–2024), the chapter analyzes how poverty transitions affect mortality risks among adults aged 50 to 79. The results show that persistent poverty and downward mobility are strongly associated with higher mortality risk.

The third chapter examines the health consequences of climate shocks in later life, focusing on repeated drought exposure among older adults in rural India. As climate change intensifies environmental uncertainty, its health impacts are likely to be unevenly distributed, amplifying existing social and economic inequalities. Using longitudinal data from two waves of the India Human Development Survey, the findings show that repeated drought exposure significantly increases the risk of functional deterioration, with the strongest effects concentrated among economically disadvantaged households. The chapter further shows that social capital acts as a crisis-activated resource to buffer against these shocks.

Taken together, the three chapters argue that in a society undergoing rapid demographic, epidemiological, economic, and climatic transitions, social stratification remains consequential for health and demographic outcomes. It becomes consequential in new ways. The specific risks change, and the mechanisms linking caste, class, religion, gender, and place to health and demographic outcomes evolve. Yet the underlying structure of advantage and disadvantage persists, reorganizing

through the opportunities and vulnerabilities created by each new context. This dissertation makes three central contributions. First, it shows that economic growth does not dissolve traditional hierarchies, but alters how they operate across the life course. Second, it provides rare longitudinal, population-scale evidence from a low- and middle-income country on how economic mobility, aging, and environmental shocks shape health and survival. Third, it integrates demography, social stratification, environmental inequality, and life-course perspectives to show how cumulative disadvantage is dynamically produced during periods of rapid structural change. In doing so, the dissertation extends fundamental cause theory beyond its original high-income Western context, treats caste and religion as fundamental causes of health inequality in their own right, and applies life-course approaches to an aging population in the Global South.

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by

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Dissertation submitted to the Faculty of the Graduate School of the
University of Maryland, College Park, in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
2026

Advisory Committee:
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Acknowledgements

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Contents

Abstract i

Acknowledgements ii

Introduction 1

Acknowledgements 1

Introduction 1
- Demographic, Epidemiological, and Economic Transition in India . . . 2
- Social Stratification in India . . . 5
- Theoretical Frameworks . . . 10
- Contributions and Chapter Overview . . . 14

Chapter 1: Convergence, Divergence or Persistence: How is India's Long-Term Economic Growth Reflected in Women's Nutritional Status? 19
- Abstract . . . 19
- Introduction . . . 20
- Background . . . 21
- Research Questions and Hypotheses . . . 27
- Data and Methods . . . 28
- Results . . . 32
- Conclusions and Discussion . . . 41

Chapter 2: Unequal Paths to Aging: How Poverty Transitions Shape Mortality in Rural India 44
- Abstract . . . 44
- Introduction . . . 45
- Background . . . 46
- Research Questions and Hypotheses . . . 52
- Data and Methods . . . 53
- Results . . . 58
- Conclusions and Discussions . . . 64

Chapter 3: Weathering the Drought: Risks and Resilience Patterns in Functional Health of Older Adults Across Rural India 67
- Abstract . . . 67
- Introduction . . . 68
- Background . . . 69
- Hypotheses and Conceptual Framework . . . 75
- Data and Methods . . . 76
- Results . . . 83

Conclusions and Discussion 93

Conclusions & Discussions **96**
What the Three Chapters Found 97
Policy Implications 101
Limitations and Next Steps 103

Appendix **105**
Appendix A1. Assessment of Attrition Bias 105
Appendix A2. All Multinomial Logit Models 107
Appendix A3. Disaggregated Social Capital Models 113
Appendix B. Chapter 2 Sensitivity Check: Discrete-Time Logistic Regression 120
Appendix C. Chapter 1 Sensitivity Checks 123

List of Tables

1.1 Sample Characteristics by Survey Round, Analytic Sample, Ever-Married Women Aged 25–49, India (NFHS 1998—2019) . . . 32
1.2 Relative Risk Ratios (RRR) from Multinomial Logistic Regression of Women's BMI Status, India, Ever-Married Women, Aged 25–49 (NFHS 1998–2019) . . . 33
1.3 Adjusted Predicted Probabilities of Underweight by State, 1998 and 2019, Sorted by 1998 Prevalence . . . 40
1.4 Adjusted Predicted Probabilities of Obesity by State, 1998 and 2019 . . . 41
2.1 Mortality status between Wave 2 and Wave 3 among rural older adults aged 50–79 in India, by household poverty transition category Wave 1 to Wave 2 . . . 58
2.2 Cox Proportional Hazards Models of Mortality, Rural India, Ages 50–79 (IHDS Wave 2 to Wave 3) . . . 61
2.3 Adjusted Predicted Survival Probabilities by Poverty Transition and Caste Group . 63
3.1 Descriptive Statistics, Rural Adults Aged 40 and Older in IHDS Wave 1 ($N = 32{,}248$) 83
3.2 Multinomial Logistic Regression of Functional Limitation Deterioration by Drought Exposure, Socioeconomic, and Demographic Characteristics. Rural Adults Aged 40 and Older (IHDS, Wave 1 to Wave 2) . . . 86
3.3 Predicted Probabilities of Functional Limitation Deterioration by Drought Exposure, Wealth Tertiles, and Social Groups among Adults Aged 47 and Older, Rural India (IHDS, Wave 1 to Wave 2), with 90% Confidence Intervals . . . 88
3.4 Predicted Probabilities of Functional Limitation Deterioration by Drought Exposure, Social Capital, Wealth Tertiles, and Social Groups, Adults Aged 47 and Older, Rural India (IHDS, Wave 1 to Wave 2), with 90% Confidence Intervals . . . 92
A.1 Row percentages showing share of each subgroup retained vs. lost to follow-up. IHDS Panel, Waves 1 and 2. Individuals aged 40 and above in Wave 1. . . . 106
A.2 Multinomial logistic regression of functional limitation and mortality. Rural Adults aged 40 and older (IHDS, Wave 1 to Wave 2). . . . 107
A.3 Resilience Models: Multinomial logistic regression of functional limitation and mortality. Rural Adults aged 40 and older (IHDS, Wave 1 to Wave 2). . . . 110
A.4 Distribution of Bonding and Bridging Social Capital Membership by Social Group, Wealth Tertile, and Drought Exposure, Rural India, IHDS 2004–05 . . . 113
A.5 Bonding Capital × Drought Predicted Probabilities of Functional Health Deterioration (Model 13) . . . 115
A.6 Bridging Capital × Drought Predicted Probabilities of Functional Health Deterioration (Model 14) . . . 117
B.1 Logistic Regression Models Predicting Mortality, Rural Adults Aged 50–79, IHDS 2011–2022 . . . 121
B.2 Predicted Probability of Death by Poverty Transition and Social Group, Rural Adults Aged 50–79 . . . 122
B.3 Row Percentages Showing Share of Each Subgroup Retained vs. Lost to Follow-Up. IHDS Panel, Waves 1 and 2. Rural Individuals Aged 43–73 in Wave 1 (2004–05). . 122
C.1 Relative Risk Ratios from Multinomial Logistic Regression of Women's BMI Status, Round-Stratified Subsample ($N = 200{,}000$) . . . 124

C.2 Relative Risk Ratios from Multinomial Logistic Regression of Women's BMI Status, Round-Stratified Subsample with Normalised Survey Weights ($N = 956{,}420$) . . . 125

List of Figures

1.1 Predicted Probabilities of Underweight by Wealth Quintile and Survey Year, Ever-Married Women, Aged 25–49 (NFHS, 1998–2019). 35
1.2 Predicted Probabilities of Obesity by Wealth Quintile and Survey Year, Ever-Married Women, Aged 25–49 (NFHS, 1998–2019). 37
1.3 Adjusted Predicted Probabilities of Underweight by State, 1998 and 2019 (NFHS). 38
1.4 Adjusted Predicted Probabilities of Obesity by State, 1998 and 2019 (NFHS). . . . 39
2.1 Kaplan–Meier survival curves by household poverty transition status, rural older adults aged 50–79, India. 59
2.2 Kaplan–Meier survival curves by caste group, rural older adults aged 50–79, India. 60
3.1 Stratified Risks and Resilience Framework Linking Drought Exposure to Functional Limitations 76
3.2 Functional health trajectories by drought exposure, wealth, social group, and social capital status, rural adults aged 40 and over, IHDS Wave 1 to Wave 2. 85
3.3 Predicted probabilities of functional health deterioration by drought exposure and socioeconomic stratifiers, rural India (IHDS, 2004–05 to 2011–12). 88
3.4 Predicted probabilities of functional health deterioration by social capital status, rural India (IHDS, 2004–05 to 2011–12). 90
3.5 Predicted probabilities of functional health deterioration by social capital, stratified by assets and social groups, rural India (IHDS, 2004–05 to 2011–12). 91

Introduction

Economic development has long been associated with improvements in population health.

This dissertation examines how social stratification shape health and demographic outcomes in a context of rapid economic, demographic, and environmental change. Focusing on India, it asks how long-standing hierarchies of caste, class, gender, and place are reproduced, transformed, or reconfigured as the country undergoes sustained economic growth, widespread poverty transitions, population aging, and increasing exposure to climate-related stress. India offers a critical setting for this analysis. It is experiencing one of the world's largest and fastest demographic transitions, yet these changes are unfolding within deeply institutionalized systems of inequality that continue to shape access to resources, risks, and protection. Across three empirical chapters, the dissertation shows that aggregate development does not eliminate health inequality. Rather, social advantage and disadvantage are reorganized across new domains, from women's nutritional change to older adults' functional health and survival.

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How Stratification Shapes Health in the Face of Rapid Economic, Demographic, and Epidemiological Change: Insights from India

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Contents

List of Tables

List of Figures

Introduction

Economic development has long been associated with improvements in population health. As incomes increase, people gain access to better nutrition, housing, sanitation, and healthcare, leading to improvements in health and demographic indicators, including life expectancy, infant mortality, and disease burden. The relationship between national income and population health is well established. Richer societies are, on average, healthier societies (Preston, 1975). Nevertheless, aggregate improvement does not ensure equitable improvement in health and demographic indicators. In developing economies, the allocation of health gains follows the distribution of income and wealth. Consequently, when economic growth is accompanied by increasing inequality, the health benefits of this growth tend to accrue disproportionately to the already advantaged, while the least advantaged experience marginal or slower gains (Deaton, 2013; R. Wilkinson & Pickett, 2009). The result is that periods of rapid growth can simultaneously produce better average health outcomes and wider health disparities, a pattern extensively documented across low- and middle-income countries undergoing economic transformation (Subramanian & Kawachi, 2004).

A deeper and more theoretically challenging pattern emerges when the focus shifts from the distribution of growth to social positions as a determinant of health. Even in societies where economic development has substantially raised living standards across the income distribution, the relative gradient in health by social position does not disappear (Marmot, 2004). Individuals in higher social strata consistently enjoy longer lifespans, encounter fewer health issues, and recover more effectively from setbacks. This phenomenon is not solely attributable to greater financial resources, but also to social standing, which provides supplementary benefits beyond income. These

benefits include access to knowledge, institutions, social networks, and political influence (Link & Phelan, 1995). As the specific diseases and risks driving health risks like infectious diseases give way to chronic illnesses, new environmental hazards, or new medical technologies emerge, advantaged groups deploy these resources to protect themselves against risks or take advantage of new technologies. Meanwhile, disadvantaged groups often lack the capacity to adapt to these changes or incorporate new knowledge and technologies (Clouston & Link, 2021; Phelan et al., 2010). Thus the disparity in health and demographic outcomes do not go away, instead, they reorganizes and reasserts themselves through new pathways.

India, now the world's most populous nation, presents a particularly significant context for examining this process. Over the past four decades, India has experienced sustained economic growth, increasing consumption, enhanced life expectancy, and significant reductions in fertility and mortality rates. (Bank, 2018; IIPS & IFC, 2021; V. Mishra, 2020a). Nevertheless, despite rising incomes, traditional forms of social stratification continue to shape material outcomes (Desai & Dubey, 2011; Deshpande, 2011). If health gradients persist, shift, or widen under these conditions, they reveal how social position shapes outcomes even as the specific diseases, exposures, and climate risks change.

Demographic, Epidemiological, and Economic Transition in India

With 1.4 billion people accounting for approximately one-fifth of the global population, India has recently overtaken China to become the world's most populous nation (Nations, 2022). Demographic Transition theory posits that as societies undergo modernization, they transition from a pre-modern regime characterized by high fertility and mortality rates to a regime marked by low

fertility and mortality rates (Kirk, 1996). Over the past decade, India has witnessed a significant rise in life expectancy. From 2011 to 2021, life expectancy for men rose from 64.9 to 69.4 years, while for women it increased from 68.2 to 72.8 years (V. Mishra, 2020a). Simultaneously, birth rates have been steadily declining for half a century, with the Total Fertility Rate (TFR) reaching 2.0 in 2020, below the replacement level (IIPS & IFC, 2021). The combined effect of falling mortality and fertility rates has resulted in a notable shift in the country's age structure, with the median age rising from 18.2 in 1979 to approximately 27.6 in 2021 (Nations, 2022). As a result, India is experiencing substantial growth in its elderly population. Recent estimates indicate that India has the world's second-largest population of individuals over 65 years old, constituting 5.0% of the Indian population in January 2011 and 10.8% of the global over-65 population. Projections suggest that the male population aged 65 and above will expand from 32.37 million to 42.84 million between 2011 and 2021. Similarly, the female population aged 65 and over is expected to increase from 33.82 million to 46.84 million during the same ten-year period (V. Mishra, 2020a).

While life expectancy has risen in India, the country continues to experience high infant and child mortality rates, notably higher than those observed in other lower-middle-income countries (LMICs) with similar income levels (Coffey & Spears, 2021). In 2016, communicable diseases and nutritional deficiencies accounted for 27.5% of total deaths in India, while non-communicable diseases and injuries contributed to 61.8% of deaths (Dandona et al., 2017). This shift in the disease burden is typical of the epidemiological transition. The prevalence of communicable diseases remained steady between 2004 and 2014; at the same time, the prevalence of cardiovascular diseases (CVDs) doubled (Banerjee & Dwivedi, 2016). Thus, India is currently experiencing what is known as the double burden of disease, where the country faces a simultaneous rise in non-communicable diseases such as cardiovascular diseases, diabetes, and cancer, alongside a persistent struggle

with infectious diseases like tuberculosis, malaria, and diarrheal infections (Dandona et al., 2017). This "double burden" of both communicable and chronic diseases poses a significant public health challenge (Wang et al., 2012).

India is experiencing a swift economic transition following the economic reforms initiated in the early 1990s. The Indian economy grew by an average of over 5 percent between 1991 and 2003. The pace of growth accelerated to an average of over 7 percent per year between 2003 and 2017, resulting in a threefold increase in per capita income since the economic reforms (Bank, 2018). However, this economic growth has been uneven across various regions of India, and economic inequality has risen dramatically. The share of income for the top 10 percent of the population has risen from 35 to approximately 55 percent, while the share of income for the bottom half has dwindled from around 22 to 15 percent between the 1990s and 2015 (Chancel & Piketty, 2019a; Po & Subramanian, 2011). The growth of the economy and the surge in incomes have not been uniform, with the western and southern regions experiencing higher economic growth than the northern and eastern regions. For instance, Uttar Pradesh recorded a per capita domestic product growth of only 3 percent between 1991 and 2020, while Gujarat exhibited nearly 7 percent (Ghosh, 2022).

Substantial growth in the private health sector could widen the gap in healthcare access, leading to increased inequality in health outcomes (Basu, 2020). On the other hand, the government has made significant efforts to enhance health services, expand insurance, and improve public healthcare, including sanitation. For instance, a major universal health insurance scheme was launched in 2018 to assist every impoverished family (Basu, 2020). These governmental policies may act as equalizers, potentially reducing health disparities.

These demographic, epidemiological, and economic transitions unfold against a further

backdrop that is global in origin but acutely local in consequence. In India, the intensity and frequency of droughts have increased markedly over the past 60 years. Climate models project these trends will worsen, with droughts becoming both more frequent and severe (Mujumdar et al., 2020). Rural India's economy is heavily dependent on agriculture and is therefore highly exposed to increasingly frequent droughts (Mujumdar et al., 2020). Consistent with this vulnerability, adverse natural events have been shown to significantly affect consumption expenditures in rural areas (Tamuly & Mukhopadhyay, 2022).

Social Stratification in India

These dynamics take a distinctive form in India, where older and newer axes of stratification interact in ways that complicate simple modernization narratives. India's social order has historically been organized around caste, a system of hereditary hierarchy that assigns social membership at birth and links ritual status to occupation, marriage, commensality, and everyday social interaction.

At its most formal, caste ranks groups according to ideas of purity and pollution, but its consequences have never been only symbolic. Caste has also structured access to land, labor, education, political authority, and social protection, making it both a cultural system of status and a material system of advantage and exclusion (Beteille, 1971; Jodhka, 2017). Dumont's influential account in *Homo Hierarchicus* emphasized the ideological basis of this hierarchy, arguing that caste is organized less by economic power than by a religious logic of purity, pollution, and separation (Dumont, 1980). Social groups are ranked according to their relative ritual purity, and the boundary between pure and impure becomes a social boundary. Pollution rules in a society primarily aim to safeguard symbolic and social boundaries, defining impurity as anything that breaches categorical

lines, thereby endangering the order (Douglas, 2003). In the caste context, this logic translates into an elaborate system of rules governing commensality, touch, and spatial proximity, each designed to prevent the ritual contamination of higher groups through contact with lower ones (Ghurye, 1969).

While caste is rooted in the symbolic logic of purity and pollution, its consequences are material. In agrarian India, land remains the primary productive asset, with upper-caste households historically maintaining control through ownership, tenancy, and sharecropping systems (Beteille, 1971; Srinivas, 1962). Tenancy and sharecropping arrangements formally tied lower-caste labor to upper-caste property. Thus, these relationships were both economic and ritualistic, with the social authority that maintained the caste system also enforcing the terms of the arrangement (Bhaduri, 1973). The effects of this dispossession did not remain confined to agriculture, they were carried over across generations through the interlocking of land, credit, and opportunity (Deshpande, 2011). Households denied land ownership were also denied collateral, limiting their access to credit for agriculture, education, and enterprise (Munshi, 2019).

Beyond land, caste has structured occupational hierarchies through both assignment and exclusion. Its most visible form was the hereditary assignment of stigmatized labor to Dalits, the traditionally lowest-caste groups, including work associated with death, waste, leather, sanitation, and carcasses. These occupations were marked as ritually polluting and economically devalued, confining entire communities to poorly paid and socially degraded work (Jodhka, 2017; Shah, 2006). At the same time, caste operated through exclusion from valued occupations. Upper castes have historically monopolized priestly, scribal, administrative, and political roles, using ritual purity to legitimize economic and political closure (D. Gupta, 2000; Srinivas, 1962). The consequences of caste-based occupational segregation extended beyond the labor market. Stigmatized and low-demand work kept wages at the lower end of the income distribution, with no market exit for those

limited by caste-based employment constraints (Deshpande, 2011).

The consequences of caste-based occupational segregation extended well beyond the labor market. Proximately, hereditary assignment to stigmatized and low-demand work suppressed wages at the floor of the income distribution. Low and unstable earnings hinder asset accumulation. Households without surplus cannot save, invest in land or businesses, or fund children's education, perpetuating poverty across generations through the same intergenerational transmission mechanism triggered by land dispossession (Deshpande, 2011; Munshi, 2019). But the consequences of occupational stigma were not confined to income and assets alone. This stigma followed individuals beyond their jobs, limiting access to housing, credit, marriage, and social networks regardless of income or employment (Deshpande, 2011; Shah, 2006). Consequently, occupational exclusion, asset deprivation, and social stigma reinforced each other across generations, forming a system of cumulative disadvantage that no single intervention could easily reverse (Deshpande, 2011).

The preceding sections have established what caste is and how it affects outcomes. A separate and equally important question is whether caste continues to matter amid rapid economic growth, urbanization, and class formation. This question is not merely academic. If caste disparities dissolve as India modernizes, then class-based interventions targeting income and education are sufficient to address health inequality. If caste persists independently of class, then interventions that ignore caste will systematically fail the most disadvantaged groups.

Economic development is expected to erode caste distinctions by creating a class structure organized around market position rather than hereditary status (Desai et al., 2021; Deshpande, 2011). The core argument is that as education expanded, labor markets formalized, and urbanization increased, caste identity would retreat to the domain of ritual and symbolic practice while becoming progressively irrelevant to material life. Despite three decades of economic growth and two decades

of affirmative action policy, caste disparities in education, income, and social networks persisted (Desai & Dubey, 2011). Deshpande (2011) extends this argument theoretically, showing that even where individual Dalits have achieved upward mobility, group-level disadvantage persists because the mechanisms through which caste reproduces inequality operate at the group level and are not undone by individual mobility. Thorat and Newman (2010) show that identical job applications from Dalit and upper-caste candidates receive systematically different responses, demonstrating that caste identity functions as a signal that triggers discrimination independently of educational credentials or skills.

The relationship between caste, class, and health outcomes in India is complex and still being explored. Health outcomes vary based on the specific indicators being measured. Studies on the social gradient of health often focus on class, usually measured by household assets or expenditure, while others focus on social groups such as caste and religious groups. Generally, socioeconomic resources or caste are important predictors of health and mortality. However, the evidence is inconclusive. Some studies suggest that caste is less important than economic indicators or that its influence is mediated through economic opportunities (Po & Subramanian, 2011). Other studies indicate that caste and religion have independent effects on outcomes such as infant mortality, children's health, and mental health (Childers and Chiou 2016). Caste differences in health outcomes are more pronounced at lower SES levels and tend to converge at higher SES levels (Uddin et al. 2020). Researchers have also found a negative correlation between income and chronic conditions but a positive correlation with infectious diseases, complicating the association between social groups and health conditions (Childers & Chiou, 2016). The mortality evidence is stark. Gupta and Sudharsanan (2022) show that individuals from Scheduled Castes and Scheduled Tribes have drastically and persistently lower life expectancies than high-caste individuals. Critically, economic

status accounts for less than half of these gaps, indicating that caste operates as an independent determinant of survival beyond what income and assets alone can explain (Vyas et al., 2022).

Scholars have debated whether this persistence reflects the mutual constitution of caste and class (the argument that India's class structure was built on caste foundations and cannot be disentangled from them) or whether caste and class are analytically distinct axes that happen to overlap empirically but can and should be separated for analytical purposes (Béteille, 1965; Deshpande, 2011; Jodhka, 2007). This dissertation does not attempt to resolve that debate. What the evidence reviewed above establishes, and what is sufficient for the purposes of this dissertation, is a more limited but empirically robust claim: that caste continues to shape health and demographic outcomes in contemporary India independently of class, that class position shapes those same outcomes independently of caste, and that the two axes interact in ways that make their joint consideration analytically necessary. Chapters 2 and 3 both treat caste and class as analytically distinct yet empirically entangled variables. Chapter 2 examines whether poverty trajectories, a class-based measure of economic position over time shape mortality among older adults, and whether these effects vary by social group membership, treating caste and poverty as independent axes whose interaction is an empirical question rather than a theoretical assumption. Chapter 3 examines how caste and class jointly structure vulnerability to drought-related functional health decline, and whether social capital buffers that harm differently across social groups. This design explicitly tests the domain-specific interaction argument by examining a context of acute environmental stress in which the relative salience of caste and class as axes of protection and vulnerability may differ from their salience under stable conditions.

Theoretical Frameworks

Fundamental cause theory is one of the central theoretical frameworks of this dissertation because it provides the most powerful explanation for a pattern that runs across all three empirical chapters: that social inequality in health persists, reorganizes, and in some cases deepens even as the specific disease environment, economic conditions, and risk factors change around it.

Link and Phelan's original formulation posited that socioeconomic position is causally upstream of health, conferring access to flexible resources such as money, knowledge, power, prestige, and social connections, which can be utilized to protect health irrespective of the most pressing current risks (Link & Phelan, 1995). Because these resources are flexible rather than disease-specific, advantaged groups can always redirect them toward new forms of health protection as old risks decline and new ones emerge. The socioeconomic gradient in health has proven so resistant to interventions targeting specific diseases or risk factors in isolation (Phelan et al., 2010).

A key implication is that periods of rapid change do not dissolve health inequality but rather reorganize it, as those with resources adapt to the new environment while those without them cannot (Clouston et al., 2016). This is formalized through characterizing diseases as moving through four stages: a stage of *natural mortality* in which no knowledge about risk factors, prevention, or treatment exists and the gradient is therefore flat or even reversed; a stage of *producing inequalities* in which new knowledge and protective technologies diffuse first to higher-SES groups, generating widening gradients; a stage of *reducing inequalities* in which knowledge and interventions become more widely accessible, narrowing the gap; and finally, a stage of *near-elimination* in which the disease becomes concentrated among the most disadvantaged, who are the last to benefit from prevention and treatment (Clouston et al., 2016). The mechanism underlying this dynamic is

resource-mediated adaptation. When a new risk or opportunity emerges, advantaged groups are systematically better positioned to recognize it, access protective information, modify their behavior, and deploy material resources to reduce their exposure, cushion its consequences, or adapt more effectively. Disadvantaged groups face the same threat but without the same toolkit, particularly in terms of access to knowledge and material resources.

Most importantly, in cases of rapid change, the theory does not predict a static gradient. Inequality may widen, narrow, or even reverse for particular outcomes at specific times, but the fundamental link between social position and health protection remains across these fluctuations. The direction and magnitude of the gradient at any given moment, therefore, depend not on the property of the disease or threat itself but on where that disease sits in this temporal sequence, and on how unequally the resources needed to act on available knowledge are distributed across the population. This creates patterns where the same disease or threat can produce inequality at one time and reverse inequalities at another, and why aggregate improvements in population health or incomes do not necessarily reduce health inequality and may, in some periods, widen it (Clouston & Link, 2021).

The empirical record across different types of changes and disruptions is consistent. New risks are quickly absorbed into existing structures of inequality. COVID-19 illustrates this pattern. Although early infections were concentrated among higher-SES groups, mortality soon shifted toward lower-SES groups, who were more likely to work in essential and contact-intensive jobs, live in crowded housing, and face limited access to healthcare and remote work (Clouston et al., 2021). Evidence from Hurricane Katrina shows that low-income populations were less likely to be rescued, more likely to lose housing and employment, and slower to recover. The storm was not socially selective, but the resources needed to evacuate, survive, and rebuild were unequally distributed

before it arrived (Fussell et al., 2010). Smoking was initially more common among higher-SES men, who had greater resources and social exposure to adopt the behavior. As evidence of its health risks spread, higher-SES groups were more likely to quit, shifting lung cancer mortality toward lower-SES populations, demonstrating the reversal in gradient (Link & Phelan, 2009). So too was the case with HIV. Once effective treatment became available, higher-SES groups accessed it earlier and more consistently (Clouston et al., 2016). Furthermore, the weathering hypothesis offers a biological mechanism linking the life course and fundamental cause frameworks to observed health outcomes. Sustained exposure to socioeconomic disadvantage, discrimination, and chronic stress produces accelerated biological aging—a process of cumulative physiological deterioration that manifests in earlier onset of chronic disease, faster functional decline, and elevated mortality risk among socially marginalized groups, independent of current income or health behaviors (Geronimus et al., 2006). This has a direct theoretical implication. Fundamental cause theory was developed primarily in the context of high-income, Western societies where socioeconomic position is typically operationalized through income, education, and occupational class. Extending it to India requires recognizing that caste and religion function as fundamental causes in their own right.

Life Course Perspective and Cumulative Disadvantage

The life course perspective offers a complementary and equally central theoretical framework in this thesis for understanding how social stratification produces health and demographic inequality. Where fundamental cause theory explains why the socioeconomic gradient in health persists across changing disease environments, the life course perspective explains how that gradient evolves over the life time, and why the health consequences of social position cannot be read off from a person's circumstances at any single point in time (Elder et al., 2003). This perspective looks at

individual lives not as a series of discrete cross-sectional states and events, but as temporally ordered trajectories in which earlier experiences shape later ones, and in which the timing, sequencing, and duration of exposures, transitions, and resource accumulations matter independently of their content (Elder et al., 2003).

Cumulative advantage and disadvantage theory, developed at the intersection of life course sociology and stratification research, formalizes this insight. It posits that advantages and disadvantages accumulate over an individual's life course, shaping key outcomes, including health. According to this framework, social stratification significantly influences health outcomes and perpetuates health disparities. Those with early advantages, such as, access to healthcare, education, and economic resources tend to accrue further advantages, leading to better health outcomes. Conversely, individuals from marginalized social positions are more likely to experience chronic disadvantages that contribute to poorer health outcomes (DiPrete & Eirich, 2006). Cumulative disadvantage theory emphasizes that social structures, rather than random events or individual choices, play a crucial role in shaping health disparities, as access to resources and opportunities is dictated by social systems and exclusionary practices (Dannefer, 2020). The theory predicts that disparities in health based on SES widen as individuals age. Early disadvantages tend to accumulate, diminishing economic security, shaping health behaviors, and worsening health status over time (O'Rand, 1996). Taken together, these processes do not produce parallel trajectories of the advantaged and disadvantaged but trajectories that diverge with age, as those with resources accumulate more and those without fall progressively further behind.

The combined explanatory power of the life course perspective and fundamental cause theory is particularly evident in India, where caste position structures not a single moment of disadvantage but an entire trajectory of resource deprivation that begins before birth and compounds

across the life course. Lower-caste and Scheduled Tribe women enter pregnancy with higher rates of undernutrition and anemia than upper-caste women, producing a fetal environment that already reflects the accumulated nutritional deprivations of the caste system before an individual has made a single choice (Coffey, 2015; Subramanian et al., 2006). Children born into lower-caste households are more likely to be stunted, more likely to attend under-resourced schools, and more likely to enter the labor market through the restricted occupational channels that caste-based social closure is maintained with each transition compounding the disadvantage (Deshpande, 2011; Coffey & Spears, 2017).

India's demographic transition adds urgency to this argument. Declining fertility and rising life expectancy have produced a rapidly growing older adult population, and it is this population that most fully embodies the cumulative health penalties of a lifetime of caste-based deprivation. Older SC/ST adults have spent their lives in the most physically demanding and economically precarious occupations, with the least access to formal healthcare and the fewest assets with which to buffer health shocks in old age (A. Gupta & Sudharsanan, 2022). The cumulative disadvantage framework predicts that caste and SES gradients in functional health and mortality will be widest precisely among older adults, because compounding processes have had the most time to operate (Elder et al., 2003).

Contributions and Chapter Overview

Taken together, this dissertation makes several contributions to sociology, demography, and the study of health inequality in India. Theoretically, it extends fundamental cause theory beyond its original high-income, Western context by treating caste and religion as fundamental causes in their

own right. Independent, institutionally embedded axes of resources that shape health protection through mechanisms that standard SES measures incompletely capture. This extension is not merely contextual. It argues that FCT's core framework requires modification, not just application, when the stratification system operates through hereditary group membership and network-based closure rather than through income and education alone. The dissertation also extends the life course and cumulative disadvantage framework to an aging population in the Global South, a setting where life course health evidence is scarce, showing that the compounding of caste-based disadvantage across the life course produces health penalties among older adults that are historically specific, biologically embedded through weathering, and irreducible to current economic circumstances. Chapter 3 introduces an original theoretical mechanism, crisis-activated social capital, arguing that organizational network ties that remain largely dormant under stable conditions become protective under acute environmental stress, offering a theoretically motivated account of why social capital's health benefits are context-dependent and most visible among the most vulnerable.

Empirically, the dissertation generates rare longitudinal, population-scale evidence on the joint operation of caste and class across multiple health and demographic domains in India a contribution to a literature that has relied too heavily on cross-sectional data and single health outcomes. Chapter 1 provides one of the few analyses of the nutritional double burden across four rounds of nationally representative survey data, documenting how the gradient reorganized along wealth and gender lines as the disease environment changed. Chapter 2 uses three waves of IHDS panel data and survival analysis, with age as the time scale, to examine how poverty trajectories shape mortality risk among older rural adults, contributing longitudinal evidence to a question that cross-sectional studies cannot adequately address. Chapter 3 exploits exogenous variation in village-level drought exposure to estimate the effect of climate stress on functional health outcomes

among older adults, a methodological approach that is rare in the Indian aging literature and that allows stronger causal inference than observational designs permit. Together, the three chapters advance the empirical literature on health inequality in India, which has extensively documented the existence of gradients but has had less to say about the mechanisms by which they are produced, the life-course processes through which they deepen, and the conditions under which they can be partially buffered.

The remainder of this dissertation is organized into three self-contained empirical chapters and a concluding chapter, each examining a distinct domain of health and demographic inequality in India and drawing on the theoretical frameworks developed above to motivate its research questions, empirical strategy, and interpretation of findings.

Chapter 1, examines the nutritional double burden among women of reproductive age in India across two decades of rapid economic growth. Drawing on four rounds of the National Family and Health Survey spanning 1998 to 2021 and covering over one million women aged 25-49, the chapter asks whether economic growth has reduced nutritional inequality or merely reorganized it, shifting the gradient from undernutrition toward overweight while leaving the most disadvantaged women behind. The chapter finds that as undernutrition declined at the aggregate level, wealth and regional gradients in nutritional status reorganized rather than flattened, with advantaged women transitioning out of undernutrition first while disadvantaged women remained disproportionately burdened, precisely the pattern of inequality reasserting itself through new pathways that fundamental cause theory predicts. Chapter 2, examines how poverty trajectories shape mortality risk among older adults in rural India using three waves of the India Human Development Survey spanning 2004 to 2024. Rather than treating poverty as a static attribute, the chapter classifies individuals into poverty transition categories: persistently poor, upwardly

mobile, downwardly mobile, and never poor, and examines how the timing, duration, and direction of poverty spells shape survival outcomes among adults aged 45 and above. Using Cox proportional hazards models with age as the time scale and delayed entry to account for left truncation, the chapter finds that persistent poverty carries the heaviest mortality penalty, that downward mobility into poverty is more harmful than stable poverty in some specifications, and that these effects vary across social group membership in ways consistent with the cumulative disadvantage framework. The chapter contributes longitudinal evidence on a question that cross-sectional studies cannot adequately address: it is not just where you are economically at a given moment, but where you have been, and for how long, that determines your survival chances in later life.

Chapter 3, examines how drought exposure shapes the risk of functional health decline among older adults in rural India, and whether social capital buffers this harm differentially across caste and class groups. Using two waves of the India Human Development Survey, which exploits exogenous variation in drought exposure, the chapter finds that drought worsens functional health trajectories among older rural adults. It further finds that the harm is most severe among the most socioeconomically disadvantaged. Critically, the chapter finds that social capital buffers drought-related functional decline most strongly for the most disadvantaged groups. It acts as a crisis-activated mechanism introduced in the theoretical framework. Social ties that are largely dormant under stable conditions become protective resources under acute environmental stress.

Chapter 4 synthesizes the findings across the three empirical papers, returns to the theoretical frameworks developed in this introduction, and draws out their collective implications. It examines what the three chapters together reveal about the durability of caste and class-based health inequality across changing demographic, epidemiological, and climatic conditions. The chapter closes with a discussion of the policy relevance of the dissertation's findings for social protection, health systems,

and climate resilience programming in India and comparable low- and middle-income country settings, and identifies directions for future research that the dissertation's findings open up.

Chapter 1: Convergence, Divergence or Persistence: How is India's Long-Term Economic Growth Reflected in Women's Nutritional Status?

Abstract

This chapter examines how India's long-term economic growth has been reflected in women's nutritional status between 1998 and 2021. Drawing on four rounds of the National Family Health Survey (NFHS) for ever-married women aged 25–49 ($N = 956{,}420$), it asks whether BMI outcomes show convergence, divergence, or persistence across socioeconomic and geographic groups. The chapter finds that convergence and divergence occurred simultaneously at different ends of the BMI distribution. Underweight declined across all wealth quintiles, with larger absolute reductions among poorer and middle-SES women, producing clear socioeconomic convergence in undernutrition. Obesity increased across all quintiles, but absolute gains were largest among middle and upper-SES women, producing divergence in obesity risk. State-level patterns mirror these findings: underweight converged across states, while obesity diverged, advancing fastest in more economically developed states. Viewed through fundamental cause theory, these results show that nutritional inequality did not disappear with economic growth but shifted its form, from undernutrition to unequal exposure to obesity risk, while its axis remained structured by socioeconomic and geographic advantage.

Introduction

While economic expansion generally improves health outcomes through increased access to nutrition, education, and healthcare (Bloom & Canning, 2000; Preston, 1975), rising inequality can simultaneously undermine these gains by concentrating resources among the affluent and leaving disadvantaged groups behind (Marmot, 2006; R. Wilkinson & Pickett, 2009). Over the past three decades, India has experienced extraordinary economic growth; however, this progress has been accompanied by a sharp rise in income inequality (Chancel & Piketty, 2019b). This paper poses a central question: How has India's long-term economic growth reflected in the adult nutritional status, as measured by Body Mass Index (BMI)? The paper uses 4 rounds of the National Family Health Survey (NFHS), the Indian version of the Demographic Health Surveys, conducted in 1998-99, 2004-05, 2015-16, and 2019-21. The analysis examines women's BMI to show how patterns of undernutrition and obesity have changed over time. Studying BMI among Indian women is particularly important given the country's dual challenges of widespread undernutrition and increasing obesity rates, both of which have profound implications for maternal and public health (Coffey, 2019; Coffey & Spears, 2021). This study contributes to the stratification literature by showing how socioeconomic inequality shapes divergent health trajectories amid economic growth. It also contributes to demographic research by linking macroeconomic changes to measurable changes in population health, highlighting the interlinked effects of development and inequality on nutritional outcomes.

Background

Economic Growth vs Rising Inequality

A foundational finding in population research is the positive association between national income and population health. Higher income levels facilitate greater access to essential health resources, including food, clean water, healthcare, and education, all of which contribute to improved health indicators. Empirical studies established a positive correlation between national income levels and life expectancy, demonstrating that economic growth can significantly benefit population health (Bloom & Canning, 2000; Preston, 1975). The oft-cited Preston curve illustrates that improvements in income have a particularly significant impact, especially in lower-income countries where basic health infrastructure is still developing. Although the basic premises of this relationship are broadly accepted, the mechanisms underlying it remain contested (Bloom & Canning, 2000).

Four pathways linking income growth to improved health outcomes have received consistent empirical support. First, increased income levels enable better dietary choices, improving nutritional status and overall health. Fogel (2004) emphasizes the fundamental role of nutrition in long-term health improvements, noting that access to sufficient, high-quality food contributes to the development of physiological capital, thereby enhancing immune resilience, organ function, and longevity. Second, income growth enables greater access to clean water and sanitation. D. Cutler and Miller (2005) demonstrate that improvements in water and sanitation were responsible for nearly half of the total mortality reduction in early 20th-century U.S. cities. Third, higher income levels facilitate better access to healthcare services, enabling individuals to seek preventive and curative medical care (D. M. Cutler & McClellan, 2001). Lastly, economic growth is closely linked

to education and health awareness, as higher income levels often correlate with improved literacy, better hygiene knowledge, and greater awareness of nutritional and healthcare needs.

A crucial pathway linking economic growth to health outcomes is through improved nutrition. The nutrition transition refers to a shift in dietary patterns from diets low in calories and nutrients to diets high in calories but still lacking a balance of essential nutrients (Paarlberg, 2011). This transition is influenced by broader economic, demographic, and epidemiological trends that alter dietary needs and consumption patterns (Popkin, 1994, 2002). Economic growth, urbanization, and agricultural advancements contribute to changing food environments, increasing the availability of processed and calorie-dense foods while reducing the consumption of traditional, nutrient-rich diets (Johnston & Mellor, 1961; W. A. Masters et al., 2016).

On the other hand, widening income inequality intensifies disparities in physical and mental well-being. Research consistently demonstrates that societies with larger income gaps experience worse health outcomes, as economic disparity fosters social stratification, stress, and reduced access to essential resources (R. Wilkinson & Pickett, 2009). Inequality not only limits access to healthcare and nutritious food for lower-income populations but also creates psychosocial stressors that contribute to chronic diseases (Lynch et al., 2004; Marmot, 2006). The stress of financial insecurity and relative deprivation has been linked to negative physiological responses, including heightened cortisol levels and weakened immune function (R. G. Wilkinson, 1997, 2020). Moreover, income inequality weakens social cohesion and trust, reducing civic engagement and support for public health initiatives (Kawachi & Kennedy, 1999). While greater access to a diverse food supply has improved food security in many regions, the spread of ultra-processed foods and sedentary lifestyles has contributed to a rise in obesity and diet-related non-communicable diseases (NCDs) in low- and middle-income countries (Popkin, 2002).

India's Case: Growth and Inequality

India's rapid economic transitions provide a compelling context to examine how income growth and public health services influence women's BMI trends. India is undergoing a rapid economic transformation following the economic reforms introduced in the early 1990s. The Indian economy grew at an average annual rate of over 5 percent between 1991 and 2003, accelerating to over 7 percent per year between 2003 and 2017, resulting in a threefold increase in per capita income since the reforms (Bank, 2018). However, this economic growth has been uneven across various regions, and economic inequality has risen dramatically. The share of income for the top 10 percent of the population has risen from 35 to approximately 55 percent, while the share of income for the bottom half has dwindled from around 22 to 15 percent between the 1990s and 2015 (Chancel & Piketty, 2019b).

The expansion of economic opportunities and rising per capita income in India have contributed to shifts in dietary patterns and access to nutrition. However, as noted by Chancel and Piketty (2019b), economic inequality has widened considerably, resulting in significant disparities in health outcomes across different socioeconomic groups. While wealthier individuals may experience an increase in obesity due to dietary shifts, poorer populations continue to face challenges related to undernutrition and micronutrient deficiencies. This "double burden of malnutrition"—the coexistence of obesity and undernutrition—presents a significant public health challenge.

Studying BMI and nutrition among women in India is crucial due to the high prevalence of undernutrition and its profound implications for maternal and neonatal health outcomes. 20.1% of Indian women aged 18–49 were underweight, with 31.1% of women aged 18–24 classified as underweight in 2015-26 (Pengpid & Peltzer, 2019). Undernutrition among women in India

remains alarmingly high, with 42.2% of pregnant women underweight compared to 16.5% in sub-Saharan Africa (Coffey, 2015). India, which accounts for 27% of global neonatal deaths, suffers disproportionately from neonatal mortality relative to its share of global births (Coffey & Spears, 2021).

The burden of undernutrition in India is unevenly distributed across demographic and socioeconomic lines. Women from lower socioeconomic backgrounds have an underweight prevalence of 26.2%, compared to 8.1% among women in the wealthiest quintile. Schedule tribe women are particularly affected, with an underweight prevalence of 28.5%, reflecting systemic marginalization, poorer living conditions, and limited access to healthcare and nutrition (Montgomery et al., 2014). Rural women are more likely to be underweight than their urban counterparts, with rates of 23.0% and 15.5%, respectively. Additionally, tobacco use among women, with a prevalence of 8.5% nationally, has been identified as a significant correlate of underweight (Pengpid & Peltzer, 2019).

Regional Heterogeneity

National averages are a limited summary measure, given that they characterize the entire distribution of health within a population. Furthermore, in contexts of significant inequality, such averages can be misleading if interpreted as indicative of widespread improvement. Aggregate improvement can coexist with deepening subnational inequality when gains are concentrated among already advantaged groups while the worst-off are left behind. When the U.S. population is segmented by race, geography, urbanicity, and income, the disparity in life expectancy between the most and least advantaged groups exceeds twenty years. Such disparities are comparable to the differences observed between nations at markedly different stages of development and cannot be solely attributed to race, income, or healthcare access (Murray et al., 2006). This

subnational divergence has widened over time rather than narrowing. between 1980 and 2014, geographic inequalities in U.S. life expectancy grew substantially, even as national life expectancy improved (Dwyer-Lindgren et al., 2017). Location has a greater impact on the poor than on the wealthy. The lowest income group exhibits considerably more variation, whereas high-income Americans demonstrate significantly less geographic variation (Chetty et al., 2016). Subnational inequality is therefore most consequential for the populations that national averages are most likely to misrepresent. In addition, spatial disparities tend to widen during the early and middle stages of economic growth, as investment, infrastructure, and labor markets concentrate in already advantaged regions, before stabilizing or narrowing at later stages of development (Williamson, 1965). Health inequalities may track this pattern, but they need not move in lockstep with economic inequality. The translation of regional economic divergence into health outcomes is mediated by public institutions, service delivery, and redistributive policy (Hosseinpoor et al., 2016).

For India, this makes the empirical question especially important. India has experienced a swift economic transition following the economic reforms initiated in the early 1990s. The Indian economy grew by an average of over 5 percent between 1991 and 2003. The pace of growth accelerated to an average of over 7 percent per year between 2003 and 2017. This resulted in a threefold increase in per capita income since the economic reforms (Bank, 2018). However, this economic growth has been uneven across various regions of India, and economic inequality has risen dramatically. The share of income for the top 10 percent of the population has risen from 35 to approximately 55 percent, while the share of income for the bottom half has dwindled from around 22 to 15 percent between the 1990s and 2015 (Chancel & Piketty, 2019a; Po & Subramanian, 2011). The growth of the economy and the surge in incomes have not been uniform, with the western and southern regions experiencing higher economic growth than the northern and eastern regions. For

instance, Uttar Pradesh, a northern state, recorded a per capita domestic product growth of only 3 percent between 1991 and 2020, while Gujarat, a western state, exhibited nearly 7 percent (Ghosh, 2022).

Substantial growth in the private health sector could widen the gap in healthcare access, leading to increased inequality in health outcomes (Basu, 2020). On the other hand, the government has made significant efforts to enhance health services, expand insurance, and improve public healthcare, including sanitation. For instance, a major universal health insurance scheme was launched in 2018 to assist every impoverished family (Basu, 2020). These governmental policies may act as equalizers, potentially reducing health disparities. This regional heterogeneity is reflected in BMI distribution as well. Comparisons of India's most underweight-burdened states with its most overweight-burdened states show that the socioeconomic and rural-urban gradient in overweight is not fixed but evolves unevenly. In states further along the transition, overweight has begun spreading down the wealth distribution and into rural areas, while in states still dominated by undernutrition, it remains concentrated among the urban and wealthy (Sengupta et al., 2015). National trend data spanning nearly four decades confirm that this diffusion has been slow and socially patterned, with overweight/obesity rising fastest among educated, urban, and higher-caste groups even as undernutrition fell broadly (Meshram et al., 2025). Wealth-based decompositions using NFHS-4 further show that income-related inequality in overweight/obesity is itself geographically concentrated, with eastern and central India, the regions carrying the heaviest undernutrition burden, also showing the sharpest socioeconomic gradients in overweight (Kumar et al., 2022).This same pattern holds across the rural-urban divide, where obesity has grown fastest in poorer rural and urban-slum populations even as undernutrition among them persists (Nguyen et al., 2021). Read together, this literature suggests that India's regional disparities in nutrition are along the same socioeconomic

and geographic divides that produced undernutrition and are now reshaping themselves around obesity.

Research Questions and Hypotheses

With this background, this paper asks: **How is India's long-term economic growth reflected in adult nutritional status (BMI)? Specifically, is there a convergence across SES and Regions?**

H1.1: Economic growth and public service expansion have led to socioeconomic convergence in undernutrition risk among women over time, as successive rounds of lower-SES women gained better access to food, education, and health infrastructure, producing larger absolute declines in underweight prevalence among poorer quintiles than among wealthier ones.

H1.2: At the same time, rising income inequality and the nutrition transition have produced divergence in obesity risk across SES groups in earlier rounds, followed by a diffusion of obesity risk to middle and lower SES groups in later rounds.

H2.1: The expansion of public services and redistributive programs across India's states has produced convergence in undernutrition risk at the subnational level over time, with states that began the period with the highest undernutrition burden recording the largest absolute declines.

H2.2: Unequal economic growth across India's regions has produced divergence in obesity risk at the subnational level, as the nutrition transition advanced more rapidly in economically developed states, widening the cross-state distribution of obese prevalence over the study period.

Data and Methods

Data and Sample

The data for this study are drawn from four waves of the National Family Health Survey (NFHS), conducted in 1998–99, 2005–06, 2015–16, and 2019–21 (for Population Sciences (IIPS) & ICF, 2017; for Population Sciences (IIPS) & International, 2007; for Population Sciences (IIPS) & Macro, 2000; IIPS & IFC, 2021). The NFHS, modeled on the Demographic and Health Surveys (DHS), provides nationally representative information on a wide range of health and demographic indicators, including direct anthropometric measures such as Body Mass Index (BMI) for ever-married women aged 18–49. To reduce heterogeneity arising from age-at-marriage variation, the analytic sample is restricted to women aged 25–49. Women who were pregnant at the time of the interview or who had been pregnant within the six months preceding the survey were excluded from the analysis, resulting in a final sample of 956,420 women.

Key Variables

The primary outcome variable is BMI, categorized into three groups: underweight (BMI $<$ 18.5), normal weight and overweight (18.5 $\leq$ BMI $<$ 30, hereafter "normal weight" for brevity), and obese (BMI $\geq$ 30). The main explanatory variable of interest is survey wave, which serves as a proxy for temporal change, enabling the analysis to capture shifts in BMI distributions across successive survey rounds. Economic status is operationalized using household asset quintiles.

Household wealth is measured using the DHS Wealth Index, a composite measure based on ownership of consumer goods, housing characteristics, and access to water and sanitation. The index

is constructed using principal components analysis and places households on a continuous scale of relative economic status (Rutstein & Staveteig, 2014). In the NFHS datasets, this scale is divided into quintiles, allowing for comparisons of BMI outcomes across distinct socioeconomic strata. To ensure comparability of state-level analysis across the study period, states were harmonized to their 1998 (NFHS-2) boundaries. This adjustment was necessary because several new states were created after the first survey round. The harmonized state variable folds newly created states back into their 1998 parent units: Uttarakhand into Uttar Pradesh, Jharkhand into Bihar, Chhattisgarh into Madhya Pradesh, Telangana into Andhra Pradesh, and Ladakh into Jammu and Kashmir. Chandigarh was merged into Haryana, and Dadra and Nagar Haveli and Daman and Diu into Gujarat. Lakshadweep, Puducherry, and the Andaman and Nicobar Islands were excluded because they were not surveyed in NFHS-2. The following Northeastern states were merged into a single unit: Manipur, Meghalaya, Mizoram, Nagaland, Sikkim, Arunachal Pradesh, and Tripura.

Covariates

The analysis adjusts for a set of demographic and socioeconomic covariates. Age, marital status, and social group affiliation (caste and community) are included. Urban–rural residence is included as a binary variable to capture variation in dietary practices, lifestyle, and access to healthcare services. Additionally, state fixed effects are included to control unobserved heterogeneity in policy environments, infrastructure, and cultural contexts.

Analytical Strategy

The analytical strategy uses three multinomial logistic regression models, each designed to isolate a distinct dimension of the convergence hypothesis. In all models, the outcome variable

is women's BMI status, classified as underweight, normal weight/overweight, or obese. Normal weight/overweight is treated as the reference category, so the models estimate the relative likelihood of being underweight or obese compared with being normal weight/overweight.

The first model estimates the overall temporal trajectory of women's BMI status net of geographic and compositional differences:

$$\ln\left[\frac{\Pr(\text{BMI}_i = k)}{\Pr(\text{BMI}_i = \text{normal \& overweight})}\right] = \alpha + \beta_1 \text{round}_i + \beta_2 \text{state}_i + \gamma \mathbf{X}_i + \varepsilon_i \qquad (1.1)$$

for each non-reference BMI category k, where $k \in \{\text{underweight, obese}\}$, $\mathbf{X}_i$ is a vector of covariates including age, social group, marital status, urban–rural residence, and household size.

The second model examines socioeconomic convergence at the national level by interacting survey round with national household wealth quintile:

$$\ln\left[\frac{\Pr(\text{BMI}_i = k)}{\Pr(\text{BMI}_i = \text{normal \& overweight})}\right] = \alpha + \beta_1 \text{round}_i + \beta_2 \text{quintile}_i + \beta_3 (\text{round}_i \times \text{quintile}_i) + \beta_4 \text{state}_i + \gamma \mathbf{X}_i + \varepsilon_i \qquad (1.2)$$

The interaction between survey round and household wealth quintile is the central term in this model. It captures whether the socioeconomic gradient in BMI status changed over time.

The third model examines geographic convergence by interacting survey round with harmonized state unit:

$$\ln\left[\frac{\Pr(\text{BMI}_i = k)}{\Pr(\text{BMI}_i = \text{normal \& overweight})}\right] = \alpha + \beta_1(\text{round}_i \times \text{state}_i) + \beta_2 \text{quintile}_i + \gamma \mathbf{X}_i + \varepsilon_i \quad (1.3)$$

A key methodological consideration is that coefficients from multinomial logistic regression are not directly comparable across groups or models due to rescaling bias (Allison, 1999; Mood, 2010). To address this, the analysis uses predicted probabilities rather than interpreting regression coefficients directly. Wave-specific national wealth quintiles are used rather than a single time-invariant wealth index, reflecting the theoretical premise of relative deprivation theory (R. G. Wilkinson, 1997). Standard errors in all models were adjusted for clustering at the Primary Sampling Unit (PSU) level, using a round-specific PSU identifier (for Population Sciences (IIPS) & ICF, 2017; for Population Sciences (IIPS) & International, 2007; for Population Sciences (IIPS) & Macro, 2000; IIPS & IFC, 2021). This identifier takes a unique value for each combination of cluster and round variables to account for the pooled cross-sectional structure of the data.

The following sensitivity checks were done, first, given that the large analytic sample may produce statistically significant results for substantively negligible associations, the main model is replicated on a round-stratified random subsample of 200,000 observations, drawing 50,000 women from each survey round. This design simultaneously addresses large-sample inflation of precision and the pronounced imbalance in round-specific sample sizes across waves. The principal findings are replicated in the subsample results are reported in Appendix C, Table C.1. Further, the main models are replicated using round-specific normalized survey weights, to assess whether the round imbalance in sample sizes affects the estimates (Solon et al., 2015). The weighted results are substantively consistent with the unweighted main models and are reported in Table C.2.

Results

Table 1.2presents the results of a multinomial logistic regression analysis with normal weight/overweight as the base category. Age is significantly associated with both ends of the BMI distribution: each additional year of age is associated with a lower risk of being underweight (RRR = 0.98, $p < 0.001$) and a higher risk of being obese (RRR = 1.04, $p < 0.001$). The survey round is strongly associated with BMI outcomes. Compared to the baseline year (1998–99), the risk of underweight declines monotonically across subsequent rounds: RRR = 0.85 ($p < 0.001$) in 2005–06, RRR = 0.38 ($p < 0.001$) in 2015–16, and RRR = 0.25 ($p < 0.001$) in 2019–21. Conversely, the risk of being obese rises sharply over time: RRR = 1.29 ($p < 0.001$) in 2005–06, RRR = 1.69 ($p < 0.001$) in 2015–16, and RRR = 2.41 ($p < 0.001$) in 2019–21, reflecting a pronounced nutrition transition. Economic status shows a strong, graded association with BMI in both directions. Compared to women in the poorest quintile, the relative risk of being underweight is significantly lower for those in higher quintiles: RRR = 0.67 in the second quintile, RRR = 0.47 in the middle quintile, RRR = 0.32 in the fourth quintile, and RRR = 0.18 in the richest quintile (all $p < 0.001$). In contrast, the likelihood of being obese increases monotonically with economic status: RRR = 1.73, 2.74, 4.17, and 6.01 across the second through richest quintiles (all $p < 0.001$).

Table 1.1. Sample Characteristics by Survey Round, Analytic Sample, Ever-Married Women Aged 25–49, India (NFHS 1998—2019)

	1998–99	**2005–06**	**2015–16**	**2019–21**	**Pooled**
N (unweighted)	59,901	68,710	402,357	425,452	956,420
Age (years)					

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	1998–99	2005–06	2015–16	2019–21	Pooled
Mean (SD)	35.3 (6.9)	35.3 (6.9)	35.8 (7.1)	36.1 (7.2)	35.9 (7.1)
Residence, %					
Urban	33.9	45.9	29.5	24.9	28.9
Rural	66.1	54.1	70.5	75.1	71.1
Household Wealth Quintile, %					
Lowest	14.4	11.5	19.3	20.1	18.8
Second	15.2	14.1	20.7	21.6	20.3
Middle	19.1	18.5	20.5	21.1	20.5
Fourth	23.1	23.7	19.7	19.6	20.2
Highest	28.3	32.2	19.7	17.6	20.2
Social Group, %					
General caste	43.2	36.3	21.9	20.0	23.4
Scheduled Caste	16.4	16.9	18.4	20.0	18.9
Scheduled Tribe	11.7	13.5	19.1	19.9	18.6
Other Backward Caste	28.8	33.4	40.6	40.1	39.1
Marital Status, %					
Currently married	92.6	88.4	89.7	89.1	89.5
Currently unmarried	7.4	11.6	10.3	10.9	10.5
BMI Category, %					
Underweight (BMI $<$ 18.5)	29.4	24.2	16.2	11.8	15.6
Normal weight/overweight (18.5–29.9)	67.1	70.6	77.9	80.9	78.0
Obese (BMI $\geq$ 30)	3.5	5.3	5.9	7.4	6.4

Note: All figures are unweighted. Percentages may not sum to 100 due to rounding. Analytic sample restricted to non-pregnant ever-married women aged 25–49 with valid social group codes, as defined by the estimation sample of the main multinomial logistic regression model. Wealth quintiles are wave-specific and constructed at the household level by DHS; the distribution of women across quintiles reflects household size and composition and may deviate from uniform in earlier rounds. State boundaries harmonized to 1998 (NFHS-2) units. *Source:* Author's calculations from NFHS 1998–2019.

Table 1.2. Relative Risk Ratios (RRR) from Multinomial Logistic Regression of Women's BMI Status, India, Ever-Married Women, Aged 25–49 (NFHS 1998–2019)

	Underweight			Obese		
	RRR	S.E.	P value	RRR	S.E.	P value
Age	0.98	0.00	0.000	1.04	0.00	0.000
Survey Year (ref: 1998)						
2005	0.85	0.01	0.001	1.29	0.04	0.000

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Table 1.2 (continued)

	Underweight			Obese		
	RRR	**S.E.**	**P value**	**RRR**	**S.E.**	**P value**
2015	0.38	0.00	0.000	1.69	0.04	0.000
2019	0.25	0.00	0.000	2.41	0.06	0.000
Asset Quintile (ref: Poorest)						
Poorer	0.67	0.01	0.000	1.73	0.04	0.000
Middle	0.47	0.00	0.000	2.74	0.06	0.000
Richer	0.32	0.00	0.000	4.17	0.10	0.000
Richest	0.18	0.00	0.000	6.01	0.14	0.000
Social Group (ref: General Castes)						
Scheduled Caste	1.17	0.01	0.000	0.81	0.01	0.000
Scheduled Tribes	0.97	0.01	0.000	0.59	0.01	0.000
Other Backward Castes	1.13	0.01	0.000	0.86	0.01	0.000
Marital Status (ref: Currently Married)						
Currently Unmarried	0.81	0.01	0.003	1.28	0.02	0.000
Location of Residence (ref: Urban)						
Rural	1.26	0.01	0.000	0.70	0.01	0.000

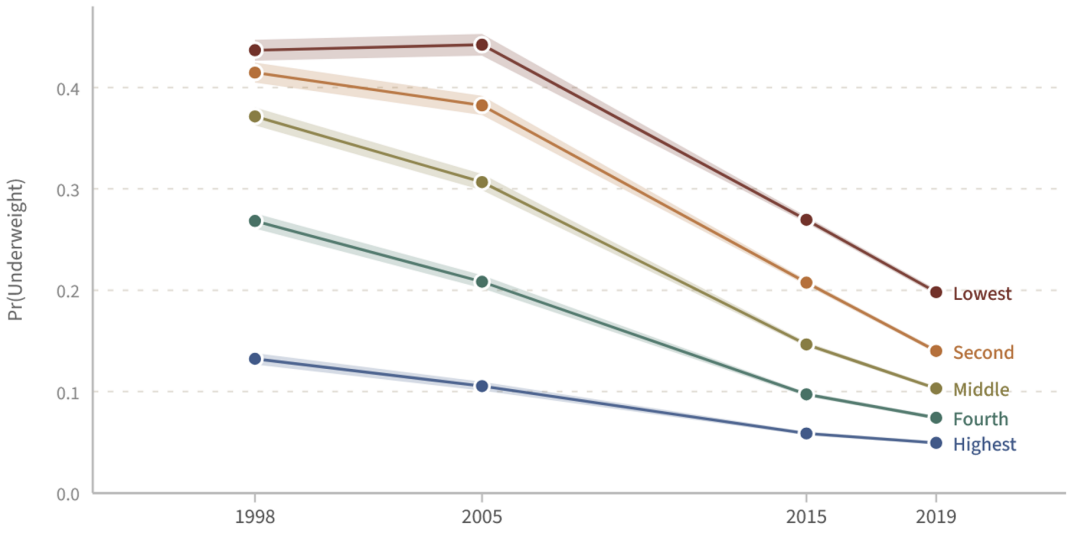
Notes: Reference category is normal/overweight BMI (18.5–29.9). All models include state fixed effects.
Source: Author's calculations from NFHS 1998–2019.

Figure 1.1 presents the predicted probabilities of being underweight by wealth quintile and survey year, along with 95% confidence intervals. In 1998–99, the probability of underweight was highest among the poorest quintile at 43.7% (CI 42.7%, 44.7%), declining steadily across the wealth distribution to 13.2% (CI 12.7%, 13.8%) among the richest quintile. By 2005–06, the socioeconomic gradient persisted: the poorest quintile showed an underweight probability of 44.2% (CI 43.2%, 45.3%), while the richest quintile had fallen modestly to 10.5% (CI 10.1%, 11.0%). A sharp decline is evident by 2015–16, when the proportion of underweight women fell to 26.9% (CI 26.6%, 27.3%) among the poorest and 5.9% (CI 5.7%, 6.0%) among the richest. The downward trend continued through 2019–21, with predicted probabilities of 19.8% (CI 19.5%, 20.1%) in the poorest quintile and 4.9% (CI 4.8%, 5.1%) in the richest quintile.

Between 1998–99 and 2019–21, underweight prevalence declined across all wealth quintiles,

with substantially larger absolute reductions among lower- and middle-SES groups. The steepest declines occurred in the second quintile (−27.4 percentage points) and middle quintile (−26.8 pp), followed closely by the lowest quintile (−23.9 pp). In contrast, reductions were more modest among higher-SES women, falling by 19.4 pp in the fourth quintile and 8.3 pp in the highest quintile. These patterns indicate pronounced socioeconomic convergence in undernutrition over time, driven primarily by rapid improvements among poorer households, even as nontrivial disparities persist.

Figure 1.1. Predicted Probabilities of Underweight by Wealth Quintile and Survey Year, Ever-Married Women, Aged 25–49 (NFHS, 1998–2019).



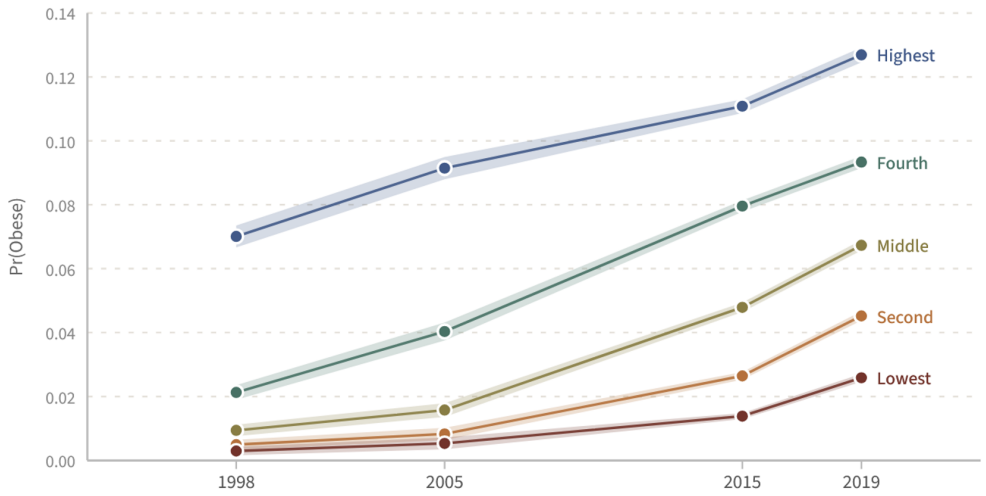
Note: Adjusted predicted probabilities from pooled multinomial logistic regression with survey round × wealth quintile interactions.

Figure 1.2 presents the predicted probabilities of obesity (BMI $\geq$ 30) by wealth quintile and survey year. In 1998–99, obesity was highly concentrated among the wealthy and virtually absent among the poor: the predicted probability was 0.3% (CI 0.2%, 0.4%) in the poorest quintile and 7.0% (CI 6.7%, 7.4%) in the richest quintile—a gap of 6.7 percentage points. By 2005–06, prevalence rose modestly across all groups. The increase accelerated by 2015–16, reaching 1.4% (CI 1.3%, 1.5%) in the poorest quintile and 11.1% (CI 10.9%, 11.3%) in the richest. By 2019–21,

obesity had increased nearly ninefold among the poorest women relative to 1998, reaching 2.6% (CI 2.5%, 2.7%), while continuing to rise among the affluent to 12.7% (CI 12.5%, 12.9%).

Absolute increases in obesity between 1998–99 and 2019–21 were smallest among the poorest women (+2.3 percentage points) and rose steadily through the wealth distribution, peaking in the fourth quintile (+7.2 pp) before moderating in the highest quintile (+5.6 pp). The cross-quintile gap in obesity prevalence therefore widened over the study period: the difference between the poorest and richest quintiles expanded from 6.7 percentage points in 1998 to 10.1 percentage points in 2019, indicating socioeconomic divergence in obesity risk. Although obesity remained most concentrated among higher-SES women throughout the period, the proportionally faster growth among lower and middle quintiles signals the early stages of a downward diffusion of obesity risk consistent with the nutrition transition literature and with fundamental cause theory's prediction that as obesity shifts from a condition of affluence to a generalized risk, lower-SES groups will be the last to gain the knowledge and resources needed to protect themselves (Link & Phelan, 1995; Monteiro et al., 2004; Popkin, 2002).

Figure 1.2. Predicted Probabilities of Obesity by Wealth Quintile and Survey Year, Ever-Married Women, Aged 25–49 (NFHS, 1998–2019).

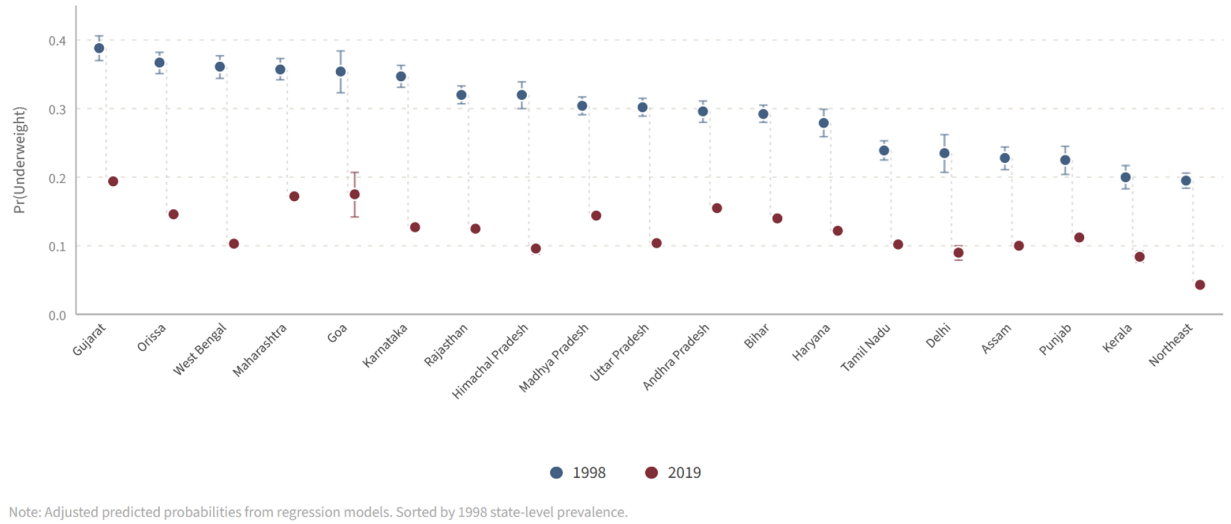


Note: Adjusted predicted probabilities from pooled multinomial logistic regression with survey round × wealth quintile interactions. Obesity defined as BMI ≥ 30.

State-Level Convergence in Undernutrition, 1998–2019

Figure 1.3 presents the adjusted predicted probabilities of underweight for all states in 1998 and 2019. The results reveal a pronounced, broad-based decline in undernutrition risk across all states over the two-decade period, accompanied by a substantial narrowing of the cross-state distribution—constituting strong evidence of subnational convergence in undernutrition.

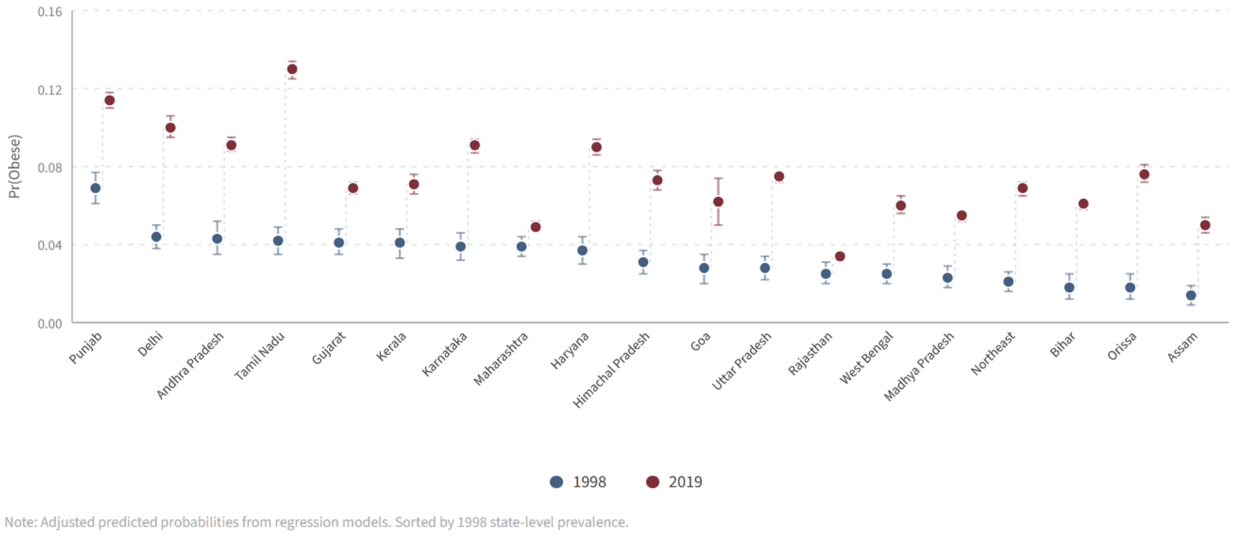
Figure 1.3. Adjusted Predicted Probabilities of Underweight by State, 1998 and 2019 (NFHS).



Note: Predicted probabilities estimated from separate multinomial logistic regression models for 1998 and 2019, adjusting for age, household wealth quintile, social group, marital status, urban–rural residence, and household size. States are harmonized to 1998 (NFHS-2) boundaries. *Source:* Author's calculations from NFHS.

In 1998, the adjusted predicted probabilities of underweight ranged from 19.5% (95% CI: 18.4%, 20.6%) in the Northeast to 38.8% (95% CI: 37.0%, 40.6%) in Gujarat, a spread of approximately 19 percentage points. By 2019, the highest predicted probability of underweight was observed in Gujarat at 19.4% (95% CI: 18.8%, 19.9%)—a level that would have placed it among the lowest-risk states in 1998. The pattern of absolute decline further reinforces the convergence narrative. States that entered the period with the highest undernutrition burden recorded among the largest absolute reductions: West Bengal fell by 25.8 percentage points, Himachal Pradesh by 22.4 points, Orissa by 22.1 points, and Karnataka by 21.9 points. By contrast, states that were already relatively low in 1998 experienced more modest absolute declines: Punjab fell by 11.3 points, Kerala by 11.6 points, and Assam by 12.8 points.

Figure 1.4. Adjusted Predicted Probabilities of Obesity by State, 1998 and 2019 (NFHS).



Note: Predicted probabilities estimated from separate multinomial logistic regression models for 1998 and 2019, adjusting for age, household wealth quintile, social group, marital status, urban–rural residence, and household size. States are harmonized to 1998 (NFHS-2) boundaries. *Source:* Author's calculations from NFHS.

Figure 1.4 presents the state-level trajectory of obesity, which presents a contrasting picture. In 1998, obesity prevalence was uniformly low across all states, ranging from 1.4% (95% CI: 0.9%, 1.9%) in Assam to 6.9% (95% CI: 6.1%, 7.7%) in Punjab—a spread of approximately 5.5 percentage points. By 2019, obesity prevalence had risen in every state, and the distribution had both shifted upward and widened considerably. Tamil Nadu recorded the highest predicted probability at 13.0% (95% CI: 12.5%, 13.4%), followed by Punjab at 11.4% (95% CI: 11.0%, 11.8%) and Delhi at 10.0% (95% CI: 9.5%, 10.6%). The cross-state range expanded from approximately 5.5 percentage points in 1998 to approximately 9.6 percentage points in 2019, indicating that unlike underweight—where the distribution compressed—obesity diverged across states over the study period.

The contrasting state-level trajectories of underweight and obesity—convergence in the former, divergence in the latter—are consistent with the theoretical predictions of both fundamental

cause theory and the nutrition transition literature. As undernutrition declined, the improvements were most concentrated where the burden was highest. As obesity rose, it followed the resource gradient in the opposite direction—advancing fastest in states where higher incomes, urbanization, and dietary change were most pronounced.

Table 1.3. Adjusted Predicted Probabilities of Underweight by State, 1998 and 2019, Sorted by 1998 Prevalence

State	**1998**	**95% CI**	**2019**	**95% CI**	**Δ (pp)**
Gujarat	0.388	(0.370, 0.406)	0.194	(0.188, 0.199)	−19.5
Orissa	0.367	(0.351, 0.382)	0.146	(0.141, 0.150)	−22.1
West Bengal	0.361	(0.344, 0.377)	0.103	(0.097, 0.108)	−25.8
Maharashtra	0.357	(0.342, 0.373)	0.172	(0.167, 0.177)	−18.5
Goa	0.354	(0.323, 0.384)	0.175	(0.142, 0.207)	−17.9
Karnataka	0.347	(0.331, 0.363)	0.127	(0.123, 0.132)	−21.9
Rajasthan	0.320	(0.307, 0.333)	0.125	(0.121, 0.129)	−19.5
Himachal Pradesh	0.320	(0.300, 0.339)	0.096	(0.088, 0.103)	−22.4
Madhya Pradesh	0.304	(0.291, 0.317)	0.144	(0.141, 0.147)	−16.0
Uttar Pradesh	0.302	(0.289, 0.315)	0.104	(0.102, 0.107)	−19.8
Andhra Pradesh	0.296	(0.280, 0.311)	0.155	(0.150, 0.159)	−14.1
Bihar	0.292	(0.280, 0.305)	0.140	(0.137, 0.143)	−15.2
Haryana	0.279	(0.259, 0.299)	0.122	(0.115, 0.128)	−15.7
Tamil Nadu	0.239	(0.225, 0.253)	0.102	(0.097, 0.107)	−13.7
Delhi	0.235	(0.207, 0.262)	0.090	(0.079, 0.100)	−14.5
Assam	0.228	(0.211, 0.244)	0.100	(0.096, 0.105)	−12.8
Punjab	0.225	(0.204, 0.245)	0.112	(0.105, 0.119)	−11.3
Kerala	0.200	(0.183, 0.217)	0.084	(0.076, 0.092)	−11.6
Northeast (excl. Assam)	0.195	(0.184, 0.206)	0.043	(0.041, 0.045)	−15.2

Note: Predicted probabilities from separate multinomial logistic regression models for 1998 and 2019, adjusting for age, household wealth quintile, social group, marital status, urban–rural residence, and household size. Δ denotes the absolute change in predicted probability in percentage points between 1998 and 2019. States are harmonized to 1998 (NFHS-2) boundaries. The Northeast category comprises Manipur, Meghalaya, Mizoram, Nagaland, Sikkim, Arunachal Pradesh, and Tripura. 95% confidence intervals are estimated using the delta method.

Table 1.4. Adjusted Predicted Probabilities of Obesity by State, 1998 and 2019

State	Obese 1998	95% CI	Obese 2019	95% CI	Δ (pp)
Andhra Pradesh	0.043	(0.035, 0.052)	0.091	(0.088, 0.095)	4.8
Assam	0.014	(0.009, 0.019)	0.050	(0.046, 0.054)	3.6
Bihar	0.018	(0.012, 0.025)	0.061	(0.058, 0.063)	4.3
Goa	0.028	(0.020, 0.035)	0.062	(0.050, 0.074)	3.4
Gujarat	0.041	(0.035, 0.048)	0.069	(0.066, 0.072)	2.8
Haryana	0.037	(0.030, 0.044)	0.090	(0.086, 0.094)	5.3
Himachal Pradesh	0.031	(0.025, 0.037)	0.073	(0.068, 0.078)	4.2
Karnataka	0.039	(0.032, 0.046)	0.091	(0.087, 0.094)	5.2
Kerala	0.041	(0.033, 0.048)	0.071	(0.066, 0.076)	3.1
Madhya Pradesh	0.023	(0.018, 0.029)	0.055	(0.052, 0.057)	3.1
Maharashtra	0.039	(0.034, 0.044)	0.049	(0.047, 0.052)	1.1
Orissa	0.018	(0.012, 0.025)	0.076	(0.072, 0.081)	5.8
Punjab	0.069	(0.061, 0.077)	0.114	(0.110, 0.118)	4.5
Rajasthan	0.025	(0.020, 0.031)	0.034	(0.032, 0.036)	0.9
Tamil Nadu	0.042	(0.035, 0.049)	0.130	(0.125, 0.134)	8.8
West Bengal	0.025	(0.020, 0.030)	0.060	(0.056, 0.065)	3.5
Uttar Pradesh	0.028	(0.022, 0.034)	0.075	(0.072, 0.077)	4.7
Delhi	0.044	(0.038, 0.050)	0.100	(0.095, 0.106)	5.6
Northeast (excl. Assam)	0.021	(0.016, 0.026)	0.069	(0.065, 0.072)	4.8

Note: Predicted probabilities from separate multinomial logistic regression models for 1998 and 2019, adjusting for age, household wealth quintile, social group, marital status, urban–rural residence, and household size. States are harmonized to 1998 (NFHS-2) boundaries.

Conclusions and Discussion

Chapter 1 examined how India's long-term economic growth has been reflected in women's nutritional status between 1998 and 2021, a period marked by rapid income growth, expanding public services, and rising inequality. Drawing on four rounds of nationally representative NFHS data for women aged 25–49, the chapter asked whether women's BMI outcomes show convergence, divergence, or persistence across socioeconomic and geographic groups. The answer is not one or the other. Rather, convergence and divergence occurred simultaneously at different ends of the BMI distribution. Underweight declined across all wealth quintiles, with larger absolute reductions among

poorer and middle-SES women, producing clear socioeconomic convergence in undernutrition. Yet in 2019–21, nearly one in five women in the poorest quintile remained underweight, compared with roughly one in twenty in the richest quintile. At the same time, obesity increased across all wealth quintiles, but absolute gains were largest among middle and upper-SES women, producing divergence in obesity risk, even as the proportional increase among poorer women signals the early stages of downward diffusion.

The subnational results show a similar pattern. Underweight converged across states, with the largest absolute declines occurring in states that began the period with the highest burden. Obesity, by contrast, diverged across states, with higher-risk and more economically advanced states continuing to pull ahead. Together, these findings show that India's nutrition transition is not a simple story of uniform improvement. Economic growth reduced one form of nutritional deprivation while expanding another form of nutritional risk, and both processes remained structured by socioeconomic and geographic inequality.

Viewed through the lens of fundamental cause theory, these results show that nutritional inequality did not disappear with economic growth but shifted from undernutrition to unequal exposure to obesity-related risks. Advantaged women exited undernutrition earlier, but they also entered obesity risk earlier. Disadvantaged women followed with a lag, continuing to face residual undernutrition even as obesity risk began to rise among them. The axis of inequality therefore remained stable even as the dominant nutritional risk changed. This pattern is consistent with broader evidence on gradient reversal during economic and epidemiological transition. In the case of tobacco, use initially spread among higher-SES groups, but as knowledge of its risks increased, advantaged groups were also the first to reduce consumption, leaving tobacco-related disease increasingly concentrated among disadvantaged populations (Link & Phelan, 2009; Pampel

& Denney, 2011).

The findings from Chapter 1 suggest that India's double burden of malnutrition requires a dual policy response. Policies aimed at reducing undernutrition among the poorest women remain essential. At the same time, overweight and obesity are rising across the socioeconomic distribution, creating a new set of health risks that will increasingly affect middle- and lower-SES groups. The state-level findings further reinforce the need for geographically differentiated policy, as aggregate economic growth does not automatically translate into nutritional improvement.

Several limitations should be noted. First, the use of wave-specific wealth quintiles measures relative rather than absolute economic position, meaning women in the poorest quintile in 2019 may be materially better off than women in the poorest quintile in 1998. A future extension using the Cross-wave Comparative Wealth Index (Rutstein & Staveteig, 2014) would allow economic position to be measured on a time-invariant asset scale. Second, the main analysis uses national wealth quintiles, which may combine convergence between states and convergence within states. Future work could construct state-specific wealth quintiles to examine whether nutritional gaps are closing within states.

Overall, the chapter shows that India's long-term economic growth has produced a mixed nutritional transition: substantial reductions in undernutrition, especially among the previously most disadvantaged, but also new and widening inequalities in obesity. Growth did not dissolve nutritional inequality, it merely transformed it.

Chapter 2: Unequal Paths to Aging: How Poverty Transitions Shape Mortality in Rural India

Abstract

Poverty and caste remain major sources of inequality in India, yet little is known about how movements into and out of poverty shape later-life mortality. Using three waves of the India Human Development Survey (2004–05, 2011–12, and 2022–24), this study examined how poverty transitions between Wave 1 and Wave 2 influenced mortality risk between Wave 2 and Wave 3 among rural adults aged 50–79. Poverty transitions were classified as persistently poor, upwardly mobile, downwardly mobile, and persistently non-poor. Mortality was analyzed using Cox proportional hazards models with age as the time scale, stratified by gender. Socially disadvantaged individuals faced significantly higher mortality than Higher Castes across poverty trajectories. Escaping poverty was associated with a higher probability of survival. The survival benefit of upward mobility did not differ significantly across caste groups, indicating that caste and poverty shaped mortality additively rather than interactively. The findings suggest that poverty reduction can improve survival in later life, but reducing caste-based mortality inequality will require structural interventions beyond economic mobility alone.

Introduction

Economic growth is often viewed as a pathway to improved health, longevity, and well-being. Yet the benefits of growth are rarely shared equally. In stratified societies like India, social identity and economic position intersect to shape who moves ahead and who remains behind. The life course perspective and cumulative disadvantage framework suggest that early-life poverty and structural inequalities, such as caste and gender, accumulate across time, embedding disadvantage in health trajectories and mortality (Dannefer, 2020; DiPrete & Eirich, 2006; Hayward & Gorman, 2004). While sustained upward mobility can mitigate some of these harms, downward mobility or recurrent hardship may worsen them, accelerating declines in physical functioning and well-being (Adena & Myck, 2014; Zang & Tian, 2025). Despite India's rapid economic expansion, deep social hierarchies continue to shape access to opportunity. Moreover, recent analyses using the India Human Development Survey reveal that poverty transitions in India are increasingly bidirectional: while many households have moved out of poverty amid economic growth, a significant share continue to fall back into deprivation due to life shocks such as illness, job loss, or natural disasters (Desai et al., 2025). Drawing on three waves of the India Human Development Survey (IHDS, 2004–2024), this paper examines how poverty transitions shape the risk of mortality in later life, and whether these effects vary by caste in India. In doing so, the study bridges the gap between economic mobility research and life-course health and mortality inequality, providing new evidence on how structural hierarchies shape aging and well-being in a rapidly changing society.

Background

Life-Course, Cumulative Disadvantage, and Economic Mobility

The life course perspective provides a useful framework for understanding mortality in later life as the cumulative result of biological, social, and economic processes that unfold across an individual's life. It highlights that mortality in old age is shaped not only by proximate conditions in later life, but also by the timing, duration, and sequence of exposures from early childhood through adulthood (Elder et al., 2003; Hayward & Gorman, 2004). From this standpoint, survival and longevity reflect the layering of advantages and disadvantages across earlier life stages. Early-life conditions such as nutrition, education, and household resources set trajectories that shape later access to opportunities, stress exposures, and health behaviors. For example, inadequate nutrition and poor living conditions during childhood can impair physical growth and immune function, resulting in long-term physiological vulnerabilities (Hayward & Gorman, 2004). Limited parental education and household income constrain early cognitive development and reduce access to higher-quality schooling and stable employment (Willson et al., 2007). Cumulative Disadvantage Theory extends this argument by emphasizing that early advantages and disadvantages compound over time, producing widening inequalities in survival and longevity (DiPrete & Eirich, 2006). It highlights how structural inequalities—through access to education, safe work, and healthcare—systematically favor the already advantaged and constrain recovery for the disadvantaged (Dannefer, 2020). Race, ethnicity, and economic position represent perhaps the most consequential axes through which cumulative disadvantage becomes inscribed in the body and, ultimately, in survival chances.

Ascribed identities such as race and ethnicity are persistent sources of cumulative disadvan-

tage, influencing exposure to material hardship, stress, and institutional exclusion throughout life. The mechanisms are multiple and mutually reinforcing. First, these axes of stratification channel individuals into unequal material conditions, including differences in income, wealth, schooling, housing quality, neighborhood environments, and occupational safety. Second, stratification structures unequal exposure to psychosocial stress through discrimination, insecurity, and chronic social exclusion. Third, it affects access to institutions that protect survival, including healthcare, stable employment, and social support. Over time, these inequalities accumulate rather than disappear, producing widening differences in physiological wear, disease vulnerability, and ultimately survival chances in later life (Dannefer, 2003, 2020; DiPrete & Eirich, 2006).

Racial and ethnic disparities remain a central feature of adult mortality in the United States, with minority populations facing persistently higher risks of death across much of the life course (Hummer & Chinn, 2011). Black–White differences in life expectancy also remain substantial and are tied to structural inequalities rather than individual characteristics alone (Hendi, 2024). Black adults not only lived fewer years than their White counterparts but also spent a disproportionately high share of those years with chronic health problems (Hayward & Heron, 1999). These mortality disparities reflect both greater exposure to cumulative disadvantage and weaker returns to advantage among Black Americans, showing that unequal survival is produced not only by deprivation itself but also by unequal capacity to convert resources into longer life (Jackson & Engelman, 2022). In Europe, mortality differentials are also visible across migrant-origin and ethnic minority populations, although the pattern is more heterogeneous. First-generation migrant groups exhibit a mortality advantage, while second-generation populations and specific origin groups face elevated mortality risks (Anson, 2004; Wallace et al., 2023). Among Indigenous populations globally, life expectancy is lower than in non-Indigenous populations across most settings studied, reflecting the long-term

effects of dispossession, exclusion, and unequal access (Anderson et al., 2016).

Just as ascribed identities do, economic deprivation is one of the key pathways through which broader systems of social inequality become translated into unequal survival. Three interconnected mechanisms link poverty to longevity. First, material constraints such as undernutrition, poor housing, and hazardous work environments increase exposure to infection and physiological stress, creating higher risk trajectories from early life (Elo & Preston, 1992; Hayward & Gorman, 2004). Second, psychosocial stress associated with economic insecurity produces allostatic load, accelerates biological aging, and impairs immune function (Montez & Hayward, 2014). Third, institutional and behavioral pathways—such as schooling, poorer neighborhoods, and barriers to preventive care—shape diet, sleep, physical activity, and health behaviors that track into obesity, smoking, and related intermediate outcomes (Montez & Hayward, 2014; Zang & Tian, 2025).

Research consistently shows a steep socioeconomic gradient in adult mortality, with mortality risk rising as income, education, and overall socioeconomic status decrease (Gutin & Hummer, 2021; Hummer & Chinn, 2011). In the United States, income differences in life expectancy were especially large, with the richest one percent living substantially longer than the poorest one percent (Chetty et al., 2016). Life-course studies further show that socioeconomic disadvantage in childhood and across adulthood is associated with a higher probability of death later in life, indicating that deprivation accumulates rather than operating only at a single moment (Pudrovska & Anikputa, 2014). Childhood disadvantages, coupled with adult socioeconomic factors, led to different survival paths for Black and White men, suggesting that racial disparities in mortality result from more than just current social status but build up over the life course through the accumulation of early and later disadvantages (Warner & Hayward, 2006).

Upward mobility can partially offset early deprivation by expanding access to health-

promoting resources and environments, while recurrent hardship or downward mobility can accelerate mortality by heightening stress and material insecurity (Adena & Myck, 2014; Zang & Tian, 2025). Higher overall exposure to poverty during both emerging and established adulthood increases the risk of early death (Colvin et al., 2025). Women experiencing upward socioeconomic mobility had markedly lower mortality hazard ratios compared to those who remained in the low socioeconomic group (Nagamine et al., 2020). Experimental and quasi-experimental evidence from low- and middle-income country settings corroborated these findings at scale. Cash transfer programs in low- and middle-income countries showed comparable results, with evidence from 37 countries indicating that government-led transfer programs were associated with approximately a 20% reduction in mortality among adult women and an 8% reduction among children under five (Richterman et al., 2023). The mortality consequences of economic change were not, however, confined to upward movements. Negative wealth shocks in later life were associated with higher subsequent all-cause mortality, indicating that downward economic mobility can have serious survival consequences (Pool et al., 2018). This evidence suggests that the direction, duration, and timing of poverty transitions, rather than simply current poverty status, are consequential for mortality and longevity.

These patterns of racial mortality disadvantage reflected not only greater exposure to deprivation but also unequal capacity to convert socioeconomic resources into survival advantages (Jackson & Engelman, 2022). Although socioeconomic position—measured by education, income, or mobility—was consistently linked to lower mortality risk, studies also found that the protective effects of socioeconomic resources varied across social identities. Education–mortality gradients changed over time and varied substantially by race and gender, suggesting that the survival benefits of education were not distributed equally across groups (Miech et al., 2011). Similarly, the mortality

gradient by education operated differently across race–gender groups, indicating that the same level of educational attainment did not yield equivalent survival advantages for Black and White adults (R. K. Masters et al., 2012). Gains in active life expectancy associated with higher education and more favorable childhood conditions were also stratified by social position, with those disadvantaged in both early and later life bearing the heaviest mortality burden despite any protective resources acquired later (Hayward & Gorman, 2004). This pattern of unequal and socially conditioned returns to economic mobility across group boundaries provides a direct theoretical foundation for the present study, which asks whether caste group membership similarly moderates the survival consequences of poverty transitions among older adults in India.

Social Stratification, Poverty Transitions, and Mortality in India

India is experiencing a swift economic transition following the economic reforms initiated in the early 1990s. The Indian economy grew by an average of over 5 percent between 1991 and 2003. The pace of growth accelerated to an average of over 7 percent per year between 2003 and 2017, resulting in a threefold increase in per capita income since the economic reforms (Bank, 2018). The second half of the 2000s saw some of the highest growth rates, moving millions out of poverty (Panagariya & Mukim, 2014). Yet the expectation that rapid economic growth would erode entrenched social inequalities, particularly those organized around caste, did not materialize. Caste disparities in education, income, and social networks persisted stubbornly into the 21st century despite two decades of economic transformation (Desai & Dubey, 2011). Discrimination in labor markets, educational institutions, and business persisted as an ongoing structural reality, continuing to reproduce poverty and disadvantage among lower-caste groups (Deshpande, 2011). Critically for the present study, this persistent social hierarchy translated directly into health and

longevity inequality. Both class and caste remain critical in determining health outcomes. Borooah (2010) found that caste affects age at death, healthcare-seeking behavior, and maternal care even after accounting for class. Caste-based health disparities are particularly pronounced at lower socioeconomic levels and tend to narrow only among the wealthiest (Uddin et al., 2020).

Poverty in India is not a static condition, but a dynamic one characterized by substantial movement in both directions, a pattern that aggregate cross-sectional measures systematically obscure. Most poor households exited poverty over the study period, while many previously non-poor households simultaneously fell back into it. These transitions were sharply stratified by caste, with only 48 percent of Adivasi poor escaping compared to 73 percent of Forward Caste poor (Thorat et al., 2017). Forward Caste households were also the most likely to move up and the least likely to move down, with these differences explained only in part by household characteristics. The research further highlighted a large vulnerable group of near-poor households at risk of falling back into poverty, which binary poverty measures failed to capture (Dang & Lanjouw, 2018a).

India's population is aging rapidly alongside these economic and social changes. Life expectancy in India is predicted to increase from 64.9 to 69.4 years for men and from 68.2 to 72.8 years for women between 2011 and 2020. As a result, India's elderly population is growing rapidly; India has the world's second-largest population of people aged 65 and above, accounting for 10.8% of the world's population aged 65 and older and 5% of India's population (V. Mishra, 2020a). Life expectancy at birth was estimated at 63.1 years for Scheduled Castes, 64.0 years for Scheduled Tribes, 65.1 years for Other Backward Classes, and 68.0 years for upper-caste groups, implying a gap of nearly five years between the most and least disadvantaged caste groups (Kumari & Mohanty, 2020). Mortality disparities between marginalized and privileged groups were evident across the life course and were increasingly driven by older-age mortality (A. Gupta & Sudharsanan, 2022). The

life expectancy gap between Muslims and upper-caste Hindus also widened between 1997–2000 and 2013–16, suggesting that caste and religious stratification in mortality was not declining over time but, in some respects, deepening (Vyas et al., 2022). Alongside caste, socioeconomic position was consistently and strongly associated with adult mortality risk in India. While poverty, income, and ethnicity, along with individual education and health behaviors, all shaped mortality risk in old age, early-life interventions were shown to matter more for survival than late-life ones (Paul & Rashmi, 2022). Adult mortality between survey waves was strongly associated with household economic status at Wave 1, regardless of the measure used (Barik et al., 2018). This evidence highlights that India's older adults face significant and compound mortality inequalities based on caste and class. The trajectory of economic circumstances across the life course, rather than current poverty status alone, may be the more consequential determinant of who survives into and through old age.

Research Questions and Hypotheses

Building on this literature, the paper asks the following question: how do poverty transitions shape the risk of mortality in later life, and do these effects vary by social group?

H1a (Upward mobility): Transitions out of poverty reduce the risk of mortality.

H1b (Downward mobility): Falling into or recurrently experiencing poverty increases the risk of mortality more than the benefits conferred by upward mobility of comparable duration.

H1c (Heterogeneity): The protective effect of upward mobility is smaller, and the penalty of downward mobility larger, for members of marginalized caste groups.

Data and Methods

Data

This study uses data from three rounds of the India Human Development Survey (IHDS): Wave 1 (2004–05), Wave 2 (2011–12), and Wave 3 (2022–24). IHDS is a nationally representative longitudinal household survey covering 41,554 households across 33 states and union territories in India. The analysis is restricted to rural households tracked across all three waves. The analytic sample consists of individuals aged 50–79 in Wave 2 who were followed forward to Wave 3, yielding an approximately 12-year follow-up period. Wave 3 records are based on individual-level roster information. In cases of a split household, individuals were followed up if they were in the root household or if the split household was in the same village; this excludes individuals who migrated from the village or refused to answer in Wave 3. Given that the difference between waves 1 to 3 is 19 years, it is important to analyse the attrition bias (Alderman et al., 2001). Table B.3 compares baseline characteristics of households retained in the panel with those lost to follow-up and indicates no substantial differences in key explanatory variables in the rural sample.

Outcome variable. The outcome of interest is a binary indicator of death between Wave 2 (2011–12) and Wave 3 (2023–24). Year of death was obtained from Wave 3 tracking records. Individuals who were alive at the time of the Wave 3 interview were treated as censored. Age at death was calculated by adding the number of years survived after Wave 2 to age at Wave 2. For individuals who remained alive at Wave 3, censoring age was defined as age at Wave 2 plus 13 years.

Primary explanatory variables. A key feature of the IHDS dataset is its consistent measurement of household consumption and poverty status across survey waves (Desai & Vanneman, 2018). Poverty

status in each wave was determined using India's official Tendulkar poverty lines. The Tendulkar Committee, constituted by the Planning Commission of India in December 2005 and reporting in 2009, revised the country's poverty measurement methodology by moving away from the earlier calorie-based norms toward a poverty line anchored in per capita consumption expenditure sufficient to cover a normative basket of food, education, health, clothing, and other essential non-food items (Planning Commission, 2009). The Committee derived state- and sector-specific (rural/urban) poverty lines, expressed as monthly per capita consumption expenditure (MPCE) in rupees, by benchmarking to the national urban poverty line for 2004-05 and adjusting for cost-of-living differences across states (Planning Commission, 2009). These state-specific rural and urban lines, subsequently updated and published for later survey rounds (Planning Commission, 2013), provide the benchmark against which household poverty status is assessed here. To construct the poverty indicator, household consumption expenditure recorded in the IHDS was divided by household size to obtain household-level MPCE. This figure was then compared with the officially published Tendulkar poverty line for the household's state and rural/urban location in the relevant survey round. Households with MPCE below their corresponding state-rural Tendulkar line were classified as poor (1), and those at or above the line were classified as not poor (0). This binary poverty indicator was constructed independently for each wave and subsequently cross-classified across waves to generate the four-category poverty transition typology used in the analysis: always poor, never poor, moved out of poverty (upwardly mobile), and moved into poverty (downwardly mobile). In this study, poverty status across Wave 1 (2004–05) and Wave 2 (2011–12) is used to capture time-varying economic position and identify transitions. Individuals are classified into four groups: those who remained poor across both waves; those who moved out of poverty between waves; those who remained non-poor in both waves; and those who fell into poverty during the period.

A key limitation of threshold-based poverty transition typologies is the potential overestimation of genuine economic mobility. Households whose consumption expenditure falls marginally above or below the poverty line may cross the threshold between waves due to transient income shocks, seasonal fluctuations, or measurement error in consumption reporting rather than any durable change in living standards (Baulch & Hoddinott, 2000). To assess the sensitivity of the typology to the choice of threshold, poverty status was additionally constructed at twice the official Tendulkar line — a commonly used near-poverty band that captures households in chronic economic vulnerability even if not technically below the official line. The contrast between the two thresholds is striking. At the official Tendulkar line, 33.4% of the analytical sample was poor in Wave 1 (2004–05), and 17% remained poor by Wave 2 (2011–12), producing a poverty transition distribution in which upward and downward movers together constitute roughly 31% of the sample. At twice the poverty line, however, 76.5% of the sample falls below the threshold in Wave 1, and 62.1% remains below by Wave 2 — suggesting that a substantial share of households classified as "never poor" or "moved out" at the official line are in fact clustered just above it, remaining economically precarious across both waves. This pattern is consistent with the concern raised by Dang and Lanjouw (Dang & Lanjouw, 2018b) that binary threshold crossings may conflate structural mobility with near-poverty churning.

Social groups are categorized into three categories. *Forward Castes* includes individuals from Hindu-dominant castes as well as religious minorities such as Christians, Jains, and Sikhs, who are traditionally not considered socially disadvantaged. *Scheduled Castes and Scheduled Tribes (SC/ST)* comprises historically marginalized communities recognized by the Indian constitution as socially and economically disadvantaged. *Muslims* includes individuals identifying as Muslim, a group that also faces structural disadvantages in the Indian context.

Control variables. The analysis adjusts for several individual-level covariates measured at Wave 2. Gender is included as a binary variable. Age is incorporated as the time scale and is therefore absorbed as a continuous variable in the modeling strategy. Marital status is classified into two categories: married and others (including widowed, separated, and divorced). Education is grouped into three categories, ranging from no education to secondary schooling and above. Baseline functional limitation is measured using the Katz index of activities of daily living at Wave 2 and is included as a continuous score ranging from 0 to 6. State dummies are also included.

Analytical Strategy

The paper uses Cox proportional hazards models to examine the association between poverty transitions and mortality. Survival time is specified using age as the underlying time scale rather than time elapsed since Wave 2, to directly account for differences in baseline mortality risk by age. Delayed entry is incorporated by specifying age at Wave 2 as the entry time, thereby accounting for left truncation. Exit time is set at age 80, such that individuals surviving beyond age 80 are censored at that age, consistent with the analytic sample definition. The model produces hazard ratios, which indicate how much higher or lower the mortality risk of one group is relative to a reference group at any point in time, holding all other characteristics constant. A hazard ratio greater than 1 indicates that the group faces a higher instantaneous risk of death relative to the reference category, while a hazard ratio less than 1 indicates a lower risk. A hazard ratio of exactly 1 indicates no difference in mortality risk relative to the reference group. The central assumption of the Cox model is that the ratio of mortality risks between any two groups remains constant across the entire follow-up period. This means that if one group faces a 10% lower mortality risk than the reference group at age 60, that same 10% difference is assumed to hold at age 70 and age 80. The

assumption does not require that the overall risk of death stays the same with age but rather that the relative difference between groups remains stable over time. The Cox model was chosen over parametric survival models. because it does not require assumptions about the shape of the baseline hazard function. Given the complexity of mortality trajectories across a heterogeneous older adult population spanning ages 50 to 80, imposing a parametric form on the baseline hazard would introduce unnecessary constraints that could bias the estimates. The Cox model estimates only how individual characteristics shift mortality risk relative to a common baseline, leaving the shape of that baseline entirely unspecified. As a sensitivity check, discrete-time logistic regression models were also estimated, treating mortality as a binary outcome within fixed observation intervals. Substantive conclusions were unchanged across both specifications, supporting the robustness of the primary findings Table B.1 .

The proportional hazards assumption was assessed after each model specification using Schoenfeld residuals. Initial models that included gender yielded evidence of global non-proportionality ($\chi^2 = 58.53$, $p < 0.001$). Gender was found to violate the proportional hazards assumption, consistent with prior evidence that male–female mortality differentials vary with age. The final models therefore stratify the baseline hazard by gender, allowing men and women to have distinct baseline hazard functions while constraining the coefficients of the substantive covariates to be equal across strata. Following stratification, the proportional hazards assumption was satisfied for the remaining covariates (global test $\chi^2 = 8.31$, $df = 8$, $p = 0.40$). A variable-specific test indicated a marginal violation for the SC/ST indicator ($\rho = -0.025$, $\chi^2(1) = 4.04$, $p = 0.044$), suggesting a modest decrease of the SC/ST mortality disadvantage over the follow-up period. However, the global test was not significant, and the substantive conclusions remained unchanged.

To complement the Cox hazard ratios, adjusted predicted survival probabilities were es-

timated using a flexible parametric survival model. Specifically, a Royston–Parmar model was fitted on the log cumulative hazard scale with three degrees of freedom for the baseline spline function (Royston & Parmar, 2002). Hazard ratios from the flexible parametric and Cox models were compared and found to be substantively similar, indicating that the parametric specification did not materially alter the estimated covariate effects. All predictions adjusted for the same covariates included in the primary Cox models, with remaining covariates held at their observed sample means. Predicted survival probabilities are conditional on survival to at least age 50 at Wave 2 and therefore represent conservative lower-bound estimates of population-level disadvantage.

Results

Table 2.1. Mortality status between Wave 2 and Wave 3 among rural older adults aged 50–79 in India, by household poverty transition category Wave 1 to Wave 2

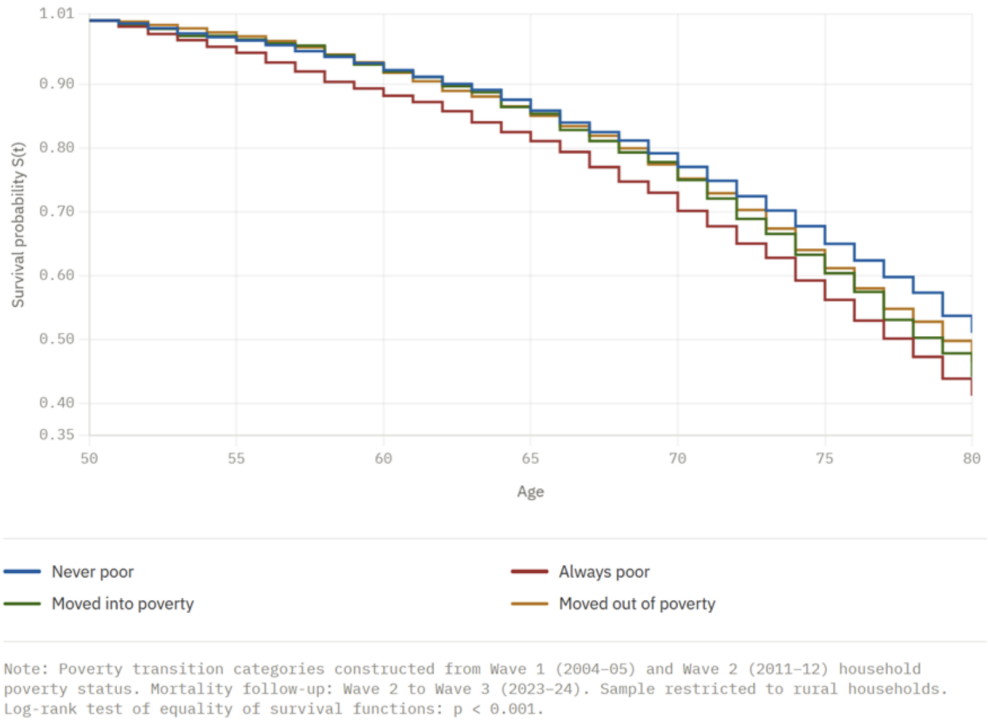
Poverty Transition (Wave 1–Wave 2)	Alive (%)	Died (%)	*N*
Persistently non-poor	72.19	27.81	14,155
Persistently poor	64.82	35.18	2,314
Downwardly mobile	66.97	33.03	1,756
Upwardly mobile	69.92	30.08	5,681
Total	**70.56**	**29.44**	**23,906**

Source: Author's calculations. IHDS Waves 1, 2 and 3

Table 2.1 summarizes mortality status between IHDS Waves 2 and 3 by household poverty transition category among rural older adults aged 50–79 in India. Overall, the persistently non-poor display the most favorable survival profile: 72.19% remained alive by Wave 3, while 27.81% died during the follow-up period. In contrast, the persistently poor experienced the worst outcomes, with only 64.82% surviving and 35.18% dying between the two waves. Respondents who moved into

poverty also faced relatively high mortality, with 33.03% dying over the follow-up period compared with 66.97% who remained alive. Those who moved out of poverty had somewhat better outcomes than the persistently poor and downwardly mobile groups, though their mortality remained higher than that of the persistently non-poor, with 30.08% dying and 69.92% surviving.

Figure 2.1. Kaplan–Meier survival curves by household poverty transition status, rural older adults aged 50–79, India.

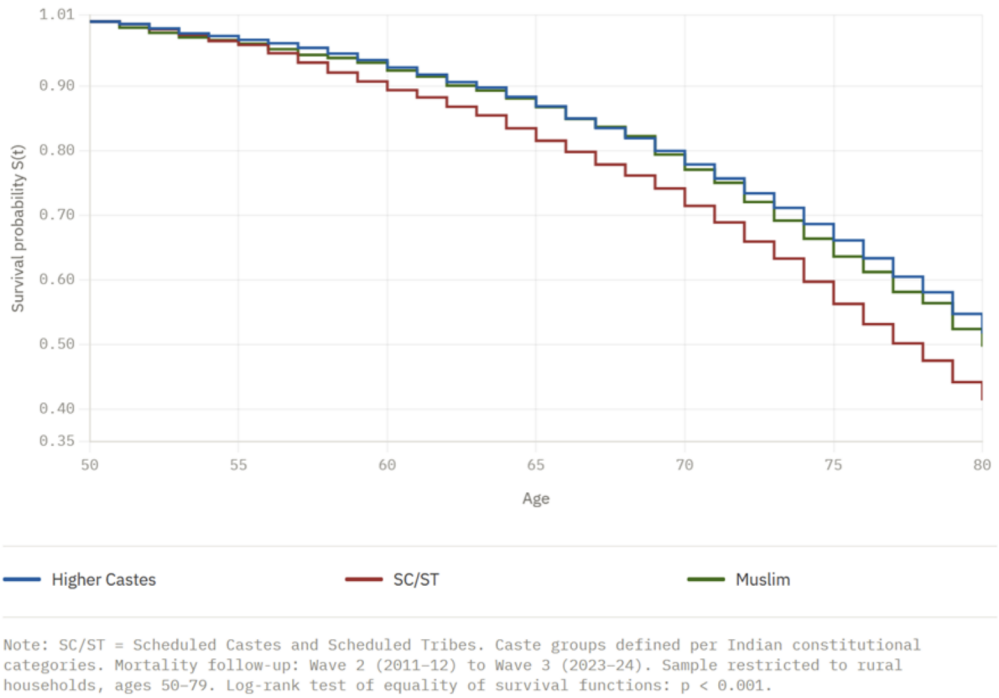


Note: Poverty transition categories constructed from Wave 1 (2004–05) and Wave 2 (2011–12) household poverty status. Mortality follow-up: Wave 2 to Wave 3 (2023–24). Sample restricted to rural households. Log-rank test of equality of survival functions: $p < 0.001$.

Figure 2.1 presents Kaplan–Meier survival curves by household poverty transition status among rural older adults aged 50–79 in India. All four groups begin with a survival probability of 1.0 at age 50 and decline monotonically through age 80. The always non-poor maintain the highest survival probability throughout the age range, reaching 0.779 at age 70 and 0.511 at age 80. In contrast, the persistently poor show the lowest survival, with probabilities falling to 0.702 at age 70 and 0.412 at age 80. Older adults who moved out of poverty track closely below the persistently non-poor, reaching 0.752 at age 70 and 0.464 at age 80, suggesting a meaningful but incomplete

recovery in survival advantage following economic improvement. Those who moved into poverty fare worse, with survival probabilities of 0.750 at age 70 and 0.442 at age 80, placing them closer to the persistently poor than to the persistently non-poor. The gap between the persistently non-poor and persistently poor widens with age, from roughly 2 percentage points at age 60 to about 7–8 percentage points by ages 75–80, consistent with cumulative disadvantage over the life course. A log-rank test confirms that the survival functions differ significantly across the four groups ($p < 0.001$).

Figure 2.2. Kaplan–Meier survival curves by caste group, rural older adults aged 50–79, India.



Note: SC/ST = Scheduled Castes and Scheduled Tribes. Caste groups defined per Indian constitutional categories. Mortality follow-up: Wave 2 (2011–12) to Wave 3 (2023–24). Sample restricted to rural households, ages 50–79. Log-rank test of equality of survival functions: p < 0.001.

Figure 2.2 shows Kaplan–Meier survival curves by caste group. All three groups begin with a survival probability of 1.0 at age 50 and decline steadily through age 80. SC/ST older adults experience substantially lower survival throughout the age range, with the gap relative to Higher Castes emerging by about age 55 and widening thereafter. At age 70, survival probabilities are 0.779 for Higher Castes, 0.771 for Muslims, and 0.715 for SC/ST individuals, implying a gap of about 6

percentage points between SC/ST and Higher Castes. By age 80, this difference widens to roughly 10 percentage points. Higher Castes and Muslims track very closely across the age range, consistent with the non-significant Muslim coefficient in the Cox model. The SC/ST disadvantage is evident well before old-old ages, appearing already by age 60, which suggests an early accumulation of mortality risk rather than compression only at older ages. A log-rank test indicates that the three survival functions are significantly different overall ($p < 0.001$).

Table 2.2. Cox Proportional Hazards Models of Mortality, Rural India, Ages 50–79 (IHDS Wave 2 to Wave 3)

	Model 1	Model 2	Model 3
Caste group (ref: Higher Caste)			
SC/ST	1.244***	1.220***	1.164
Muslim	0.991	0.988	0.812
Marital status (ref: Married)			
Not married	1.288***	1.287***	1.288***
Education (ref: No education)			
Primary/middle	0.871***	0.879***	0.878***
Secondary and above	0.726***	0.741***	0.739***
Katz index (continuous)			
	1.214***	1.215***	1.215***
Poverty transition (ref: Always poor)			
Never poor	—	0.871**	0.848*
Downward mobile	—	0.983	0.943
Upward mobile	—	0.907*	0.839*
Poverty × Caste interactions			
Never poor × SC/ST	—	—	1.012
Never poor × Muslim	—	—	1.200
Downward mobile × SC/ST	—	—	1.081
Downward mobile × Muslim	—	—	1.063
Upward mobile × SC/ST	—	—	1.123
Upward mobile × Muslim	—	—	1.393
Model fit			
N	23,835	23,835	23,835
Log-likelihood	−47,198.10	−47,191.59	−47,188.82
AIC	94,408.20	94,401.17	94,407.65

Continued on next page

Table 2.2 (continued)

	Model 1	Model 2	Model 3
BIC	94,456.67	94,473.88	94,528.83
df	6	9	15
LR test vs M1	—	$\chi^2(3) = 13.02$, $p = 0.005$	—
LR test vs M2	—	—	$\chi^2(6) = 5.52$, $p = 0.479$

Note: Hazard ratios shown. Baseline hazard stratified by gender. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Proportional hazards assumption satisfied (global Schoenfeld test: $\chi^2(8) = 8.31$, $p = 0.40$). Model 3 interaction block not significant—Model 2 retained as primary specification.

Source: Author's calculations.

Adjusted predicted survival probabilities complement the Cox model estimates by translating relative hazard differences into absolute survival chances at specific ages. Across all ages and poverty transition categories, SC/ST respondents had lower predicted survival probabilities than Higher Castes, and this gap widened with age. Among the always-poor, the SC/ST disadvantage relative to Higher Castes increased from 2.5 percentage points at age 60 to 7.8 percentage points at age 80, indicating that caste-based mortality inequality accumulated rather than narrowed at older ages. By contrast, Muslims showed predicted survival probabilities that were nearly identical to those of Higher Castes across all poverty transition groups and ages, consistent with the null Muslim effect in the Cox models. The caste gap also persisted within the never-poor category: among respondents who were never poor, predicted survival to age 80 was 0.420 for SC/ST individuals compared with 0.496 for Higher Castes, suggesting that caste-based mortality disadvantage operated through pathways beyond material deprivation alone.

The predicted probabilities also supported the conclusion that upward mobility was associated with improved survival. In all three caste groups, respondents who moved out of poverty had higher predicted survival probabilities than those who remained poor. The survival gain from upward mobility increased with age, rising from roughly 1 percentage point at age 60 to about 3.5

percentage points at age 80. Among Higher Castes, the upwardly mobile had a 3.5 percentage point higher probability of surviving to age 80 than the always-poor (0.480 versus 0.445). The corresponding gain was 3.6 percentage points among SC/ST respondents (0.403 versus 0.367) and 3.5 percentage points among Muslims (0.481 versus 0.446). Although modest in absolute size, these differences were substantively meaningful in the context of adult mortality.

Downward mobility, by contrast, produced survival trajectories that closely resembled those of the persistently poor. Among Higher Castes, for example, the downwardly mobile had only a 0.7 percentage point higher predicted probability of surviving to age 80 than the always-poor (0.452 versus 0.445). This pattern suggested that falling into poverty largely erased any prior survival advantage. Although the asymmetry hypothesized in H1b was not statistically confirmed, the predicted probabilities showed that the downwardly mobile consistently tracked much closer to the always-poor than to the never-poor, which is directionally consistent with the hypothesis.

Finally, the predicted probabilities reinforced the conclusion that caste did not significantly moderate the effects of poverty transitions. The survival gain associated with upward mobility was nearly identical across caste groups: 3.5 percentage points for Higher Castes, 3.6 percentage points for SC/ST respondents, and 3.5 percentage points for Muslims at age 80. This close similarity on the absolute probability scale, together with the non-significant interaction terms and the likelihood ratio test from the Cox models, indicates that caste and poverty transitions operated additively rather than multiplicatively.

Table 2.3. Adjusted Predicted Survival Probabilities by Poverty Transition and Caste Group

Caste Group	Poverty Transition	Age 60	Age 65	Age 70	Age 75	Age 80
Panel A: Predicted survival probabilities						

Continued on next page

Table 2.3 (continued)

Caste Group	Poverty Transition	Age 60	Age 65	Age 70	Age 75	Age 80
Higher Caste						
	Always poor	0.885	0.813	0.716	0.593	0.445
	Never poor	0.900	0.836	0.749	0.636	0.496
	Upward mobile	0.896	0.829	0.739	0.623	0.480
	Downward mobile	0.888	0.816	0.721	0.599	0.452
SC/ST						
	Always poor	0.860	0.774	0.661	0.524	0.367
	Never poor	0.878	0.801	0.699	0.571	0.420
	Upward mobile	0.872	0.793	0.688	0.556	0.403
	Downward mobile	0.863	0.778	0.667	0.530	0.374
Muslim						
	Always poor	0.886	0.813	0.716	0.594	0.446
	Never poor	0.900	0.836	0.749	0.637	0.497
	Upward mobile	0.896	0.829	0.739	0.623	0.481
	Downward mobile	0.888	0.816	0.721	0.600	0.453
Panel B: Survival gain from upward mobility (upward mobile minus always poor)						
	Higher Caste	0.011	0.016	0.023	0.030	0.035
	SC/ST	0.012	0.019	0.027	0.032	0.036
	Muslim	0.010	0.016	0.023	0.029	0.035
Panel C: Caste mortality gap (SC/ST minus Higher Caste, always poor)						
		−0.025	−0.039	−0.055	−0.069	−0.078

Note: Adjusted for education, marital status, baseline functional limitation, and gender. Rural sample, ages 50–79. Estimates from flexible parametric survival model (Royston–Parmar, $df = 3$).

Conclusions and Discussions

This study examined how poverty transitions between Wave 1 (2004–05) and Wave 2 (2011–12) shaped mortality risk between Wave 2 and Wave 3 (2023–24) among older rural adults in India, and whether these effects varied by caste group. Three findings stand out.

First, caste independently stratified mortality. SC/ST individuals faced substantially higher mortality than Higher Castes across poverty trajectories, and this gap widened with age. Among always-poor households, the difference in predicted survival between SC/ST and Higher Caste

respondents grew from 2.5 percentage points at age 60 to 7.8 percentage points at age 80, indicating that caste-based disadvantage in survival accumulated over later life and was not explained by material deprivation alone.

Second, economic mobility also shaped survival. Escaping poverty was associated with a meaningful survival advantage, increasing the predicted probability of survival to age 80 by roughly 3.5 percentage points across caste groups. By contrast, those who moved into poverty experienced mortality risks that were statistically indistinguishable from those of the persistently poor, suggesting that new poverty exposure carried survival consequences similar to chronic poverty within the 12-year follow-up period.

Third, caste and poverty transitions operated additively rather than multiplicatively. The survival benefit associated with upward mobility was nearly identical across Higher Caste, SC/ST, and Muslim households, and the formal interaction test was not significant. This suggests that caste and poverty each independently shaped mortality risk, but their effects did not amplify one another beyond their additive combination. Muslims did not show a significant mortality disadvantage relative to Higher Castes in the rural sample, a finding that may reflect the specific rural context examined here.

These findings carry important implications for research and policy. They suggest that poverty reduction can generate measurable mortality benefits across all caste groups. At the same time, such gains alone are unlikely to close the caste mortality gap, because caste continued to stratify survival even among the never-poor. Policies aimed at reducing mortality inequality in later life therefore need to address not only economic deprivation but also the structural disadvantages associated with caste, including unequal access to healthcare, occupational risk, and broader forms of social exclusion.

Several limitations should be noted. The analysis was restricted to rural households and therefore may not generalize to urban India. Because the sample included only those who survived to Wave 2, the findings are conditional on survival to mid and later life and do not capture mortality selection before study entry. Estimates for Muslims should also be interpreted cautiously because some interaction cells were underpowered. Finally, the exclusion of individuals who migrated out of the village between waves may have introduced additional selection if migrants differed systematically from those who remained.

A further limitation concerns the binary threshold-based construction of the poverty transition typology. Households clustered near the Tendulkar poverty line may cross it between waves due to transient shocks or consumption measurement error rather than durable changes in economic standing, potentially overstating the share of genuine movers. Sensitivity checks using twice the official poverty line confirm that a substantial portion of households classified as never poor or upwardly mobile at the official threshold remain in near-poverty across both waves, suggesting some upward mobility estimates should be interpreted cautiously.

Chapter 3: Weathering the Drought: Risks and Resilience Patterns in Functional Health of Older Adults Across Rural India

Abstract

As climate change accelerates, its health risks are not evenly distributed. They follow entrenched systems of social and economic stratification. Social capital acts as a resilience resource, potentially buffering the adverse health effects of recurring climate shocks. This paper examines how repeated droughts shape the risk of functional health deterioration among older adults in rural India and whether social capital enhances resilience to these impacts. Using longitudinal data, the analysis follows individuals aged 40 and older to assess changes in functional limitations over time. Results show that exposure to two or more droughts increases the risk of functional deterioration by 19% compared to no drought exposure, while single droughts show no effect. Economic position and social capital both shape resilience. The poorest households experienced deterioration in functional limitations after exposure to repeated droughts, whereas the richest did not. Social capital operated as a crisis-activated resource rather than a general health advantage, mitigating drought-related health deterioration primarily among disadvantaged groups.

Introduction

Natural disasters are often viewed as solely the result of natural forces. While events like hurricanes, floods, and earthquakes trigger disasters, the resulting crises reflect the interactions between these forces and prevailing social and economic conditions (Peek et al., 2021). Disaster risks and outcomes are therefore distributed unevenly across society, reflecting what Matthewman describes as "vastly uneven landscapes of risk" (Matthewman, 2016, p. 13). Marginalized communities often face greater challenges in disaster preparation and suffer worse physical and mental health outcomes, higher displacement, and slower recovery (Arcaya et al., 2020). In this context, social capital—defined as the total resources individuals can access through their social networks—can be a vital source of resilience. It helps in accessing information and material support, reduces negative health impacts, and aids in disaster preparedness, response, and recovery (Meyer, 2017). Older adults are particularly vulnerable to climate-related shocks because age-related declines in physiological reserve, combined with greater dependence on others for daily care and access to essential services, limit their capacity to cope with disruptions and heighten the risk of functional decline (Carnes et al., 2014). These dynamics are particularly consequential in India, now the world's most populous country and home to the second-largest population of adults over 65, estimated at 90 million and growing rapidly (V. Mishra, 2020a). This demographic shift unfolds against a backdrop where, despite rising incomes, traditional forms of stratification such as caste and religion continue to shape life chances alongside newer, class-based divisions rooted in widening economic inequality (Desai & Dubey, 2011; Deshpande, 2011). Using longitudinal data from the Indian Human Development Survey (IHDS), the paper addresses two questions: (1) How does social and economic stratification shape the risks of functional limitations among older adults in rural India

following droughts? (2) To what extent does social capital strengthen resilience by buffering these risks, and does its effect differ across social and economic groups?

Background

Aging, Functional Limitations, and Climate Change

Climate change affects individuals across the life course, but older adults face disproportionate risks from its adverse impacts because of chronic conditions, reduced physiological resilience, and greater susceptibility to environmental stressors (Kriebel-Gasparro, 2022; Madani Hosseini et al., 2024). During Hurricane Katrina, individuals aged 75 and older accounted for approximately 50% of all deaths (Brunkard et al., 2008).

Drought is broadly defined as a prolonged period of below-average precipitation compared to a region's long-term climate norm, leading to water shortages that impact ecosystems, agriculture, and human populations (Wilhite & Glantz, 1985). Unlike sudden-onset hazards such as floods, storms, and heat waves, drought emerges gradually, with boundaries, duration, and severity that are often difficult to define and highly context-specific (A. K. Mishra & Singh, 2010; Wilhite & Glantz, 1985). Rather than causing immediate, visible destruction, slow-onset and prolonged adverse events like drought produce indirect and cumulative impacts that unfold over time through pathways such as livelihood loss, food and water insecurity, economic strain, displacement, and prolonged psychosocial stress (Stanke et al., 2013; Vins et al., 2015). These features make drought harder to identify, attribute, and study, helping explain why it remains under-investigated, under-recognized, and under-reported despite its substantial long-term consequences.

For older adults, these risks may be amplified by age-related declines in thermoregulatory

capacity (McKenna et al., 2023) and cardiovascular function (Silveira et al., 2023), limiting their ability to adapt to thermal stress. Weak immunity, often associated with old age, reflects a secondary pathway that heightens susceptibility to infectious diseases, thereby increasing morbidity and mortality among older adults (Kriebel-Gasparro, 2022; Madani Hosseini et al., 2024). One important way these risks may manifest is through functional limitations, which are early signs of health decline and reduced independence in older age. Unlike chronic conditions that may remain asymptomatic, functional limitations reflect lived bodily constraints that shape social participation, quality of life, and the likelihood of subsequent health decline and mortality (Guralnik et al., 1995; Newman et al., 2006). Functional limitations are especially useful for examining social and environmental determinants of health, as they display clear gradients by age, gender, and socioeconomic status, revealing how stratification processes shape health trajectories over time (Clouston et al., 2016; Crimmins & Saito, 2001).

The literature on the association between natural disasters and functional limitations in older adults is limited, but recent studies have lent valuable insights. Psychological distress following the 2011 Great East Japan Earthquake was associated with an increased risk of functional disability among elderly survivors (Tanji et al., 2017). The rate of increase in disability prevalence among the older population was higher in disaster-stricken areas compared to non-disaster areas during the three years after the same earthquake (Tomata et al., 2015). Peri-traumatic stress and post-storm hardship both had independent, positive effects on functional limitations in older individuals, with effects evident six years after the hurricane (Pruchno et al., 2020). Evidence from once-in-a-generation extreme climate events has shown that floods in urban areas of India lead to an increased risk of developing functional limitations (Rendall, 2024).

The relationship between functional limitations and recurring climate events is more complex

and less well understood than that for once-in-a-generation disasters. A nationally representative longitudinal study in the U.S. found no association between multiple recurring, non-catastrophic climate event exposures and changes in functional limitations (Brilleman et al., 2017). This paper shifts the focus from single extreme events to recurring and compounding climate shocks, particularly droughts, contributing to the limited body of work examining this intersection (Tipaldo et al., 2024).

Uneven Risks: Class, Caste, and Climate Change in India

Since 1990, average annual real income in India has grown by nearly 5% per annum (Chancel & Piketty, 2019b). Although rising incomes and a shift toward a market-based economy were expected to erode caste-based inequalities, these disparities persist (Deshpande, 2011). While their forms may have changed, differences in outcomes remain substantial (Desai & Dubey, 2011). Both class and caste remain critical in determining health outcomes. Borooah (2010) found that caste affects age at death, healthcare-seeking behavior, and maternal care even after accounting for class. Caste-based health disparities are particularly pronounced at lower socioeconomic levels and tend to narrow only among the wealthiest (Uddin et al., 2020). Some scholars argue that class is now the primary driver of health inequality (Po & Subramanian, 2011).

As India ages, inequalities in the health and well-being of older adults become increasingly visible. Between 2005 and 2012, the share of adults aged 60 and above with at least one functional limitation rose from 9.4% to 36.6% (Paul et al., 2021). The same figure for those 50 and older stood at 44% in 2017–18 (Malik, 2020). The prevalence is higher in traditionally disadvantaged castes, the Scheduled Castes (47.8%), than among the traditionally advantaged castes (42.1%). Among individuals in the poorest quintile, 46.2% reported functional limitations, compared to 40.6% in the

wealthiest quintile (Malik, 2022).

Stratifications along the lines of class and caste not only shape health disparities but also influence how different groups experience and recover from climate-related events. In India, the intensity and frequency of droughts have increased markedly over the past 60 years. Climate models project these trends will worsen, with droughts becoming both more frequent and severe (Mujumdar et al., 2020). Rural India's economy is heavily dependent on agriculture and is therefore highly exposed to increasingly frequent droughts (Mujumdar et al., 2020). Consistent with this vulnerability, adverse natural events have been shown to significantly affect consumption expenditures in rural areas (Tamuly & Mukhopadhyay, 2022). The most prevalent coping strategy adopted by rural populations during periods of drought is reducing consumption across various food categories, particularly nutritious options such as meat, poultry, and dairy (Sam et al., 2020). Social and economic inequalities exacerbate the situation; children from marginalized groups experienced worse educational outcomes in the wake of adverse natural events compared to their non-marginalized counterparts (Khalid et al., 2024). Limited evidence exists connecting adverse climate events and functional limitations in India. Residing in a coastal city that experienced an extreme flooding event was associated with higher odds of acquiring a functional limitation compared to residing in a similar inland city (Rendall, 2024).

Resilience: Social Capital, Aging, and Climate Change

Given these vulnerabilities, understanding potential protective factors becomes crucial. One important resource that may buffer against negative health effects is social capital. Social capital refers to the resources embedded within social networks that facilitate coordination, information exchange, and collective action among individuals and groups. The individual social capital

approach, which forms the focus of this paper, views social capital as resources available through social networks that affect individuals (Bourdieu, 1986; Lin, 1999). Bourdieu (1986) conceptualizes social capital as the sum of resources—both actual and potential—that a person can access through their network of relationships.

A growing body of research has examined how social capital shapes health outcomes. The majority of research finds that social capital generally improves health outcomes (Ehsan et al., 2019), though the effect sizes are modest (X. Xue et al., 2020). Various causal mechanisms link social capital to health (Berkman & Glass, 2000; Thoits, 2010; Zhang & Centola, 2019). Established social networks facilitate the efficient flow of health information, influencing health behaviors through knowledge acquisition (Viswanath et al., 2006). Social control, which refers to overt efforts by members of a social network to monitor, encourage, persuade, or pressure individuals to adopt positive health practices, forms another significant pathway (Berkman & Glass, 2000).

These general health benefits become particularly noticeable in older adults who face increased dependency and health challenges. Social capital is demonstrated to be significantly more important for the health of older adults (60 and above) than for younger people (Muckenhuber et al., 2013). Social capital can function as a protective resource both before and after a climate event, playing a role in mitigation, preparedness, response, and recovery (Meyer, 2017). Notably, unlike physical or financial resources that are depleted in disasters, social capital is often renewed and enhanced during the emergency period, making it a reliable resource in climate events (Dynes, 2002). During the Great East Japan Earthquake, higher social cohesion was linked to lower prevalence of functional disabilities among older adults in disaster-stricken areas (Tanji et al., 2017).

Multiple mechanisms explain these effects. First, networks provide essential emotional and psychological support that helps individuals cope with trauma and stress (Wind & Komproe, 2012).

Second, social networks facilitate the diffusion of critical information about environmental risks, available resources, and recovery opportunities (Aldrich, 2012). Finally, social capital serves as an intermediary between communities and the state, enhancing adaptive capacity through collective action and coordination (Adger, 2010; Aldrich, 2010). In resource-constrained settings, social capital can serve as a substitute for absent or ineffective governmental support in the aftermath of a climate-related event (Brouwer & Nhassengo, 2006).

The distinction between bonding and bridging forms of social capital is especially important in India. Across studies using the IHDS, bridging social capital is positively associated with health service utilization and child health outcomes (Story, 2014; Story & Carpiano, 2017; Vikram, 2018; Vikram et al., 2012). In contrast, bonding social capital showed mixed associations with health behaviors and child nutrition. Social capital was also shown to reduce the likelihood of functional disability by moderating the effects of noncommunicable diseases, with protective effects that are unevenly distributed across wealth and caste groups (Patil et al., 2025).

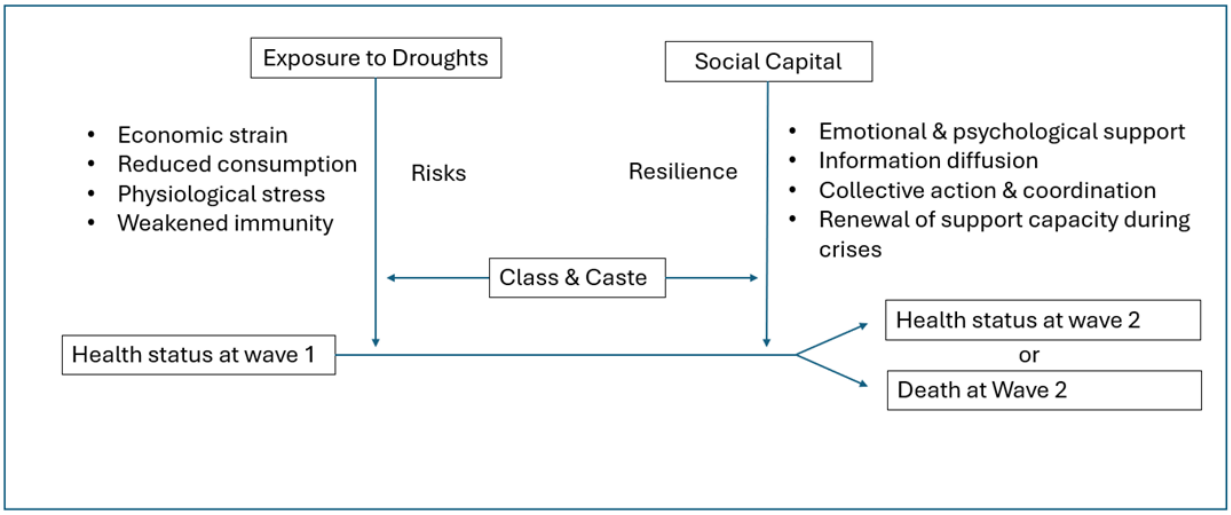
While social capital offers important benefits, access to it and its returns are uneven across social groups. Disadvantaged communities often face both a capital deficit—a smaller and less diverse network—and a return deficit, where comparable networks yield fewer benefits due to structural inequalities tied to race, class, caste, or gender (Lin, 2000). Wealth has also been shown to amplify the benefits of linking social capital, particularly in reducing child undernutrition (Story & Carpiano, 2017).

Hypotheses and Conceptual Framework

With this background, the paper asks: (1) How does social and economic stratification shape the risks of functional limitations among older adults in rural India following droughts? The paper hypothesizes that exposure to droughts increases the risk of functional limitation, and that an advantageous social and economic position can mitigate this effect. (2) To what extent does social capital strengthen resilience by buffering these risks, and does its effect differ across social and economic groups? The paper hypothesizes that social capital helps buffer the adverse effects of droughts on functional limitations, and that this protective effect is uneven, with individuals in more privileged social and economic positions receiving more protection.

Figure 3.1 presents an integrated conceptual model that positions changes in functional limitations as the product of interactions among drought exposure, social stratification, and social capital. Drought exposure is treated as an exogenous climate shock that disrupts agricultural livelihoods, reduces household consumption, increases physical strain, and heightens psychosocial stress. Social and economic stratification, defined by caste and class, is anticipated to influence baseline vulnerability and adaptive capacity, such that the effects of drought on functional health trajectories will be socially patterned. Social capital is expected to function as a protective resource through emotional and psychological support, information diffusion, collective action and coordination, and renewal of support capacity during crises. However, this buffering capacity is anticipated to be influenced by caste and class, since stratification shapes both access to social networks and the returns individuals can derive from them.

Figure 3.1. Stratified Risks and Resilience Framework Linking Drought Exposure to Functional Limitations



Data and Methods

Data and Sample

The paper utilizes data from two rounds of the India Human Development Survey (IHDS), a nationally representative longitudinal dataset. The first wave was conducted in 2004–05 and the second in 2011–12. The first wave of IHDS covered 41,544 households in 1,503 villages and 971 urban neighborhoods in India. The paper restricts the sample to adults who were at least 40 years of age in the first wave to capture early stages of functional decline. Prior work shows that functional limitations increase well before old age and represent early stages of the disablement process (Crimmins & Saito, 2001; Freedman et al., 2002). Research from India has documented that limitations in functioning begin between the ages of 40 and 55 and continue to accumulate into old age (V. Mishra, 2020b; Nagarkar et al., 2020). The analysis focuses on individuals from households

in rural PSUs with available data for both survey rounds, resulting in a sample of 32,248 individuals. Of these, 27,592 (85.6%) individuals were re-interviewed, and 4,656 (14.5%) died between the two waves. In cases of a split household, individuals were followed up if they were in the root household or if the split household was in the same village. Appendix A1.1 compares baseline characteristics of households retained in the panel with those lost to follow-up and indicates no substantial differences in key explanatory variables. Furthermore, the magnitude of climate-driven migration itself limits the potential for weather-related selective attrition. Sedova and Kalkuhl (Sedova & Kalkuhl, 2020), using the same IHDS panel, estimate that only approximately 8% of rural-urban moves between the two survey waves are attributable to precipitation anomalies. Given this relatively modest share, differential attrition between drought-exposed and non-drought-exposed households is unlikely to substantially bias our estimates. Consistent with this, attrition rates among households exposed to two or more droughts are nearly identical to those with no drought exposure (9.2% versus 9.7%), providing no evidence of systematic drought-induced panel loss.

Key Variables

Functional Limitation Score. Information on activities of daily living was collected for each household member using the question, "Does anyone in the household have a problem [ACTIVITY]?" Respondents were asked about seven activities: walking 1 km; going to the toilet without help; dressing without help; hearing normal conversation; speaking normally; seeing distant objects; and seeing near objects. If the response was yes, a follow-up question asked whether the person could still perform the activity with difficulty or was unable to perform it. Each activity was coded as 0 for no difficulty, 1 for difficulty, and 2 for inability to perform the activity. Scores were summed across the seven activities to create an individual-level functional limitation score

ranging from 0 to 14, with higher scores indicating greater limitation. The outcome variable was coded as: 0 if the score stayed the same or decreased (stable or improved health); 1 if the score increased (worsening health); and 2 if the individual died between the two survey rounds. Of the 32,248 individuals surveyed in Wave 1, 22,509 (67.3%) did not experience an increase in functional impairments, 5,083 (15.8%) saw an increase, and 4,656 (14.5%) died. An inverse-covariance-weighted (ICW) functional limitation index was constructed as a robustness check, following Anderson (2008). The ICW index is nearly identical to the baseline sum measure ($r = 0.997$).

Exposure to Drought. The village schedule of IHDS Wave 2 asked about adverse natural events the village experienced between the two survey waves. For each year between the two waves, the instrument asks if the village faced a drought. Droughts were classified into three categories: no occurrence, single occurrence, and two or more occurrences between survey waves. This measure captures recurring adverse drought conditions rather than only rare or extreme events.

Social Capital. Social capital was measured as a dichotomous variable based on household members' association with various organizations, coded 1 if anyone in the household belonged to any of the following: religious, caste, or festival organizations; women's groups; youth clubs; sports groups; reading rooms; trade unions; business or professional groups; self-help groups; credit or savings groups; development NGOs; or agricultural cooperatives (Cronbach's alpha = 0.60). In total, 65.2% of individuals had no social capital through organizational membership, while 34.8% had some form. Sensitivity analyses separating bonding and bridging capital are reported in Appendix A3.

Social Groups. Social groups are categorized into three categories. *Forward Castes* includes individuals from Hindu-dominant castes as well as religious minorities such as Christians, Jains, and Sikhs. *Scheduled Castes and Scheduled Tribes (SC/ST)* comprises historically marginalized

communities recognized by the Indian constitution as socially and economically disadvantaged. *Muslims* includes individuals identifying as Muslim.

Asset Tertiles. Asset tertiles are used as a proxy for class and are constructed based on a household asset index comprising 33 items. Households are divided into three groups: low, middle, and high based on their total asset holdings.

Control Variables. All models adjust for age (continuous), baseline functional limitation score, gender, education (three categories: no formal education; up to primary; above primary), income source (no agricultural income; some agricultural income; agriculture as primary source), marital status (married vs. widowed/separated/divorced), household composition (number of adults; number of children), a binary indicator for any outmigration or household split between waves, and binary indicators for flood and earthquake exposure between waves. State dummies are included in all models.

Analytical Strategy

To answer the first research question, "How does social and economic stratification shape the risks of functional limitations among older adults in rural India following droughts?" the paper uses multinomial logistic regression, with the outcome variable categorized into three categories: no change in functional limitations, worsening functional limitations, or death between survey waves . The first risk model (model) includes the main effects of drought exposure and socioeconomic variables independently. Results are expressed as predicted probabilities with 90% Confidence Intervals (C.I.) and in Relative Risk Ratios (RRR) and are reported in the main text. A more conservative 95% confidence interval along with full models are reported in Appendix A.2. Survey weights from wave 1 of IHDS were applied throughout to account for the complex sampling design.

The first set of models, Risk Models, take the following form:

$$\ln\left[\frac{P(Y_i=j)}{P(Y_i=0)}\right] = \alpha_j + \beta_{1j}\text{Drought}_i + \beta_{2j}\text{SocialGroup}_i + \beta_{3j}\text{Wealth}_i + \beta_{4j}\mathbf{Z}_i + \varepsilon_i \tag{3.1}$$

for $j \in \{\text{Deteriorated, Death}\}$

Where Drought_i is a three-category indicator distinguishing no drought (reference), one drought, and two or more droughts between survey waves; SocialGroup_i distinguishes forward castes (reference), Scheduled Castes and Tribes, and Muslims; Wealth_i denotes household wealth tertile with the poorest tertile as reference; and $\mathbf{Z}_i$ is a vector of individual and household controls.

The paper then introduces the interactions between the two main stratifiers, class and social group, and exposure to droughts in two separate equations (Models 2 and 3). The results of all interactions are expressed in predicted probabilities with 90% confidence intervals. These models are collectively referred to as risk models, which illustrate differences in health risks associated with drought exposure.

$$\begin{aligned}\ln\left[\frac{P(Y_i=j)}{P(Y_i=0)}\right] = {} & \alpha_j + \beta_{1j}\text{Drought}_i + \beta_{2j}\text{SocialGroup}_i\beta_{3j}\text{Wealth}_i + \delta_j(\text{Drought}_i \times \text{Wealth}_i) \\ & + \beta_{4j}\mathbf{Z}_i + \varepsilon_i\end{aligned} \tag{3.2}$$

for $j \in \{\text{Deteriorated, Death}\}$

$$\ln\left[\frac{P(Y_i=j)}{P(Y_i=0)}\right] = \alpha_j + \beta_{1j}\text{Drought}_i + \beta_{2j}\text{SocialGroup}_i\beta_{3j}\text{Wealth}_i + \theta_j(\text{Drought}_i \times \text{SocialGroup}_i) + \beta_{4j}\mathbf{Z}_i + \varepsilon_i \tag{3.3}$$

for $j \in \{\text{Deteriorated, Death}\}$

Where δ_j is the coefficient vector capturing whether the marginal effect of drought on health outcomes differs across wealth tertiles, and θ_j is the coefficient vector capturing whether that marginal effect differs across social groups.

To answer the second research question, "Does social capital mitigate these impacts?", the paper uses a multinomial logistic regression with the same outcome variable. The analytical approach begins with a main effects model that includes drought exposure, key stratifiers (class and social groups), and social capital.

$$\ln\left[\frac{P(Y_i=j)}{P(Y_i=0)}\right] = \alpha_j + \beta_{1j}\text{Drought}_i + \beta_{2j}\text{SocialGroup}_i + \beta_{3j}\text{Wealth}_i + \beta_{4j}\text{SocialCapital}_i + \beta_{5j}\mathbf{Z}_i + \varepsilon_i \tag{3.4}$$

for $j \in \{\text{Deteriorated, Death}\}$

The paper then introduces interactions between drought exposure and social capital to test whether social capital moderates the effects of droughts. These are referred to as resilience models.

$$\ln\left[\frac{P(Y_i=j)}{P(Y_i=0)}\right] = \alpha_j + \beta_{1j}\text{Drought}_i + \beta_{2j}\text{SocialGroup}_i + \beta_{3j}\text{Wealth}_i + \beta_{4j}\text{SocialCapital}_i + \lambda_j(\text{Drought}_i \times \text{SocialCapital}_i) + \beta_{5j}\mathbf{Z}_i + \varepsilon_i \tag{3.5}$$

for $j \in \{\text{Deteriorated, Death}\}$

Where the coefficient vector λ_j tests whether the marginal effect of drought on health outcomes differs between those with and without access to social capital networks. For each caste-and-class subgroup, Model 5 was re-estimated on the corresponding restricted sample, using the same outcome definition, key predictors, and control variables as in the full-sample specification. The "All" panel presents predicted probabilities estimated on the full analytic sample, while the subsequent panels present predicted probabilities estimated on subsamples stratified by wealth tertile and social group respectively.

Longitudinal studies inevitably experience attrition due to death. Disability and mortality are closely linked, individuals with poorer functional health face a substantially higher risk of death, as such mortality selectively removes the frailest (Crimmins & Saito, 2001; Ferrucci et al., 1996). Treating death as random attrition, therefore, biases the estimate by understating the health effects of adverse exposures. One of the ways used to address this is by jointly modeling mortality with functional health change over time, treating death as a competing outcome (Q.-L. Xue et al., 2012; Zimmer et al., 2012). In discrete-time analyses, multinomial logit models provide a standard approach for jointly modeling transitions across health states, including an absorbing death state (Allison, 1982; Powers & Xie, 2008). All models employ multinomial logit regression; however, the results primarily focus on the health deterioration outcome to maintain conciseness. Although

mortality was included in the models, it did not achieve statistical significance in either the risk or resilience model. Full models are available in the Appendix A1.

Results

Table 3.1. Descriptive Statistics, Rural Adults Aged 40 and Older in IHDS Wave 1 ($N = 32{,}248$)

Variable	% or Mean	SD
Outcome		
Stable or improved	70.4	
Deteriorated	15.3	
Died	14.3	
Drought Exposure		
No drought	44.9	
Single drought	23.0	
Two or more droughts	32.1	
Social Capital		
Any organizational membership	34.7	
Social Group		
Higher castes	59.8	
SC/ST	31.2	
Muslim	9.0	
Wealth Tertile		
Poor	40.9	
Middle	32.0	
Rich	27.1	
Individual Characteristics		
Age (years)	54.2	11.2
Female	49.0	
Baseline functional limitation score	0.2	1.17
Household Characteristics		
Number of adults	3.36	1.59
Number of children	1.79	1.81
Any outmigration or household split	58.1	
Income Source		
Agriculture primary income	61.6	
Some agriculture income	18.3	
No agriculture income	20.1	
Other Climate Events		

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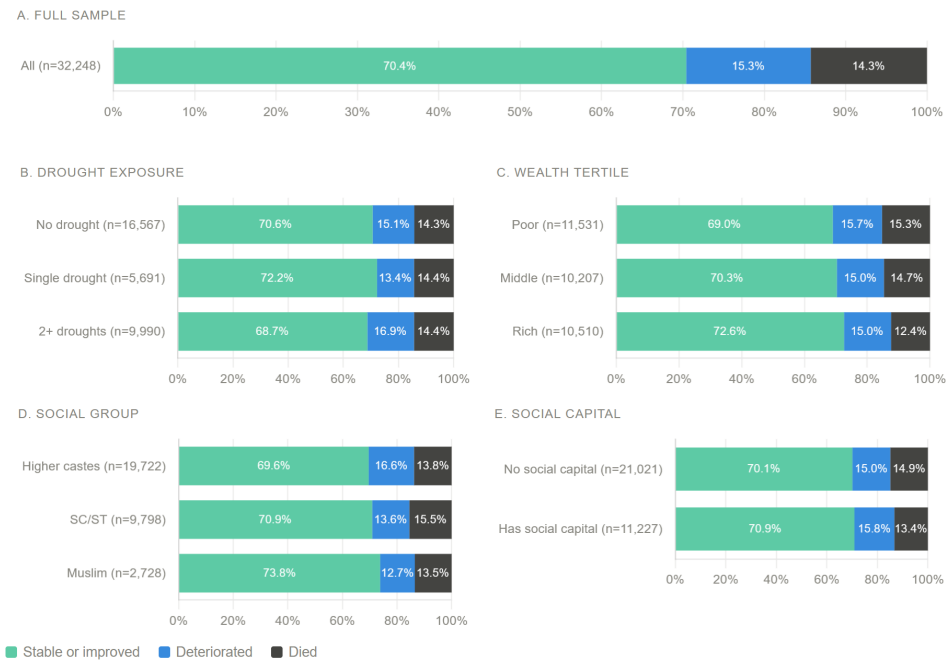
Table 3.1 continued

Variable	% or Mean	SD
Flood between waves	30.1	
Earthquake between waves	8.4	

Note: Statistics are weighted using Wave 1 IHDS survey weights. Percentages reported for categorical and binary variables; mean and standard deviation reported for continuous variables. All variables are measured at Wave 1 (2004–05), with the exception of the outcome, drought exposure, other climate events, and household outmigration or split, which capture events or changes occurring between Wave 1 and Wave 2.

Figure 3.2 presents the unadjusted distribution of functional health outcomes across five panels. The overall distribution is relatively stable across most subgroups, with the majority of individuals in each group remaining stable or improved. The most notable variation is by drought exposure—the deteriorated share rises from 15.1% with no drought to 16.9% with two or more droughts, while the stable share falls. Differences across wealth tertiles and social groups are modest in the marginal distributions. The social capital panels show virtually no difference in the marginal outcome distributions between those with and without social capital, consistent with the regression finding that social capital operates as a crisis-activated resource rather than a general health buffer.

Figure 3.2. Functional health trajectories by drought exposure, wealth, social group, and social capital status, rural adults aged 40 and over, IHDS Wave 1 to Wave 2.



Source: Author's calculations from IHDS Waves 1 (2004–05) and 2 (2011–12).

Risks

Table 3.2 presents the results of a multinomial logistic regression comparing individuals whose functional limitations deteriorated with the base group. Experiencing one drought is not statistically significantly associated with a higher risk of deterioration (RRR = 1.00, $p = 0.98$), but exposure to two or more droughts is associated with a 19% increase in risk (RRR = 1.19, $p = 0.01$). This translates to a rise in the predicted probability of functional health deterioration from 13.7% (CI 13.0%, 14.5%) with no drought to 15.6% (CI 14.6%, 16.6%) with two or more droughts.

Compared to those in the poorest asset tertile, individuals in the richest tertile have substantially lower risk of functional health decline (RRR = 0.75, $p < 0.001$). The poorest asset tertile exhibits a statistically significant increase in predicted probability of deterioration under drought

exposure, from 14.2% with no drought to 17.4% with two or more droughts. The middle tertile shows a similar rise, from 13.8% to 16.1%. In contrast, the richest tertile shows minimal change, from 12.7% with no drought to 12.3% with two or more droughts. Individuals from SC/ST exhibit a lower relative risk of deterioration compared to Hindu Forward Castes (RRR = 0.82, $p < 0.01$), as do Muslims (RRR = 0.82, $p = 0.03$). Age is consistently and significantly associated with a higher risk of functional decline (RRR = 1.08, $p < 0.001$). Women have a higher risk of functional health deterioration compared to men (RRR = 1.35, $p < 0.001$).

Table 3.2. Multinomial Logistic Regression of Functional Limitation Deterioration by Drought Exposure, Socioeconomic, and Demographic Characteristics. Rural Adults Aged 40 and Older (IHDS, Wave 1 to Wave 2)

	Risk Model (Model 1)			**Resilience Model (Model 2)**		
	R.R.R.	**S.E.**	**P value**	**R.R.R.**	**S.E.**	**P value**
Droughts						
No Drought (ref.)	1.00	.	.	1.00	.	.
One Drought	1.00	0.07	0.983	1.00	0.07	0.988
Two or More Droughts	1.19	0.07	0.006	1.19	0.07	0.006
Social Capital						
No (ref.)				1.00	.	.
Yes				0.96	0.05	0.427
Wealth Tertiles						
Poorest Tertile (ref.)	1.00	.	.	1.00	.	.
Middle Tertile	0.90	0.06	0.103	0.90	0.06	0.115
Richest Tertile	0.75	0.06	0.000	0.75	0.06	0.000
Social Groups						
Forward Castes (ref.)	1.00	.	.	1.00	.	.
Scheduled Castes & Tribes	0.82	0.05	0.001	0.82	0.05	0.001
Muslims	0.82	0.08	0.028	0.82	0.08	0.028
Gender						
Men (ref.)	1.00	.	.	1.00	.	.
Women	1.35	0.08	0.000	1.35	0.08	0.000
Age	1.08	0.00	0.000	1.08	0.00	0.000
Baseline Functional Limitation Score	0.82	0.02	0.000	0.82	0.02	0.000

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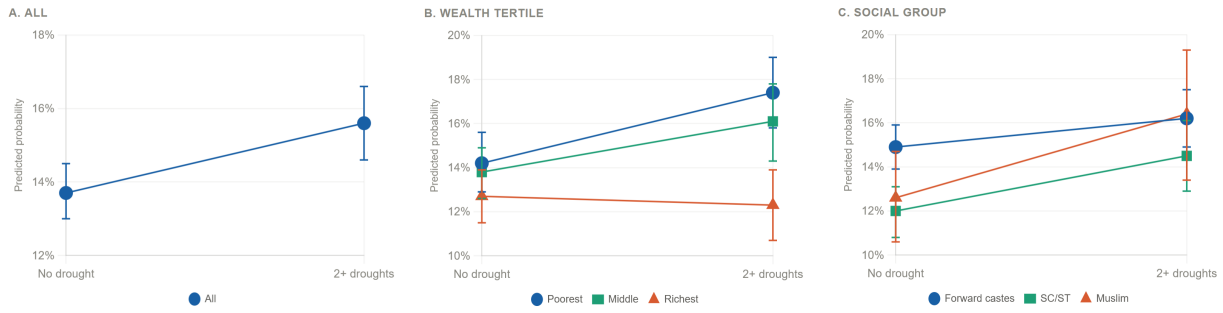
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	Risk Model (Model 1)			Resilience Model (Model 2)		
	R.R.R.	**S.E.**	**P value**	**R.R.R.**	**S.E.**	**P value**
Education						
No Formal Education (ref.)	1.00	.	.	1.00	.	.
Up to Primary	0.92	0.07	0.231	0.92	0.07	0.242
Above Primary	0.84	0.07	0.036	0.84	0.07	0.037
Income Source						
No Agriculture Income (ref.)	1.00	.	.	1.00	.	.
Some Agriculture Income	1.00	0.09	0.990	1.00	0.09	0.967
Agriculture as Primary Source	0.90	0.06	0.129	0.90	0.06	0.134
Marital Status						
Married (ref.)	1.00	.	.	1.00	.	.
Widowed, separated, divorced	1.13	0.08	0.088	1.14	0.08	0.083
Number of Adults	0.96	0.02	0.041	0.96	0.02	0.044
Number of Children	0.99	0.02	0.618	0.99	0.02	0.620
Any outmigration or household split between waves						
No (ref.)	1.00	.	.	1.00	.	.
Yes	1.06	0.06	0.312	1.06	0.06	0.313
Flood(s) between two rounds						
No (ref.)	1.00	.	.	1.00	.	.
Yes	1.10	0.06	0.119	1.10	0.06	0.115
Earthquake(s) between two waves						
No (ref.)	1.00	.	.	1.00	.	.
Yes	0.86	0.09	0.153	0.86	0.09	0.148
Intercept	0.00	0.00	0.000	0.00	0.00	0.000
Model Fit Statistics						
Sample size (N)		32,248			32,248	
Chi^2		3,203.01			3,218.75	
df		72			74	
McFadden's Pseudo-R^2		0.16			0.16	

Note: Select variables and outcome reported; full regression in Appendix A2.

Source: Author's calculations from IHDS Waves 1 (2004–05) and 2 (2011–12).

Figure 3.3. Predicted probabilities of functional health deterioration by drought exposure and socioeconomic stratifiers, rural India (IHDS, 2004–05 to 2011–12).



Note: Predicted probabilities for Panel A are derived from the main Risk Model (Model 1). For Panels B and C, from interaction Risk Models (Models 2 and 3, respectively). *Source:* Author's calculations from IHDS Waves 1 (2004–05) and 2 (2011–12).

Table 3.3. Predicted Probabilities of Functional Limitation Deterioration by Drought Exposure, Wealth Tertiles, and Social Groups among Adults Aged 47 and Older, Rural India (IHDS, Wave 1 to Wave 2), with 90% Confidence Intervals

	Pred. Prob.	**S.E.**	**Lower CI**	**Upper CI**
Outcome: Health deterioration				
No Drought	0.137	0.00	0.130	0.145
One Drought	0.136	0.01	0.124	0.148
Two or More Droughts	0.156	0.01	0.146	0.166
Asset Tertile				
Poorest × No Drought	0.142	0.01	0.129	0.156
Poorest × One Drought	0.151	0.01	0.133	0.169
Poorest × Two or More Droughts	0.174	0.01	0.158	0.190
Middle × No Drought	0.138	0.01	0.126	0.149
Middle × One Drought	0.127	0.01	0.104	0.150
Middle × Two or More Droughts	0.161	0.01	0.143	0.178
Richest × No Drought	0.127	0.01	0.115	0.139
Richest × One Drought	0.122	0.01	0.098	0.146
Richest × Two or More Droughts	0.123	0.01	0.107	0.139
Social Groups				
Hindu Forward Castes × No Drought	0.149	0.01	0.139	0.159
Hindu Forward Castes × One Drought	0.152	0.01	0.135	0.170

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	Pred. Prob.	S.E.	Lower CI	Upper CI
Hindu Forward Castes × Two or More Droughts	0.162	0.01	0.149	0.175
SC/ST × No Drought	0.120	0.01	0.108	0.131
SC/ST × One Drought	0.120	0.01	0.103	0.137
SC/ST × Two or More Droughts	0.145	0.01	0.129	0.161
Muslims/Others × No Drought	0.126	0.01	0.106	0.147
Muslims/Others × One Drought	0.087	0.02	0.058	0.115
Muslims/Others × Two or More Droughts	0.164	0.02	0.134	0.193

Note: Predicted probabilities are from Model 1 for main effects, Model 2 for interactions with wealth groups, and Model 3 for interactions with social groups. All models were run on the full sample. *Source:* Author's calculations from IHDS Waves 1 (2004–05) and 2 (2011–12).

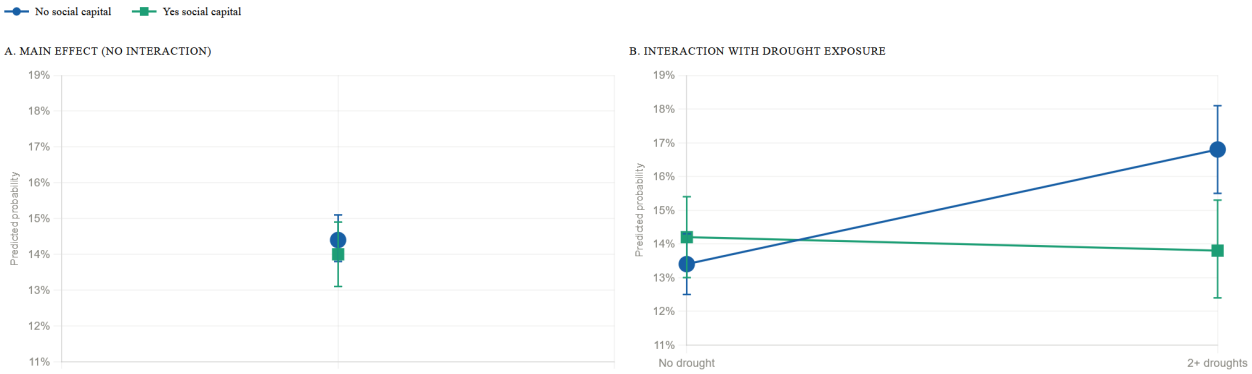
Resilience

The resilience model (Model 2, Table 3.2) adds the social capital variable to the risk model. Adding social capital does not change the effect of two or more droughts, which still carries a 19% higher risk of health deterioration (RRR = 1.19, $p = 0.01$). Having social capital shows no significant protective effect compared to those without any social capital (RRR = 0.96, $p = 0.43$). The predicted probability of functional health deterioration is 14.4% (CI 13.8%, 15.1%) for those without social capital and 14.0% (CI 13.1%, 14.9%) for those with social capital, indicating no significant difference at baseline.

However, a separate model including the interaction of social capital and drought levels reveals important differential effects. For individuals with no social capital, the predicted probability of functional health deterioration increases significantly from 13.4% (CI 12.5%, 14.3%) with no drought to 16.8% (CI 15.5%, 18.1%) with two or more droughts. Those with social capital show no statistically significant change, with probabilities remaining stable from 14.2% with no drought to 13.8% with two or more droughts. This suggests that social capital functions as a crisis-activated protective resource, buffering against drought-related health deterioration rather than providing

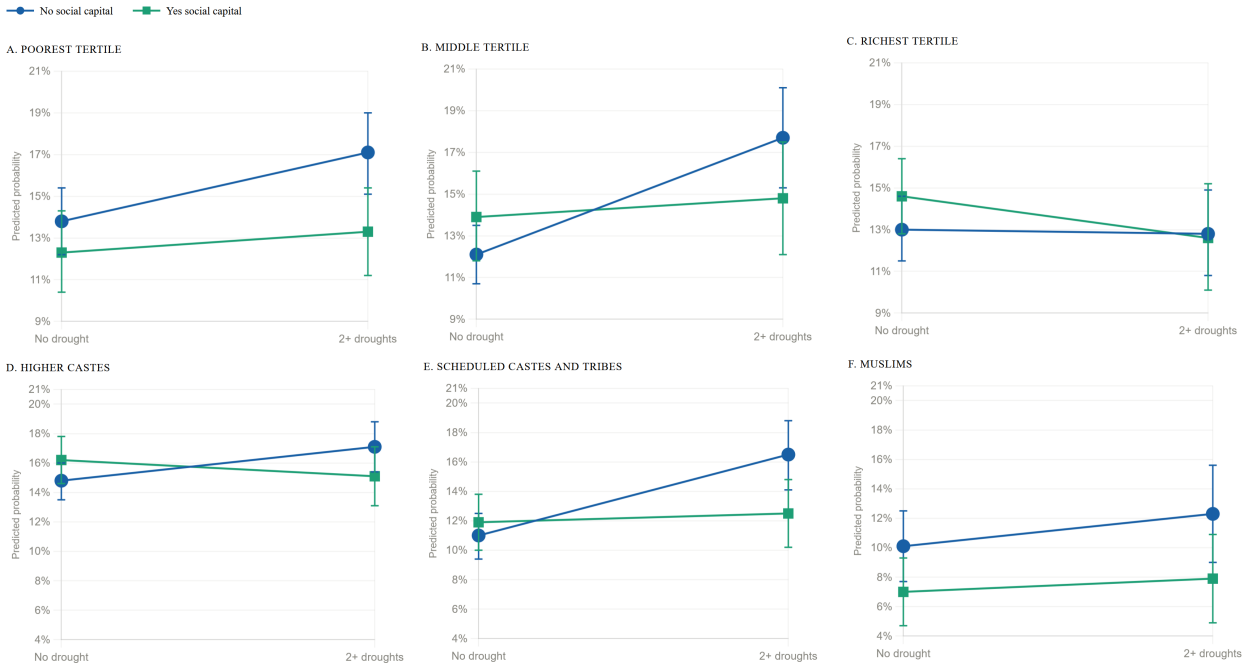
general health benefits under normal conditions.

Figure 3.4. Predicted probabilities of functional health deterioration by social capital status, rural India (IHDS, 2004–05 to 2011–12).



Note: Predicted probabilities for Panel A are derived from the main Resilience Model (Model 4). For Panel B, from the interaction Resilience Model (Model 5). *Source:* Author's calculations from IHDS Waves 1 (2004–05) and 2 (2011–12).

Figure 3.5. Predicted probabilities of functional health deterioration by social capital, stratified by assets and social groups, rural India (IHDS, 2004–05 to 2011–12).



Note: Predicted probabilities for all panels are derived from Model 5 run on restricted subsamples: poorest tertile ($N = 11{,}531$), middle tertile ($N = 10{,}207$), richest tertile ($N = 10{,}510$), forward castes ($N = 19{,}722$), Scheduled Castes and Tribes ($N = 9{,}798$), and Muslims ($N = 2{,}728$). *Source:* Author's calculations from IHDS Waves 1 (2004–05) and 2 (2011–12).

For Scheduled Castes and Tribes with no social capital, predicted probabilities increase significantly from 11.0% (CI 9.4%, 12.5%) with no drought to 16.5% (CI 14.1%, 18.8%) with two or more droughts, representing a statistically significant rise with non-overlapping confidence intervals. Those with social capital show no statistically significant change, remaining relatively stable from 11.9% with no drought to 12.5% with two or more droughts. For individuals in the poorest tertile with no social capital, the predicted probability increases significantly from 13.8% (CI 12.2%, 15.4%) with no drought to 17.1% (CI 15.1%, 19.0%) with two or more droughts. Those

with social capital show no statistically significant change. For middle tertile individuals with no social capital, predicted probabilities increase significantly from 12.1% to 17.7%, while those with social capital show stable probabilities. For the richest tertile, predicted probabilities show no statistically significant change regardless of social capital status. Table 3.4 presents the full set of predicted probabilities from the resilience models.

Table 3.4. Predicted Probabilities of Functional Limitation Deterioration by Drought Exposure, Social Capital, Wealth Tertiles, and Social Groups, Adults Aged 47 and Older, Rural India (IHDS, Wave 1 to Wave 2), with 90% Confidence Intervals

	Pred. Prob.	**S.E.**	**Lower CI**	**Upper CI**
Outcome: Health deterioration				
All				
No Social Capital	0.144	0.00	0.138	0.151
Yes Social Capital	0.140	0.01	0.131	0.149
Interactions				
No SC × No Drought	0.134	0.01	0.125	0.143
No SC × One Drought	0.133	0.01	0.119	0.147
No SC × Two or More Droughts	0.168	0.01	0.155	0.181
Yes SC × No Drought	0.142	0.01	0.130	0.154
Yes SC × One Drought	0.144	0.01	0.121	0.166
Yes SC × Two or More Droughts	0.138	0.01	0.124	0.153
Poorest Tertile				
No SC × No Drought	0.138	0.01	0.122	0.154
No SC × Two or More Droughts	0.171	0.01	0.151	0.190
Yes SC × No Drought	0.123	0.01	0.104	0.143
Yes SC × Two or More Droughts	0.133	0.01	0.112	0.154
Middle Tertile				
No SC × No Drought	0.121	0.01	0.107	0.135
No SC × Two or More Droughts	0.177	0.01	0.153	0.201
Yes SC × No Drought	0.139	0.01	0.118	0.161
Yes SC × Two or More Droughts	0.148	0.02	0.121	0.175
Richest Tertile				
No SC × No Drought	0.130	0.01	0.115	0.146
No SC × Two or More Droughts	0.128	0.01	0.108	0.149
Yes SC × No Drought	0.146	0.01	0.128	0.164

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	Pred. Prob.	S.E.	Lower CI	Upper CI
Yes SC × Two or More Droughts	0.126	0.02	0.101	0.152
Higher Castes				
No SC × No Drought	0.148	0.01	0.135	0.160
No SC × Two or More Droughts	0.171	0.01	0.154	0.188
Yes SC × No Drought	0.162	0.01	0.146	0.178
Yes SC × Two or More Droughts	0.151	0.01	0.131	0.171
Scheduled Castes and Tribes				
No SC × No Drought	0.110	0.01	0.094	0.125
No SC × Two or More Droughts	0.165	0.01	0.141	0.188
Yes SC × No Drought	0.119	0.01	0.100	0.138
Yes SC × Two or More Droughts	0.125	0.01	0.102	0.148
Muslims				
No SC × No Drought	0.101	0.01	0.077	0.125
No SC × Two or More Droughts	0.123	0.02	0.090	0.156
Yes SC × No Drought	0.070	0.01	0.047	0.093
Yes SC × Two or More Droughts	0.079	0.02	0.049	0.109

The predicted probabilities for the "All" panel, without interaction, are derived from Model 4. Predicted probabilities from the interactions are derived from Model 5. The "All" panel is estimated on the full analytic sample ($N = 32{,}248$). Subgroup panels are estimated on restricted subsamples: poorest tertile ($N = 11{,}531$), middle tertile ($N = 10{,}207$), richest tertile ($N = 10{,}510$), forward castes ($N = 19{,}722$), SC/ST ($N = 9{,}798$), and Muslims ($N = 2{,}728$). *Source:* Author's calculations from IHDS Waves 1 (2004–05) and 2 (2011–12).

Conclusions and Discussion

The first set of hypotheses focused on risks, proposing that exposure to droughts increases the risks of functional health deterioration among older adults in rural India. Results show that exposure to two or more droughts is associated with a 19% higher risk of deterioration, whereas exposure to a single drought shows no difference from no drought at all. This pattern suggests that, unlike once-in-a-generation disasters, which have immediate impacts, repeated, lower-intensity events exert a cumulative effect that becomes evident only after multiple exposures. The paper further hypothesized that an advantageous social and economic position can mitigate these risks.

Economic position plays a crucial role: the poorest asset tertile exhibits a statistically significant increase in functional deterioration following drought exposure, whereas the richest tertile shows no statistically significant change regardless of drought exposure. These results reinforce the notion that climate events systematically amplify pre-existing inequalities.

A further limitation of this study concerns the measurement of drought exposure. Droughts are identified using self-reported information from the IHDS, which does not allow for verification of drought intensity or severity using external meteorological indicators such as precipitation or standardized rainfall anomalies. Future research could strengthen inference by integrating survey data with high-resolution gridded precipitation or standardized precipitation indices.

The second set of hypotheses focuses on resilience, proposing that social capital helps buffer the negative effects of droughts on functional limitations. Social capital itself is not statistically significantly associated with better baseline health outcomes under normal conditions. However, the paper finds that social capital acts as a crisis-activated protective resource, effectively buffering against health deterioration associated with drought. For individuals with no social capital, the predicted probability of functional health deterioration increases significantly from no drought to two or more droughts. Those with social capital show no statistically significant change, with probabilities remaining stable. This finding suggests that social capital is as important a resource as wealth in buffering against the adverse effects of climate events. Just as wealth provides households with financial insurance, social capital provides informal insurance by mobilizing networks. Network theory conceptualizes social capital as resources embedded in social structures that can be accessed and mobilized for purposive action, implying that ties may remain relatively latent in stable periods but become consequential when households face acute need (Lin, 2017).

This study encounters a limitation in the use of a binary measure of social capital that does

not distinguish between bonding and bridging forms. Unfortunately, a limited analytic sample size prohibited this level of differentiation in the modeling strategy. The Appendix A3 reports results from analyses of bonding and bridging social capital separately, and the results show that both forms provide protective effects. Bonding social capital, which is often theorized to reinforce exclusionary norms, does not appear to affect functional health negatively; on the contrary, it appears to provide protective effects, particularly among individuals in the lowest and middle wealth tertiles and among Scheduled Castes and Tribes. Similarly, bridging capital also helps buffer against the negative effects of drought in certain subgroups. The consistency in the direction of findings across bonding and bridging models provides further assurance that the use of a composite measure does not conceal substantively divergent effects.

Finally, the paper hypothesized that the protective effect of social capital is uneven, with individuals in more privileged social and economic positions receiving higher levels of protection. The results provide only partial confirmation. Among the poorest and middle asset tertiles, as well as SC/ST households, functional health deteriorated with repeated droughts when social capital was absent but remained stable when it was present, showing a clear protective effect. This outcome contradicts the initial hypothesis. In the richest tertile and forward castes, however, there was little evidence of deterioration to begin with, leaving no scope for social capital to demonstrate additional benefits. This pattern suggests that social capital and wealth function as partial substitutes in the face of climate shocks. When material resources are sufficient, wealth alone provides adequate buffering; when they are not, social capital becomes a critical line of defense. Taken together, the findings reframe social capital not as a resource that reinforces existing privilege but as a form of resilience infrastructure that is most consequential among the most disadvantaged.

Conclusions & Discussions

This dissertation examines how social stratification shapes health and demographic outcomes amid rapid economic, demographic, and environmental change. India presents a critical case study, given its sustained economic growth in recent decades, an aging population, and escalating climate stresses. These changes are occurring alongside enduring traditional forms of social stratification of caste, class, gender, religion, and geographic location. The central argument of the dissertation is that social stratification does not become less consequential as India grows economically and undergoes demographic and epidemiological transformation. Instead, stratification becomes consequential through new mechanisms, new risks, and new stages of the life course.

Across three empirical chapters, I explore this argument through different but related areas: women's nutritional changes during economic growth, poverty transitions and mortality in later life, and the impact of drought exposure and social capital on functional health among older rural adults. Although these chapters focus on different life stages, outcomes, and exposures, they ask a common question: who benefits from change, who remains vulnerable, and who can mobilize protection when new risks emerge? This question links the dissertation's empirical chapters to its broader theoretical concern with the persistence and transformation of inequality. The chapters do not treat caste, class, religion, gender, and place as static background characteristics. Rather, they examine how these social positions structure access to resources, exposure to risk, and the capacity to adapt across changing social and environmental conditions.

Interpreted through fundamental cause theory and the life-course perspective, the findings show that health and demographic gradients are reproduced across changing risks, exposures, and

life-course stages. Chapter 1 shows that although the gradient in undernutrition has narrowed, a new gradient in overweight and obesity has emerged, suggesting that nutritional inequality has shifted rather than disappeared. As India's access to health care and nutrition changed, the economically advantaged were better positioned to move out of undernutrition, but they were also the first to experience the risks associated with excess weight. Chapter 2 shows that both poverty transitions and social position matter independently for survival in later life. Escaping poverty improves survival prospects, but it does not fully erase the mortality disadvantages associated with caste. Chapter 3 shows that economic and social position shape vulnerability to functional health deterioration under drought exposure, but social capital can buffer this risk, especially among the most vulnerable. In this case, social ties serve as a protective resource that becomes most evident under acute stress. Together, these findings show that the form of inequality changes, but the underlying structure of protection and vulnerability persists.

What the Three Chapters Found

Chapter 1 examined the nutritional status among women aged 25–49 in India between 1998 and 2021, coinciding with two decades of high economic growth but rising inequality. The chapter asked whether there was convergence or divergence in women's nutritional status across economic status. The answer was both, and the distinction matters theoretically. Underweight prevalence declined across all wealth quintiles, with larger absolute reductions among poorer women, producing real and measurable socioeconomic convergence in undernutrition. At the same time, obesity rose across all quintiles, with larger absolute increases among middle and upper SES groups, producing divergence in excess weight risk that is now beginning to diffuse downward to lower SES groups.

At the subnational level, states with the highest undernutrition burden in 1998 recorded the largest absolute declines by 2019, while obesity diverged, with more economically advanced states pulling ahead.

Viewed through the lens of fundamental cause theory, these results show that nutritional inequality did not disappear with economic growth but shifted from undernutrition to unequal exposure to and protection from obesity-related risks. The theoretical implication is precisely what fundamental cause theory predicts. As the nature of the nutritional risk changed, the gradient did not disappear but reorganized. Advantaged women experienced undernutrition first and entered obesity risk first. Disadvantaged women followed with a lag, remaining burdened by undernutrition even as obesity risk began its downward diffusion. The gradient shifted its form from undernutrition to obesity, while its axis remained the same. This pattern mirrors experiences documented elsewhere. Tobacco use first spread among higher-SES groups, but as awareness of its health risks grew, they were also the first to stop using it, concentrating the burden of tobacco-related illness among disadvantaged populations (Link & Phelan, 2009; Pampel & Denney, 2011). A similar reversal has been documented for body weight: as national income rises, the relationship between SES and body weight shifts direction, with higher-SES groups carrying higher body weight in less affluent countries and lower-SES groups carrying higher body weight in more affluent ones. China and Brazil show comparable patterns, with cardiovascular disease risk shifting from higher- to lower-SES groups in China, and rising non-communicable disease rates alongside persistent communicable disease inequality in Brazil. Chapter 1 adds to this literature by demonstrating that India's nutrition transition aligns with the same theoretical framework: economic growth diminishes certain types of deprivation but also introduces new health risks embedded in existing structures of inequality.

Chapter 2 examined how poverty trajectories shape mortality risk among older adults in

rural India, using three waves of IHDS panel data to classify individuals into poverty transition categories and track their survival risks between waves. Scheduled Tribes and Castes faced higher mortality risks at all ages. Escaping poverty was associated with a meaningful survival gain. The interaction between caste and poverty transitions was not statistically significant: upward mobility helped everyone roughly equally, but it could not close the caste gap. The chapter showed that social position and economic mobility operate together but are not interchangeable. Poverty transitions capture one dimension of class-based exposure, while caste and religious location capture more durable forms of social exclusion. This finding is key to the dissertation's argument that later-life mortality depends on both economic resources and the social position accumulated over the course of life.

The central contribution of this chapter is methodological and theoretical in equal measure. First, it provides longitudinal evidence on mortality among older adults in rural India, a population for which evidence is still limited. Much of the existing literature on caste, class, and health in India relies on cross-sectional measures of health status, child health, or self-reported morbidity. Chapter 2 instead follows older adults over time and links social position and poverty mobility to survival. Second, rather than treating poverty as a static attribute, it asks whether the timing, duration, and direction of poverty matter for survival independently of current economic position. Third, it shows that economic mobility has real but incomplete returns: escaping poverty is associated with lower mortality risk, but the persistence of caste-based mortality gaps shows that mobility does not fully erase inherited disadvantage. Fourth, the non-significant interaction between caste and poverty transitions suggests that poverty mobility improves survival across social groups without closing the underlying caste gap.

Chapter 2 also speaks to a broader literature on the SES mortality gradient. The richest 1

percent in the United States live substantially longer than the poorest 1 percent, and this gap widened in the early twenty-first century (Chetty et al., 2016). In many high-income countries, behavioral risk factors account for a large share of the gradient, whereas in lower- and middle-income settings, material deprivation, limited healthcare access, food insecurity, and weak social protection may play a larger role. Chapter 2 contributes to this literature by showing that survival in rural India depends not only on where individuals are located economically at one point in time, but also on where they have been and for how long. Persistent poverty captures prolonged exposure to deprivation, while downward mobility captures the mortality consequences of economic loss in later life. Research from the United States shows that the health returns to upward mobility are conditioned by race, with Black men receiving smaller mortality benefits from upward mobility than white men. Scheduled Castes and Tribes have persistently lower life expectancies than high-caste individuals (A. Gupta & Sudharsanan, 2022), and caste remains independently associated with mortality among older adults even after accounting for standard of living (Vyas et al., 2022). Chapter 2 adds to this literature by showing that class mobility and caste position independently structure survival.

Chapter 3 examined how drought exposure shapes the risk of functional health decline among older adults in rural India, and whether social capital buffers this harm differentially across caste and class groups. Using two waves of the India Human Development Survey, exploiting exogenous variation in district-level drought exposure, the chapter finds that drought worsens functional health trajectories among older rural adults and that this harm is most severe among the most socioeconomically disadvantaged. Social capital did not provide a general health advantage under stable conditions; its protective effect emerged specifically under drought conditions. Among individuals without social capital, the predicted probability of deterioration rose significantly from no drought to repeated drought exposure, while among those with social capital the probability

remained stable. This buffering effect was strongest among SC/ST households and the poorest asset tertile.

These results show that climate shocks do not create new inequalities so much as amplify existing ones. The crisis-activated mechanism extends fundamental cause theory's argument about flexible resources: organizational network ties that remain largely dormant under stable conditions become protective resources under acute environmental stress, functioning as informal insurance precisely where formal and material protection is weakest. This is consistent with evidence from the Great East Japan Earthquake, where higher social cohesion was linked to lower prevalence of functional disability among older adults in disaster-stricken areas (Tanji et al., 2017), and from Hurricane Katrina, where low-income populations were less likely to be rescued and slower to recover because the resources needed to survive and rebuild were unequally distributed before the storm arrived (Fussell et al., 2010).

Policy Implications

The findings from Chapter 1 suggest that India's double burden of malnutrition requires a dual policy response. Policies aimed at reducing undernutrition among the poorest women remain essential and cannot be replaced by programs focused only on overweight and obesity. At the same time, overweight and obesity are rising across the socioeconomic distribution, creating a new set of health risks that will increasingly affect middle- and lower-SES groups. If obesity is treated primarily as an affluent or urban problem, policy will miss the groups most likely to experience rising risk in the coming decade. Nutrition policy must also be sensitive to subnational variation in growth, poverty, food systems, gender inequality, sanitation, and healthcare access, since aggregate

prosperity does not automatically translate into nutritional improvement.

The findings from Chapter 2 point to the central importance of poverty reduction as health policy. Escaping poverty yields real, measurable gains in survival among older adults, and policies that improve income security, food access, housing stability, and healthcare affordability can extend life in later adulthood even among populations with long histories of deprivation. At the same time, poverty reduction alone is insufficient. Universal or poverty-targeted programs must be paired with interventions that explicitly address traditional forms of social stratification, since social protection systems that rely solely on income or consumption thresholds risk overlooking how social group membership shapes access to healthcare, institutional treatment, and social support. The findings also suggest that preventing downward mobility may be as important as promoting upward mobility. Older adults who fall into poverty face mortality risks comparable to those who remain chronically poor, pointing to the need for shock-responsive safety nets designed not only to lift households out of poverty but also to prevent re-entry after illness, crop loss, job loss, or climate-related shocks.

The findings from Chapter 3 show that climate resilience policy in rural India must address repeated drought exposure, not only single catastrophic events. For older adults, the health consequences of climate stress accumulate through recurring disruptions to income, food security, care arrangements, and physical labor demands. Adaptation policy cannot be distributionally neutral: programs that improve irrigation, crop insurance, livelihood diversification, food security, and emergency income support must be explicitly targeted toward households with the fewest assets and weakest buffers. The chapter also shows that strengthening local organizations in drought-prone communities (including self-help groups, agricultural cooperatives, savings groups, and women's organizations) can complement formal social protection by activating the informal insurance mechanisms that protect the most vulnerable under acute stress.

Across Chapters 2 and 3, the dissertation shows that India's rapidly growing older adult population faces intersecting risks from poverty trajectories, caste exclusion, rural disadvantage, and climate stress. One cross-cutting policy implication is the need to treat functional health as a central indicator of older adult well-being. Functional limitations often appear before severe clinical disease, disability, or mortality, and screening for mobility limitations and activities of daily living among older rural adults could allow earlier intervention.

Limitations and Next Steps

Chapter 1 uses wave-specific wealth quintiles, which measure relative rather than absolute economic position. The analysis can show whether poorer states are catching up to richer states, but it cannot fully establish whether poorer women within each state are catching up to richer women in the same state. Estimating within-state gradients would clarify whether nutritional inequality is narrowing inside states or whether aggregate convergence is driven mainly by changes between states.

Chapter 2 is restricted to rural older adults, so the findings may not generalize to urban India, where poverty dynamics, labor markets, healthcare access, and mortality patterns differ. The analysis also focuses on adults aged 50 and above, meaning the sample is conditional on survival to that age. The most disadvantaged individuals may die before entering the analytic sample, producing a selected older population that is healthier and more resilient than the original cohort. Future research should examine mortality in early and midlife to better understand how poverty trajectories and social position shape survival across the full life course. Poverty transitions are also measured across three IHDS waves, leaving poverty spells between survey rounds unobserved. More frequent

panel data, or linkage of survey data to administrative mortality records, health insurance claims, or verbal autopsy data, would improve the precision of poverty mobility measures and help clarify the pathways connecting poverty mobility to survival.

Chapter 3 relies on self-reported community-level drought exposure from the IHDS, which does not verify intensity, duration, or severity using external meteorological data. Future research should link household surveys to high-resolution rainfall data, standardized precipitation indices, or gridded climate measures to better separate the frequency, intensity, and duration of drought exposure. The chapter also uses a composite measure of social capital, which preserves statistical power but limits the ability to distinguish between bonding and bridging forms. Finally, while the chapter identifies social capital as a crisis-activated protective resource, the precise mechanisms, whether organizational ties buffer health decline through improved access to food, credit, care, information, emotional support, or collective claims on local institutions requires further study. Qualitative and mixed-method research in drought-prone communities would help clarify how social networks are activated during crisis, when they substitute for material resources, and when they fail to protect the most vulnerable.

Appendix

Appendix A1. Assessment of Attrition Bias

To assess whether sample attrition between IHDS Waves 1 and 2 introduces systematic bias into our estimates, I compare the baseline characteristics of households retained in the panel with those of households lost to follow-up. The retained sample is defined as respondents who were successfully interviewed in both IHDS Wave 1 and Wave 2. The IHDS tracking protocol covers households that split but remain within the same village and therefore can still be followed, but it does not capture households that migrate out of the original location. In addition, even when the household is re-interviewed at Wave 2, if a baseline individual has migrated out and is not interviewed, IHDS does not provide Wave 2 functional limitation information for that person. Accordingly, "attrition" in this study includes all baseline respondents who do not have a Wave 2 individual interview record, whether due to household-level non-interview (e.g., refusal or non-contact), household relocation or migration out of the study area, or individual-level migration.

Table A.1 presents distributions of key covariates, namely, drought exposure, baseline functional health, social capital, household asset wealth, social groups, and gender. I compare baseline characteristics of two groups: households retained in both waves of the panel ("stayed in sample"), and households present in Wave 1 but not re-interviewed in Wave 2 ("lost to follow-up"). All comparisons are weighted using Wave 1 survey weights, with the primary sampling unit (PSU) specified as the cluster identifier to account for the complex survey design. Of the full sample of individuals aged 40 and above in Wave 1, 91% were successfully re-interviewed in Wave 2, with

the remaining 9% lost to attrition.

Overall, the results indicate no substantial differences in characteristics between retained respondents and those lost to follow-up. Attrition appears broadly uniform across drought exposure, gender, social capital, asset wealth, and social group membership. Individuals exposed to two or more droughts exhibit attrition rates nearly identical to those with no drought exposure (9.2% versus 9.7%), suggesting that the primary exposure group is not differentially selected out of the panel. Respondents exposed to a single drought display the lowest attrition rate (7.2%), further indicating that drought exposure does not systematically predict panel loss. Differences across baseline functional health, gender composition, social capital, asset wealth, and social group membership are similarly small in magnitude.

Table A.1. Row percentages showing share of each subgroup retained vs. lost to follow-up. IHDS Panel, Waves 1 and 2. Individuals aged 40 and above in Wave 1.

Variable	**Retained (%)**	**Lost to Follow-up (%)**
Drought Exposure		
No drought	90.27	9.73
Single drought	92.81	7.19
Two or more droughts	90.84	9.16
Gender		
Men	90.77	9.23
Women	91.30	8.70
Social Capital		
Yes	91.50	8.50
No	90.15	9.85
Household Asset SES		
Poorest tertile	92.10	7.90
Middle tertile	90.32	9.68
Richest tertile	90.28	9.72
Social Group		
Higher castes	90.99	9.01
SC/ST	91.00	9.00

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Table A.1 (continued)

Variable	Retained (%)	Lost to Follow-up (%)
Muslims	91.38	8.62
Baseline Functional Health (mean)	0.197	0.216

Note: Survey-weighted using Wave 1 weights; PSU as cluster identifier.

Appendix A2. All Multinomial Logit Models

Table A.2. Multinomial logistic regression of functional limitation and mortality. Rural Adults aged 40 and older (IHDS, Wave 1 to Wave 2).

	Base Risk Model (M1)			Asset Interaction (M2)			Social Group Interaction (M3)		
	RRR	SE	p	RRR	SE	p	RRR	SE	p
Panel A: Functional Limitation									
Droughts (ref: No Drought)									
One Drought	1.00	0.07	0.983	1.07	0.12	0.513	1.04	0.10	0.716
Two or More Droughts	1.19	0.07	0.006	1.29	0.12	0.007	1.12	0.09	0.147
Wealth Tertiles (ref: Poorest)									
Middle Tertile	0.90	0.06	0.103	0.95	0.09	0.543	0.90	0.06	0.091
Richest Tertile	0.75	0.06	0.000	0.84	0.08	0.079	0.74	0.06	0.000
Social Groups (ref: Forward Castes)									
Scheduled Castes & Tribes	0.82	0.05	0.001	0.82	0.05	0.001	0.78	0.07	0.003
Muslims	0.82	0.08	0.028	0.82	0.08	0.031	0.82	0.10	0.106
Gender (ref: Men)									
Women	1.35	0.08	0.000	1.35	0.08	0.000	1.35	0.08	0.000
Age	1.08	0.00	0.000	1.08	0.00	0.000	1.08	0.00	0.000
Baseline Functional Limitation	0.82	0.02	0.000	0.82	0.02	0.000	0.81	0.02	0.000
Education (ref: No Formal Education)									
Up to Primary	0.92	0.07	0.231	0.92	0.07	0.246	0.92	0.07	0.222
Above Primary	0.84	0.07	0.036	0.83	0.07	0.032	0.84	0.07	0.036
Income Source (ref: No Agriculture Income)									
Some Agriculture Income	1.00	0.09	0.990	1.00	0.09	0.961	1.01	0.09	0.950
Agriculture as Primary Source	0.90	0.06	0.129	0.90	0.06	0.141	0.91	0.06	0.150
Marital Status (ref: Married)									
Widowed, separated, divorced	1.13	0.08	0.088	1.13	0.08	0.085	1.13	0.08	0.094
Number of Adults	0.96	0.02	0.041	0.96	0.02	0.034	0.96	0.02	0.038
Number of Children	0.99	0.02	0.618	0.99	0.02	0.638	0.99	0.02	0.616
Outmigration or household split (ref: No)									
Yes	1.06	0.06	0.312	1.06	0.06	0.306	1.06	0.06	0.298
Flood between waves (ref: No)									
Yes	1.10	0.06	0.119	1.10	0.06	0.101	1.09	0.06	0.148
Earthquake between waves (ref: No)									
Yes	0.86	0.09	0.153	0.86	0.09	0.137	0.85	0.09	0.129
Interactions: Wealth									
Single drought × Middle				0.87	0.15	0.442			
Single drought × Rich				0.90	0.17	0.581			

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Table A.2 continued from previous page

	Base Risk Model (M1)			Asset Interaction (M2)			Social Group Interaction (M3)		
	RRR	**SE**	**p**	**RRR**	**SE**	**p**	**RRR**	**SE**	**p**
Two+ droughts × Middle				0.95	0.12	0.688			
Two+ droughts × Rich				0.76	0.11	0.051			
Interactions: Social Groups									
One Drought × SC/ST							0.99	0.15	0.924
One Drought × Muslim							0.64	0.17	0.089
Two+ Droughts × SC/ST							1.14	0.14	0.282
Two+ Droughts × Muslim							1.25	0.23	0.237
State of Residence (ref: Uttar Pradesh)									
Mountain States	0.99	0.14	0.943	1.01	0.14	0.953	1.01	0.14	0.971
Punjab	1.90	0.30	0.000	1.83	0.29	0.000	1.89	0.30	0.000
Haryana	1.27	0.18	0.079	1.26	0.17	0.090	1.27	0.18	0.088
Rajasthan	1.57	0.19	0.000	1.59	0.19	0.000	1.57	0.19	0.000
Bihar	1.46	0.20	0.006	1.46	0.20	0.006	1.47	0.20	0.005
North-East	0.48	0.11	0.001	0.48	0.11	0.001	0.48	0.10	0.001
West Bengal	0.76	0.11	0.059	0.76	0.11	0.061	0.77	0.11	0.081
Jharkhand	1.09	0.20	0.650	1.10	0.21	0.622	1.07	0.20	0.733
Orissa	0.68	0.10	0.008	0.67	0.10	0.008	0.68	0.10	0.008
Chhattisgarh	2.66	0.35	0.000	2.70	0.36	0.000	2.65	0.35	0.000
Madhya Pradesh	3.23	0.36	0.000	3.23	0.37	0.000	3.21	0.36	0.000
Gujarat, Dadra, and Daman & Diu	1.35	0.20	0.044	1.33	0.20	0.052	1.35	0.20	0.045
Maharashtra and Goa	0.92	0.12	0.541	0.93	0.12	0.582	0.92	0.12	0.519
Andhra Pradesh	1.51	0.21	0.003	1.52	0.21	0.003	1.51	0.21	0.003
Karnataka	1.43	0.18	0.004	1.44	0.18	0.004	1.43	0.18	0.005
Kerala	6.61	1.06	0.000	6.53	1.06	0.000	6.51	1.06	0.000
Tamil Nadu and Pondicherry	1.41	0.23	0.035	1.40	0.23	0.037	1.39	0.23	0.041
Panel B: Death									
Droughts (ref: No Drought)									
One Drought	1.11	0.09	0.201	1.00	0.12	0.984	1.09	0.12	0.467
Two or More Droughts	1.16	0.08	0.039	1.11	0.11	0.301	1.13	0.10	0.182
Wealth Tertiles (ref: Poorest)									
Middle Tertile	0.94	0.06	0.332	0.88	0.09	0.192	0.94	0.06	0.329
Richest Tertile	0.69	0.06	0.000	0.64	0.07	0.000	0.69	0.06	0.000
Social Groups (ref: Forward Castes)									
Scheduled Castes & Tribes	1.14	0.07	0.039	1.14	0.07	0.036	1.11	0.10	0.249
Muslims	0.96	0.10	0.669	0.96	0.10	0.668	0.91	0.12	0.464
Gender (ref: Men)									
Women	0.63	0.04	0.000	0.63	0.04	0.000	0.63	0.04	0.000
Age	1.11	0.00	0.000	1.11	0.00	0.000	1.11	0.00	0.000
Baseline Functional Limitation	1.08	0.02	0.001	1.08	0.02	0.001	1.08	0.02	0.001
Education (ref: No Formal Education)									
Up to Primary	0.80	0.06	0.006	0.80	0.06	0.006	0.80	0.06	0.006
Above Primary	0.67	0.06	0.000	0.67	0.06	0.000	0.67	0.06	0.000
Income Source (ref: No Agriculture Income)									
Some Agriculture Income	0.83	0.08	0.041	0.83	0.08	0.036	0.83	0.08	0.041
Agriculture as Primary Source	0.89	0.06	0.125	0.89	0.06	0.117	0.89	0.06	0.124
Marital Status (ref: Married)									
Widowed, separated, divorced	1.71	0.12	0.000	1.71	0.12	0.000	1.71	0.12	0.000
Number of Adults	1.03	0.02	0.126	1.03	0.02	0.113	1.03	0.02	0.130
Number of Children	0.96	0.02	0.023	0.96	0.02	0.022	0.96	0.02	0.022
Outmigration or household split (ref: No)									
Yes	0.93	0.05	0.197	0.93	0.05	0.196	0.93	0.05	0.202
Flood between waves (ref: No)									
Yes	0.93	0.06	0.271	0.93	0.06	0.252	0.93	0.06	0.279
Earthquake between waves (ref: No)									

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Table A.2 continued from previous page

	Base Risk Model (M1)			Asset Interaction (M2)			Social Group Interaction (M3)		
	RRR	**SE**	**p**	**RRR**	**SE**	**p**	**RRR**	**SE**	**p**
Yes	1.07	0.11	0.531	1.07	0.11	0.490	1.06	0.11	0.570
Interactions: Wealth									
Single drought × Middle				1.25	0.22	0.212			
Single drought × Rich				1.20	0.24	0.378			
Two+ droughts × Middle				1.04	0.15	0.813			
Two+ droughts × Rich				1.12	0.17	0.448			
Interactions: Social Groups									
One Drought × SC/ST							1.06	0.17	0.701
One Drought × Muslim							1.02	0.26	0.928
Two+ Droughts × SC/ST							1.04	0.14	0.741
Two+ Droughts × Muslim							1.15	0.24	0.517
State of Residence (ref: Uttar Pradesh)									
Mountain States	1.14	0.18	0.402	1.13	0.18	0.424	1.14	0.18	0.407
Punjab	1.72	0.30	0.002	1.76	0.31	0.001	1.72	0.30	0.002
Haryana	1.29	0.17	0.062	1.29	0.17	0.055	1.28	0.17	0.066
Rajasthan	0.91	0.12	0.469	0.91	0.12	0.465	0.91	0.12	0.465
Bihar	1.14	0.16	0.364	1.14	0.16	0.345	1.14	0.16	0.358
Northeast	0.84	0.15	0.321	0.84	0.15	0.309	0.84	0.15	0.328
West Bengal	0.99	0.14	0.932	0.99	0.14	0.963	0.99	0.14	0.954
Jharkhand	1.07	0.21	0.709	1.06	0.20	0.742	1.07	0.21	0.737
Orissa	0.74	0.10	0.029	0.74	0.10	0.027	0.74	0.10	0.029
Chhattisgarh	1.98	0.29	0.000	1.97	0.29	0.000	1.98	0.29	0.000
Madhya Pradesh	1.46	0.18	0.002	1.45	0.18	0.002	1.46	0.18	0.002
Gujarat, Dadra, and Daman & Diu	1.42	0.23	0.026	1.44	0.23	0.021	1.42	0.23	0.028
Maharashtra and Goa	0.84	0.11	0.168	0.83	0.11	0.155	0.84	0.11	0.165
Andhra Pradesh	1.09	0.16	0.529	1.09	0.16	0.530	1.09	0.16	0.529
Karnataka	1.08	0.15	0.601	1.08	0.15	0.605	1.08	0.15	0.598
Kerala	2.58	0.52	0.000	2.64	0.53	0.000	2.57	0.52	0.000
Tamil Nadu and Pondicherry	1.10	0.22	0.623	1.11	0.22	0.605	1.10	0.22	0.638
Intercept	0.00	0.00	0.000	0.00	0.00	0.000	0.00	0.00	0.000
Model Fit									
Sample size (N)	32,248			32,248			32,248		
Chi^2	3,203.01			3,245.29			3,218.74		
df	72			80			80		

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Note: Relative risk ratios are from multinomial logistic regression models. The reference outcome category is no functional limitation and survival. Standard errors and p-values are shown in separate columns. Models include drought exposure, wealth tertiles, social group, gender, age, baseline functional limitation, education, income source, marital status, household composition, household split or outmigration, flood, earthquake, and state fixed effects.

Predicted probabilities are derived from the multinomial logistic regression models (1, 2 & 3). All predicted probabilities are estimated at observed covariate values using the margins command in Stata and are presented with standard errors and 90% and 95% confidence intervals. Results are reported in Table A.2.2; the drought probabilities are derived from model 1, and the interactions are derived from models 2 & 3.

Table A.3. Resilience Models: Multinomial logistic regression of functional limitation and mortality. Rural Adults aged 40 and older (IHDS, Wave 1 to Wave 2).

	Base Resilience Model (M4)			Interaction Resilience Model (M5)		
	RRR	**SE**	**p**	**RRR**	**SE**	**p**
Panel A: Functional Limitation						
Droughts (ref: No Drought)						
One Drought	1.00	0.07	0.988	1.01	0.09	0.948
Two or More Droughts	1.19	0.07	0.006	1.34	0.10	0.000
Social Capital (ref: No)						
Yes	0.96	0.05	0.427	1.07	0.08	0.370
Wealth Tertiles (ref: Poorest)						
Middle Tertile	0.90	0.06	0.115	0.90	0.06	0.110
Richest Tertile	0.75	0.06	0.000	0.75	0.06	0.000
Social Groups (ref: Forward Castes)						
Scheduled Castes & Tribes	0.82	0.05	0.001	0.82	0.05	0.001
Muslims	0.82	0.08	0.028	0.82	0.08	0.034
Gender (ref: Men)						
Women	1.35	0.08	0.000	1.35	0.08	0.000
Age	1.08	0.00	0.000	1.08	0.00	0.000
Baseline Functional Limitation	0.82	0.02	0.000	0.82	0.02	0.000
Education (ref: No Formal Education)						
Up to Primary	0.92	0.07	0.242	0.92	0.07	0.224
Above Primary	0.84	0.07	0.037	0.84	0.07	0.034
Income Source (ref: No Agriculture Income)						
Some Agriculture Income	1.00	0.09	0.967	1.00	0.09	0.998
Agriculture as Primary Source	0.90	0.06	0.134	0.90	0.06	0.112
Marital Status (ref: Married)						
Widowed, separated, divorced	1.14	0.08	0.083	1.14	0.08	0.079
Number of Adults	0.96	0.02	0.044	0.96	0.02	0.047
Number of Children	0.99	0.02	0.620	0.99	0.02	0.605
Outmigration or household split (ref: No)						
Yes	1.06	0.06	0.313	1.05	0.06	0.346
Flood between waves (ref: No)						
Yes	1.10	0.06	0.115	1.10	0.07	0.115
Earthquake between waves (ref: No)						
Yes	0.86	0.09	0.148	0.86	0.09	0.136
Interactions: Social Capital × Drought						
Single drought × Yes Social Capital				1.01	0.16	0.928
Two+ droughts × Yes Social Capital				0.73	0.08	0.005
State of Residence (ref: Uttar Pradesh)						
Mountain States	1.00	0.14	0.981	0.98	0.14	0.896

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	Base Resilience Model (M4)			Interaction Resilience Model (M5)		
	RRR	**SE**	**p**	**RRR**	**SE**	**p**
Punjab	1.89	0.30	0.000	1.94	0.31	0.000
Haryana	1.27	0.18	0.080	1.28	0.18	0.073
Rajasthan	1.57	0.19	0.000	1.54	0.18	0.000
Bihar	1.50	0.21	0.004	1.53	0.21	0.003
North-East	0.50	0.11	0.001	0.48	0.11	0.001
West Bengal	0.76	0.11	0.060	0.77	0.11	0.074
Jharkhand	1.10	0.21	0.606	1.09	0.20	0.649
Orissa	0.69	0.10	0.011	0.68	0.10	0.009
Chhattisgarh	2.72	0.36	0.000	2.73	0.37	0.000
Madhya Pradesh	3.25	0.37	0.000	3.22	0.36	0.000
Gujarat, Dadra, and Daman & Diu	1.36	0.20	0.038	1.37	0.20	0.037
Maharashtra and Goa	0.94	0.13	0.642	0.93	0.13	0.580
Andhra Pradesh	1.55	0.22	0.002	1.53	0.22	0.003
Karnataka	1.46	0.19	0.003	1.46	0.19	0.003
Kerala	6.81	1.12	0.000	6.61	1.09	0.000
Tamil Nadu and Pondicherry	1.43	0.23	0.029	1.42	0.23	0.031
Intercept	0.00	0.00	0.000	0.00	0.00	0.000
Panel B: Death						
Droughts (ref: No Drought)						
One Drought	1.10	0.09	0.218	1.13	0.11	0.232
Two or More Droughts	1.15	0.08	0.040	1.23	0.11	0.019
Social Capital (ref: No)						
Yes	0.94	0.06	0.290	1.00	0.09	0.987
Wealth Tertiles (ref: Poorest)						
Middle Tertile	0.94	0.06	0.375	0.94	0.06	0.365
Richest Tertile	0.70	0.06	0.000	0.70	0.06	0.000
Social Groups (ref: Forward Castes)						
Scheduled Castes & Tribes	1.15	0.07	0.032	1.14	0.07	0.035
Muslims	0.96	0.10	0.668	0.96	0.10	0.674
Gender (ref: Men)						
Women	0.63	0.04	0.000	0.63	0.04	0.000
Age	1.11	0.00	0.000	1.11	0.00	0.000
Baseline Functional Limitation	1.08	0.02	0.001	1.08	0.02	0.001
Education (ref: No Formal Education)						
Up to Primary	0.81	0.06	0.007	0.81	0.06	0.007
Above Primary	0.67	0.06	0.000	0.67	0.06	0.000
Income Source (ref: No Agriculture Income)						
Some Agriculture Income	0.83	0.08	0.045	0.83	0.08	0.043
Agriculture as Primary Source	0.90	0.07	0.133	0.89	0.06	0.120
Marital Status (ref: Married)						

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	Base Resilience Model (M4)			Interaction Resilience Model (M5)		
	RRR	**SE**	**p**	**RRR**	**SE**	**p**
Widowed, separated, divorced	1.72	0.12	0.000	1.72	0.12	0.000
Number of Adults	1.03	0.02	0.115	1.03	0.02	0.114
Number of Children	0.96	0.02	0.023	0.96	0.02	0.023
Outmigration or household split (ref: No)						
Yes	0.93	0.05	0.196	0.93	0.05	0.186
Flood between waves (ref: No)						
Yes	0.93	0.06	0.283	0.93	0.06	0.284
Earthquake between waves (ref: No)						
Yes	1.07	0.11	0.547	1.07	0.11	0.544
Interactions: Social Capital × Drought						
Single drought × Yes Social Capital				0.94	0.15	0.718
Two+ droughts × Yes Social Capital				0.85	0.11	0.204
Intercept	0.00	0.00	0.000	0.00	0.00	0.000
State of Residence (ref: Uttar Pradesh)						
Mountain States	1.15	0.18	0.367	1.15	0.18	0.383
Punjab	1.71	0.30	0.002	1.74	0.31	0.002
Haryana	1.29	0.17	0.063	1.29	0.18	0.059
Rajasthan	0.92	0.12	0.496	0.91	0.12	0.473
Bihar	1.18	0.18	0.257	1.20	0.18	0.228
North-East	0.88	0.16	0.464	0.86	0.16	0.412
West Bengal	0.99	0.14	0.947	1.00	0.14	0.990
Jharkhand	1.09	0.21	0.649	1.09	0.21	0.659
Orissa	0.76	0.11	0.046	0.76	0.11	0.045
Chhattisgarh	2.04	0.31	0.000	2.05	0.31	0.000
Madhya Pradesh	1.47	0.18	0.002	1.47	0.18	0.002
Gujarat, Dadra, and Daman & Diu	1.44	0.23	0.021	1.45	0.23	0.021
Maharashtra and Goa	0.86	0.11	0.249	0.86	0.11	0.237
Andhra Pradesh	1.13	0.17	0.394	1.13	0.17	0.391
Karnataka	1.10	0.16	0.492	1.11	0.16	0.475
Kerala	2.70	0.56	0.000	2.66	0.55	0.000
Tamil Nadu and Pondicherry	1.12	0.23	0.567	1.12	0.23	0.569
Model Fit						
Sample size (N)		32,248			32,248	
Chi^2		3,218.75			3,251.30	
df		74			78	
McFadden's Pseudo-R^2		0.16			0.16	

Appendix A3. Disaggregated Social Capital Models

Table A.4 presents the distribution of social capital membership across bonding and bridging categories for the full analytic sample and for subgroups defined by social group, wealth tertile, and drought exposure. Households are classified into four mutually exclusive categories: neither bonding nor bridging membership, bonding-only membership (caste, religious, or festival organizations), bridging-only membership (self-help groups, development NGOs, cooperatives, and similar organizations), and membership in both types. The table is provided to justify the decision to use a composite social capital indicator in the fully stratified subgroup models. The overall sample provides adequate cell sizes for models that include separate bonding and bridging capital indicators as main effects (3,908 bonding-only, 4,563 bridging-only, and 2,756 dual-member households) across the full sample. However, once models are stratified by social group and wealth tertile simultaneously, cell sizes become problematic in several subgroups.

Table A.4. Distribution of Bonding and Bridging Social Capital Membership by Social Group, Wealth Tertile, and Drought Exposure, Rural India, IHDS 2004–05

Group	**Neither** *N*	**Bonding Only** *N*	**Bridging Only** *N*	**Both** *N*	**Total** *N*
Full Sample	21,021	3,908	4,563	2,756	32,248
Social Group					
Forward Caste	12,825	2,299	2,911	1,687	19,722
SC/ST	6,303	1,168	1,457	870	9,798
Muslim	1,893	441	195	199	2,728
Wealth Tertile					
Poorest	8,087	1,600	1,244	600	11,531
Middle	6,342	1,323	1,571	971	10,207
Richest	6,592	985	1,748	1,185	10,510
Drought Exposure					
No Drought	10,600	2,063	2,199	1,705	16,567

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Table A.4 (continued)

Group	Neither	Bonding Only	Bridging Only	Both	Total
One Drought	3,995	615	739	342	5,691
Two or More Droughts	6,426	1,230	1,625	709	9,990

The composite social capital indicator used in the main analysis combines participation in bonding and bridging networks, which may operate through distinct mechanisms. Bonding capital facilitates resource sharing and solidarity within relatively homogeneous groups, while bridging capital enables access to information and resources across group boundaries. To assess whether the composite measure conceals divergent effects, I estimate two additional models. Model 13 is the base specification, adding bonding and bridging as separate main effects. It interacts drought exposure with bonding social capital while controlling for bridging social capital; Model 14 reverses this, interacting drought with bridging social capital while controlling for bonding social capital. This strategy follows prior work using the same dataset (Story, 2014; Vikram, 2018; Vikram et al., 2012). Results are reported in Tables A.4.3a and A.4.3b.

The resilience model equations for the disaggregated specifications are:

$$\begin{aligned} \ln\left[\frac{P(Y_i=j)}{P(Y_i=0)}\right] &= \alpha_j + \beta_{1j}\text{Drought}_i + \beta_{2j}\text{SocialGroup}_i \\ &\quad + \beta_{3j}\text{Wealth}_i + \beta_{4j}\text{Bonding}_i + \beta_{5j}\text{Bridging}_i \\ &\quad + \beta_{6j}\mathbf{Z}_i + \varepsilon_i \end{aligned} \tag{12}$$

$$\ln\left[\frac{P(Y_i=j)}{P(Y_i=0)}\right] = \alpha_j + \beta_{1j}\text{Drought}_i + \beta_{2j}\text{SocialGroup}_i + \beta_{3j}\text{Wealth}_i + \beta_{4j}\text{Bonding}_i + \beta_{5j}\text{Bridging}_i + \lambda_j(\text{Drought}_i \times \text{Bonding}_i) + \beta_{6j}\mathbf{Z}_i + \varepsilon_i \tag{13}$$

$$\ln\left[\frac{P(Y_i=j)}{P(Y_i=0)}\right] = \alpha_j + \beta_{1j}\text{Drought}_i + \beta_{2j}\text{SocialGroup}_i + \beta_{3j}\text{Wealth}_i + \beta_{4j}\text{Bridging}_i + \beta_{5j}\text{Bonding}_i + \lambda_j(\text{Drought}_i \times \text{Bridging}_i) + \beta_{6j}\mathbf{Z}_i + \varepsilon_i \tag{14}$$

for $j \in \{\text{Deteriorated, Death}\}$.

The predicted probabilities reported in Tables A.4.3a and A.4.3b are derived from two sets of models. The full interaction probabilities (All and Interactions panels) are estimated from Models 13 and 14, respectively, using the full analytic sample ($N = 32{,}248$). The subgroup panels were estimated from six additional models, three stratifying by wealth tertile and three stratifying by social group, each replicating the specification of Models 13 and 14 on the corresponding restricted subsample. Predicted probabilities are estimated at variable means within each subsample, reported with 90% confidence intervals.

Table A.5. Bonding Capital × Drought Predicted Probabilities of Functional Health Deterioration (Model 13)

	Pred. Prob.	**S.E.**	**Lower CI**	**Upper CI**
All				
No Bonding	0.144	0.004	0.138	0.150
Yes Bonding	0.139	0.007	0.127	0.150
Interactions				
No Bonding × No Drought	0.137	0.005	0.128	0.145
No Bonding × One Drought	0.132	0.008	0.120	0.145

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	Pred. Prob.	S.E.	Lower CI	Upper CI
No Bonding × Two or More Droughts	0.164	0.007	0.152	0.176
Yes Bonding × No Drought	0.139	0.009	0.125	0.153
Yes Bonding × One Drought	0.153	0.019	0.122	0.185
Yes Bonding × Two or More Droughts	0.135	0.011	0.116	0.153
Poorest Tertile				
No Bonding × No Drought	0.138	0.009	0.123	0.154
No Bonding × One Drought	0.137	0.011	0.119	0.154
No Bonding × Two or More Droughts	0.173	0.011	0.154	0.191
Yes Bonding × No Drought	0.116	0.013	0.094	0.138
Yes Bonding × One Drought	0.160	0.030	0.111	0.209
Yes Bonding × Two or More Droughts	0.117	0.015	0.093	0.141
Middle Tertile				
No Bonding × No Drought	0.123	0.008	0.110	0.135
No Bonding × One Drought	0.128	0.015	0.103	0.153
No Bonding × Two or More Droughts	0.173	0.013	0.152	0.194
Yes Bonding × No Drought	0.146	0.017	0.117	0.174
Yes Bonding × One Drought	0.123	0.024	0.084	0.163
Yes Bonding × Two or More Droughts	0.145	0.021	0.110	0.180
Richest Tertile				
No Bonding × No Drought	0.136	0.008	0.122	0.150
No Bonding × One Drought	0.126	0.016	0.100	0.151
No Bonding × Two or More Droughts	0.120	0.011	0.102	0.138
Yes Bonding × No Drought	0.139	0.014	0.116	0.161
Yes Bonding × One Drought	0.154	0.046	0.078	0.229
Yes Bonding × Two or More Droughts	0.150	0.024	0.111	0.189
Forward Castes				
No Bonding × No Drought	0.148	0.007	0.137	0.159
No Bonding × One Drought	0.145	0.012	0.126	0.164
No Bonding × Two or More Droughts	0.168	0.009	0.152	0.183
Yes Bonding × No Drought	0.169	0.012	0.149	0.190
Yes Bonding × One Drought	0.190	0.027	0.145	0.235
Yes Bonding × Two or More Droughts	0.152	0.016	0.125	0.179
Scheduled Castes & Tribes				
No Bonding × No Drought	0.120	0.008	0.106	0.134
No Bonding × One Drought	0.124	0.012	0.105	0.143
No Bonding × Two or More Droughts	0.165	0.013	0.144	0.187
Yes Bonding × No Drought	0.094	0.013	0.073	0.115
Yes Bonding × One Drought	0.086	0.022	0.050	0.123

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	Pred. Prob.	S.E.	Lower CI	Upper CI
Yes Bonding × Two or More Droughts	0.106	0.016	0.079	0.132
Muslims				
No Bonding × No Drought	0.096	0.014	0.074	0.119
No Bonding × One Drought	0.062	0.013	0.041	0.083
No Bonding × Two or More Droughts	0.112	0.018	0.083	0.141
Yes Bonding × No Drought	0.079	0.018	0.050	0.108
Yes Bonding × One Drought	0.075	0.042	0.005	0.145
Yes Bonding × Two or More Droughts	0.094	0.024	0.055	0.133

Note: 90% confidence intervals. Full sample and subgroup panels estimated on restricted subsamples.

Table A.6. Bridging Capital × Drought Predicted Probabilities of Functional Health Deterioration (Model 14)

	Pred. Prob.	S.E.	Lower CI	Upper CI
All				
No Bridging	0.143	0.004	0.137	0.149
Yes Bridging	0.141	0.007	0.131	0.152
Interactions				
No Bridging × No Drought	0.135	0.005	0.126	0.143
No Bridging × One Drought	0.137	0.008	0.124	0.150
No Bridging × Two or More Droughts	0.160	0.007	0.149	0.172
Yes Bridging × No Drought	0.147	0.009	0.133	0.161
Yes Bridging × One Drought	0.130	0.016	0.104	0.156
Yes Bridging × Two or More Droughts	0.141	0.011	0.124	0.159
Poorest Tertile				
No Bridging × No Drought	0.134	0.009	0.120	0.149
No Bridging × One Drought	0.139	0.011	0.122	0.156
No Bridging × Two or More Droughts	0.158	0.010	0.141	0.174
Yes Bridging × No Drought	0.131	0.017	0.103	0.159
Yes Bridging × One Drought	0.138	0.030	0.088	0.188
Yes Bridging × Two or More Droughts	0.161	0.020	0.128	0.194
Middle Tertile				
No Bridging × No Drought	0.125	0.008	0.112	0.139
No Bridging × One Drought	0.131	0.015	0.106	0.156
No Bridging × Two or More Droughts	0.170	0.013	0.148	0.191
Yes Bridging × No Drought	0.138	0.014	0.114	0.161
Yes Bridging × One Drought	0.112	0.022	0.075	0.149

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	Pred. Prob.	S.E.	Lower CI	Upper CI
Yes Bridging × Two or More Droughts	0.153	0.021	0.119	0.187
Richest Tertile				
No Bridging × No Drought	0.130	0.008	0.116	0.144
No Bridging × One Drought	0.131	0.017	0.102	0.159
No Bridging × Two or More Droughts	0.139	0.013	0.117	0.161
Yes Bridging × No Drought	0.151	0.013	0.129	0.173
Yes Bridging × One Drought	0.129	0.028	0.082	0.175
Yes Bridging × Two or More Droughts	0.105	0.015	0.081	0.129
Forward Castes				
No Bridging × No Drought	0.149	0.007	0.138	0.160
No Bridging × One Drought	0.158	0.012	0.139	0.178
No Bridging × Two or More Droughts	0.169	0.010	0.154	0.185
Yes Bridging × No Drought	0.165	0.012	0.146	0.184
Yes Bridging × One Drought	0.129	0.022	0.092	0.165
Yes Bridging × Two or More Droughts	0.140	0.014	0.117	0.163
Scheduled Castes & Tribes				
No Bridging × No Drought	0.109	0.008	0.095	0.122
No Bridging × One Drought	0.111	0.011	0.093	0.130
No Bridging × Two or More Droughts	0.146	0.012	0.126	0.165
Yes Bridging × No Drought	0.133	0.014	0.109	0.156
Yes Bridging × One Drought	0.128	0.024	0.089	0.167
Yes Bridging × Two or More Droughts	0.165	0.021	0.130	0.200
Muslims				
No Bridging × No Drought	0.098	0.013	0.077	0.119
No Bridging × One Drought	0.064	0.013	0.042	0.085
No Bridging × Two or More Droughts	0.115	0.017	0.088	0.142
Yes Bridging × No Drought	0.058	0.016	0.032	0.084
Yes Bridging × One Drought	0.061	0.036	0.002	0.120
Yes Bridging × Two or More Droughts	0.064	0.024	0.025	0.103

Note: 90% confidence intervals. Full sample and subgroup panels estimated on restricted subsamples.

Neither bonding nor bridging capital appears to confer a general health advantage in the absence of climatic stress: baseline predicted probabilities of functional health deterioration are statistically indistinguishable between those with and without bonding capital and between those with and without bridging capital, as indicated by overlapping confidence intervals. However, both

forms of social capital matter under conditions of repeated drought exposure. Among individuals without bonding or bridging capital, the predicted probability of functional health deterioration rises statistically significantly with exposure to two or more droughts, whereas among those with bonding or bridging capital, deterioration risks remain stable, indicating that social capital functions primarily as a crisis-activated buffer rather than a general protective factor.

Stratified models interacting drought exposure and bonding capital reveal heterogeneous patterns across social and economic groups. Among higher-caste individuals, the predicted probability of functional health deterioration increases with repeated drought exposure for those without bonding capital, although the confidence intervals overlap slightly; in contrast, deterioration risks among those with bonding capital remain stable across drought categories. For Scheduled Castes and Tribes, individuals without bonding capital experience a statistically significant increase in deterioration risk under repeated drought exposure, while those with bonding capital show no such increase, indicating a clear buffering effect. In the poorest asset tertile, individuals without bonding capital exhibit an increase in deterioration risk with repeated drought exposure, though confidence intervals overlap marginally, whereas those with bonding capital show stable predicted probabilities across exposure levels. In the middle tertile, deterioration risk rises significantly among individuals without bonding capital but does not increase among those with bonding capital. By contrast, in the richest tertile, predicted probabilities of functional health deterioration remain stable regardless of drought exposure or bonding capital status.

The risks of functional health deterioration are similar for individuals with and without bridging social capital in models that do not interact social capital with drought exposure, indicating no baseline health advantage associated with bridging ties. Under repeated drought exposure, the risk of deterioration increases significantly among individuals without bridging capital, as indicated by

non-overlapping confidence intervals, whereas it remains largely stable among those with bridging capital, suggesting a buffering effect. Among higher-caste individuals without bridging capital, the predicted probability of deterioration increases with repeated drought exposure, though the increase is not statistically significant due to overlapping confidence intervals. Among Scheduled Castes and Tribes, the risk of deterioration rises with repeated drought exposure both among those with and without bridging capital, though these increases are not statistically significant. For Muslim individuals, the deterioration risk does not increase with drought exposure regardless of bridging capital status. Across wealth groups, the poorest tertile shows an increase in deterioration risk under repeated drought exposure both with and without bridging capital, though these changes are not statistically significant. In the middle wealth tertile, deterioration risk rises significantly among those without bridging capital, but remains stable among those with bridging ties. Among the richest tertile, deterioration risk does not increase with drought exposure regardless of bridging capital status. The divergence between bonding and bridging capital is most pronounced among Scheduled Castes and Tribes and Muslims, and the direction of the mismatch is theoretically interpretable.

Appendix B. Chapter 2 Sensitivity Check: Discrete-Time Logistic Regression

As a robustness check, Cox proportional hazards models were re-estimated as discrete-time logistic regression models, treating mortality as a binary outcome within fixed observation intervals. Table B.1 presents odds ratios from two models: Model 1 includes poverty transitions and social group as main effects; Model 2 adds their interaction. Table B.2 presents average adjusted predicted probabilities of death by poverty transition and social group, derived from both models. Substantive conclusions are unchanged across both specifications, supporting the robustness of the primary Cox

model findings reported in Chapter 2.

Table B.1. Logistic Regression Models Predicting Mortality, Rural Adults Aged 50–79, IHDS 2011–2022

	Model 1		Model 2	
	OR	**95% CI**	**OR**	**95% CI**
Poverty Transition (ref: Always Poor)				
Never poor	0.819***	[0.741, 0.906]	0.798***	[0.685, 0.929]
Moved into poverty	0.940	[0.819, 1.078]	0.877	[0.715, 1.077]
Moved out of poverty	0.800***	[0.718, 0.891]	0.729***	[0.617, 0.860]
Social Group (ref: Higher Castes)				
SC/ST	1.080*	[1.011, 1.154]	1.028	[0.853, 1.240]
Muslim	0.881*	[0.788, 0.984]	0.689†	[0.469, 1.016]
Poverty × Social Group Interactions				
Never poor × SC/ST	—	—	0.980	[0.796, 1.207]
Never poor × Muslim	—	—	1.305	[0.862, 1.974]
Moved into poverty × SC/ST	—	—	1.169	[0.878, 1.556]
Moved into poverty × Muslim	—	—	1.016	[0.579, 1.784]
Moved out × SC/ST	—	—	1.165	[0.931, 1.460]
Moved out × Muslim	—	—	1.431	[0.919, 2.226]
Marital Status (ref: Married)				
Not married	2.166***	[2.021, 2.321]	2.167***	[2.022, 2.323]
Education (ref: No Formal Education)				
Up to primary	0.736***	[0.679, 0.798]	0.735***	[0.678, 0.797]
Above primary	0.557***	[0.512, 0.606]	0.556***	[0.511, 0.604]
Baseline functional limitations	1.448***	[1.409, 1.488]	1.448***	[1.409, 1.488]
Sex (ref: Male)				
Female	0.459***	[0.430, 0.491]	0.459***	[0.430, 0.491]
Model Fit				
N	23,899		23,899	
Log likelihood	−13,495.75		−13,490.76	
LR chi^2	1,981.69		1,991.67	
Pseudo R^2	0.068		0.069	

$\dagger p < 0.10$; $* p < 0.05$; $** p < 0.01$; $*** p < 0.001$. Odds ratios reported. Models estimated on rural subsample. Reference categories: always poor, higher castes, married, no formal education, male. *Source:* Author's calculations from IHDS Waves 2 (2011–12) and 3 (2023–24).

Table B.2. Predicted Probability of Death by Poverty Transition and Social Group, Rural Adults Aged 50–79

	All Groups (Model 1)	Higher Castes (Model 2)	SC/ST (Model 2)	Muslim (Model 2)
Never poor	0.290 [0.282, 0.297]	0.290 [0.281, 0.299]	0.291 [0.276, 0.307]	0.270 [0.245, 0.295]
Always poor	0.329 [0.310, 0.347]	0.334 [0.305, 0.364]	0.340 [0.315, 0.365]	0.263 [0.199, 0.327]
Moved into poverty	0.316 [0.296, 0.337]	0.308 [0.280, 0.337]	0.345 [0.312, 0.379]	0.243 [0.179, 0.308]
Moved out of poverty	0.285 [0.274, 0.296]	0.273 [0.258, 0.288]	0.307 [0.289, 0.326]	0.271 [0.235, 0.306]

Note: Predicted probabilities represent the average probability of death during follow-up for each group, adjusted for marital status, education, baseline functional limitations, and sex, with remaining covariates held at observed sample means. The "All Groups" column is derived from Model 1 (no interaction term). Higher Castes, SC/ST, and Muslim columns are derived from Model 2 (poverty transition × social group interaction). Standard errors estimated using the delta method. 95% confidence intervals in brackets. *Source:* Author's calculations from IHDS Waves 2 (2011–12) and 3 (2023–24).

Table B.3. Row Percentages Showing Share of Each Subgroup Retained vs. Lost to Follow-Up. IHDS Panel, Waves 1 and 2. Rural Individuals Aged 43–73 in Wave 1 (2004–05).

Variable	Retained (%)	Lost to Follow-Up (%)	N
Total	90.93	9.07	34,174
Poverty Status (2005)			
Not poor	89.98	10.02	22,714
Poor	92.83	7.17	11,460
Gender			
Male	91.02	8.98	16,864
Female	90.85	9.15	17,310
Social Group			
Higher Castes	90.85	9.15	20,758
ST	89.40	10.60	3,434
SC	92.56	7.44	6,975
Muslims	89.46	10.54	3,007
Age (mean, years)			
Mean age	55.28	55.45	34,174

Notes: Sample definition: The base population is all IHDS Wave 1 (2004–05) rural respondents aged 43–73. The lower bound of 43 corresponds to Wave 2 age 50, the analytical sample entry point, adjusted backwards by approximately 7 years, the interval between Wave 1 and Wave 2 fieldwork. The upper bound of 73 corresponds to Wave 2 age 80.

Attrition definition: An individual is classified as lost to follow-up if they are not observed in all three waves . This includes those absent from Wave 2 only, absent from Wave 3 only, and absent from both Waves 2 and 3. Individuals with `hhwave` = 110, present in Waves 1 and 3 but not Wave 2, are also classified as lost, as the analytical poverty transition typology requires consecutive Wave 1→Wave 2 observation.

Social group classification: Wave 1 uses an 8-category caste/religion variable, recoded into four groups. Higher Castes includes Brahmin, High Caste, OBC, Sikh/Jain, and Christian; ST includes Adivasi; SC includes Dalit; Muslims includes Muslim. OBC is collapsed into Higher Castes to maintain comparability with the Wave 2–3 analytical sample classification used in the main models.

Seven duplicate records on the 2005 person identifier keys were dropped (<0.004% of the base sample). Rural status defined using `URBAN2005` from the IHDS Wave 1 household file.

Appendix C. Chapter 1 Sensitivity Checks

The pooled analytic sample of 956,420 observations is sufficiently large that even substantively negligible associations may achieve conventional levels of statistical significance. To make sure that the principal findings are not an artefact of sample size, the main multinomial logistic regression model is replicated on a round-stratified random subsample. Fifty thousand observations are drawn at random from each of the four survey rounds, yielding a balanced subsample of 200,000 women in which each round contributes exactly 25 percent of observations. This design simultaneously addresses two concerns: the inflated precision associated with very large samples, and the pronounced imbalance in round-specific sample sizes across waves, which ranges from 59,901 in 1998–99 to 425,452 in 2019–21 in the full analytic sample. The model specification, covariate set, and clustering structure are identical to the main analysis. Results are presented in Appendix Table C.1

Table C.1. Relative Risk Ratios from Multinomial Logistic Regression of Women's BMI Status, Round-Stratified Subsample ($N = 200{,}000$)

	Underweight			Obese		
	RRR	**S.E.**	**p**	**RRR**	**S.E.**	**p**
Age	0.98	0.00	<0.001	1.05	0.00	<0.001
Survey Round (ref: 1998–99)						
1998–99	1	.	.	1	.	.
2005–06	0.85	0.02	<0.001	1.43	0.06	<0.001
2015–16	0.37	0.01	<0.001	2.11	0.08	<0.001
2019–21	0.25	0.01	<0.001	2.71	0.10	<0.001
Asset Quintile (ref: Lowest Quintile)						
Lowest quintile	1	.	.	1	.	.
Second quintile	0.76	0.01	<0.001	1.63	0.11	<0.001
Middle quintile	0.57	0.01	<0.001	2.57	0.17	<0.001
Fourth quintile	0.38	0.01	<0.001	4.00	0.26	<0.001
Highest quintile	0.18	0.01	<0.001	6.52	0.42	<0.001
Social Group (ref: General Castes)						
General castes	1	.	.	1	.	.
Scheduled Caste	1.21	0.02	<0.001	0.70	0.02	<0.001
Scheduled Tribe	1.11	0.03	<0.001	0.54	0.03	<0.001
Other Backward Caste	1.12	0.02	<0.001	0.77	0.02	<0.001
Marital Status (ref: Currently Married)						
Currently married	1	.	.	1	.	.
Currently unmarried	0.80	0.02	<0.001	1.29	0.05	<0.001
Location of Residence (ref: Urban)						
Urban	1	.	.	1	.	.
Rural	1.25	0.02	<0.001	0.65	0.02	<0.001

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Note:

The main analysis is estimated on unweighted data, which treats each observation equally regardless of the survey design. To assess whether the round imbalance in sample sizes influences the estimates, the main model is replicated using round-specific normalised survey weights. Weights are scaled so that each round contributes equally to the pooled likelihood, (Solon et al., 2015).

Table C.2 uses these weights and re-estimates the main, multinomial logistic regression model.

Table C.2. Relative Risk Ratios from Multinomial Logistic Regression of Women's BMI Status, Round-Stratified Subsample with Normalised Survey Weights ($N = 956{,}420$)

	Underweight			Obese		
	RRR	**S.E.**	**p**	**RRR**	**S.E.**	**p**
Age	0.98	0.00	<0.001	1.05	0.00	<0.001
Survey Round (ref: 1998–99)						
1998–99	1	.	.	1	.	.
2005–06	0.86	0.02	<0.001	1.44	0.06	<0.001
2015–16	0.36	0.01	<0.001	2.21	0.10	<0.001
2019–21	0.25	0.01	<0.001	3.04	0.13	<0.001
Asset Quintile (ref: Lowest Quintile)						
Lowest quintile	1	.	.	1	.	.
Second quintile	0.82	0.02	<0.001	1.46	0.18	0.002
Middle quintile	0.62	0.02	<0.001	2.08	0.24	<0.001
Fourth quintile	0.39	0.01	<0.001	3.85	0.42	<0.001
Highest quintile	0.18	0.01	<0.001	7.60	0.84	<0.001
Social Group (ref: General Castes)						
General castes	1	.	.	1	.	.
Scheduled Caste	1.23	0.03	<0.001	0.64	0.03	<0.001
Scheduled Tribe	1.14	0.04	<0.001	0.59	0.05	<0.001
Other Backward Caste	1.10	0.03	<0.001	0.80	0.03	<0.001
Marital Status (ref: Currently Married)						
Currently married	1	.	.	1	.	.
Currently unmarried	0.86	0.02	<0.001	1.16	0.07	0.017
Location of Residence (ref: Urban)						
Urban	1	.	.	1	.	.
Rural	1.24	0.03	<0.001	0.60	0.02	<0.001

Note: Reference category for BMI is normal weight and overweight combined. RRRs are exponentiated multinomial logistic regression coefficients; standard errors are delta-method approximations. Models estimated with round-specific normalised survey weights (Solon et al., 2015); weights scaled so each round sums to 1,000. State fixed effects included but not shown. Standard errors clustered at the PSU-round level (50,983 clusters). Sample restricted to non-pregnant ever-married women aged 25–49 with valid social group codes. Fifty thousand observations drawn at random from each survey round. Wealth quintiles are national and wave-specific. State boundaries harmonized to 1998 (NFHS-2) units. *Source:* Author's calculations from NFHS 1998–2019.

Bibliography

Adena, M., & Myck, M. (2014). Poverty and transitions in health in later life. *Social Science & Medicine*, *116*, 202–210.

Adger, W. N. (2010). Social capital, collective action, and adaptation to climate change. In M. Voss (Ed.), *Der klimawandel: Sozialwissenschaftliche perspektiven* (pp. 327–345). VS Verlag für Sozialwissenschaften.

Alderman, H., Behrman, J. R., Kohler, H.-P., Maluccio, J. A., & Watkins, S. C. (2001). Attrition in longitudinal household survey data: Some tests for three developing-country samples. *Demographic research*, *5*, 79–124.

Aldrich, D. P. (2010). Separate and unequal: Post-tsunami aid distribution in southern india. *Social Science Quarterly*, *91*(5), 1369–1389.

Aldrich, D. P. (2012). *Building resilience: Social capital in post-disaster recovery*. University of Chicago Press.

Allison, P. D. (1982). Discrete-time methods for the analysis of event histories. *Sociological Methodology*, *13*, 61–98.

Allison, P. D. (1999). Comparing logit and probit coefficients across groups. *Sociological Methods & Research*, *28*(2), 186–208.

Anderson, I., Robson, B., Connolly, M., Al-Yaman, F., Bjertness, E., King, A., Tynan, M., Madden, R., Bang, A., & Coimbra, C. E. (2016). Indigenous and tribal peoples' health (the lancet–lowitja institute global collaboration): A population study. *The Lancet*, *388*(10040), 131–157.

Anson, J. (2004). The migrant mortality advantage: A 70 month follow-up of the brussels population. *European Journal of Population*, *20*(3), 191–218.

Arcaya, M., Raker, E. J., & Waters, M. C. (2020). The social consequences of disasters: Individual and community change. *Annual Review of Sociology*, *46*(1), 671–691.

Banerjee, A., & Dwivedi, S. N. (2016). Trends in cardiovascular disease risk factors in india. *Indian Journal of Community Medicine*, *41*(1), 14–19.

Bank, W. (2018). *India development update, march 2018: India's growth story*.

Barik, D., Desai, S., & Vanneman, R. (2018). Economic status and adult mortality in india: Is the relationship sensitive to choice of indicators. *World Development*, *103*, 176–187.

Basu, S. (2020). Rethinking india's health systems. *Economic and Political Weekly*, *55*(25), 15–19.

Baulch, B., & Hoddinott, J. (2000). Economic mobility and poverty dynamics in developing countries. *The Journal of Development Studies*, *36*(6), 1–24.

Berkman, L. F., & Glass, T. (2000). Social integration, social networks, social support, and health. *Social Epidemiology*, *1*(6), 137–173.

Beteille, A. (1971). *Caste, class and power*. University of California Press.

Béteille, A. (1965). *Caste, class and power*. Oxford University Press.

Bhaduri, A. (1973). A study in agricultural backwardness under semi-feudalism. *Economic Journal*, *83*(329), 120–137.

Bloom, D. E., & Canning, D. (2000). The health and wealth of nations. *Science*, *287*(5456), 1207–1209.

Borooah, V. (2010). *Inequality in health outcomes in india: The role of caste and religion*.

Bourdieu, P. (1986). The forms of capital. In J. G. Richardson (Ed.), *Handbook of theory: Research for the sociology of education* (pp. 241–258). Greenwood Press.

Brilleman, S. L., Wolfe, R., Moreno-Betancur, M., Sales, A. E., Langa, K. M., Li, Y., Daugherty Biddison, E. L., Rubinson, L., & Iwashyna, T. J. (2017). Associations between community-level disaster exposure and individual-level changes in disability and risk of death for older americans. *Social Science & Medicine*, *173*, 118–125.

Brouwer, R., & Nhassengo, J. (2006). About bridges and bonds: Community responses to the 2000 floods in mabalane district, mozambique. *Disasters*, *30*(2), 234–255.

Brunkard, J., Namulanda, G., & Ratard, R. (2008). Hurricane katrina deaths, louisiana, 2005. *Disaster Medicine and Public Health Preparedness*, *2*(4), 215–223.

Carnes, B. A., Staats, D., & Sonntag, W. E. (2014). Does senescence give rise to disease. *Mechanisms of Ageing and Development*, *135*, 67–75.

Chancel, L., & Piketty, T. (2019a). Indian income inequality, 1922–2015. *Review of Income and Wealth*, *65*(S1), S33–S62.

Chancel, L., & Piketty, T. (2019b). Indian income inequality, 1922–2015: From british raj to billionaire raj. *Review of Income and Wealth*, *65*(S1), S33–S62.

Chetty, R., Stepner, M., Abraham, S., Lin, S., Scuderi, B., Turner, N., Bergeron, A., & Cutler, D. (2016). The association between income and life expectancy in the united states, 2001–2014. *JAMA*, *315*(16), 1750–1766.

Childers, T. B., & Chiou, K. (2016). Socioeconomic status, religion and health in india: An examination of chronic and communicable diseases. *The Review of Black Political Economy*, *43*(2), 149–164.

Clouston, S. A. P., & Link, B. G. (2021). A retrospective on fundamental cause theory: State of the evidence and future directions. *Annual Review of Sociology*, *47*(1), 131–156.

Clouston, S. A. P., Natale, G., & Link, B. G. (2021). Socioeconomic inequalities in the spread of coronavirus-19 in the united states. *Social Science & Medicine*, *268*, 113554.

Clouston, S. A. P., Rubin, M. S., Phelan, J. C., & Link, B. G. (2016). A social history of disease: Contextualizing the rise and fall of social inequalities in cause-specific mortality. *Demography*, *53*(5), 1631–1656.

Coffey, D. (2015). Prepregnancy body mass and weight gain during pregnancy in india and sub-saharan africa. *Proceedings of the National Academy of Sciences*, *112*(11), 3302–3307.

Coffey, D. (2019). The association between neonatal death and facility birth in regions of india. *Demographic Research*, *40*, 417–430.

Coffey, D., & Spears, D. (2021). *Where india goes: Abandoned toilets, stunted development and the costs of caste*. HarperCollins.

Colvin, C. L., Swift, S. L., Yu, X., Kezios, K. L., & Al Hazzouri, A. Z. (2025). Investigating associations between long-term poverty exposure and premature mortality: Evidence from the national longitudinal survey of youth 1979 prospective cohort. *The Lancet Public Health*, *10*(11), e971–e978.

Crimmins, E. M., & Saito, Y. (2001). Trends in healthy life expectancy in the united states, 1970–1990: Gender, racial, and educational differences. *Social Science & Medicine*, *52*(11), 1629–1641.

Cutler, D., & Miller, G. (2005). The role of public health improvements in health advances: The twentieth-century united states. *Demography*, *42*(1), 1–22.

Cutler, D. M., & McClellan, M. (2001). Is technological change in medicine worth it. *Health Affairs*, *20*(5), 11–29.

Dandona, L., Dandona, R., Kumar, G. A., Shukla, D. K., Paul, V. K., Balakrishnan, K., & Bhalla, K. (2017). Nations within a nation: Variations in epidemiological transition across the states of india, 1990–2016. *The Lancet*, *390*(10111), 2437–2460.

Dang, H.-A. H., & Lanjouw, P. F. (2018a). Poverty dynamics in india between 2004 and 2012: Insights from longitudinal analysis using synthetic panel data. *Economic Development and Cultural Change*, *67*(1), 131–170.

Dang, H.-A. H., & Lanjouw, P. F. (2018b). Poverty dynamics in india between 2004 and 2012: Insights from longitudinal analysis using synthetic panel data. *Economic Development and Cultural Change*, *67*(1), 131–170.

Dannefer, D. (2003). Cumulative advantage/disadvantage and the life course: Cross-fertilizing age and social science theory. *The Journals of Gerontology Series B: Psychological Sciences and Social Sciences*, *58*(6), S327–S337.

Dannefer, D. (2020). Systemic and reflexive: Foundations of cumulative dis/advantage and life-course processes. *The Journals of Gerontology: Series B*, *75*(6), 1249–1263.

Deaton, A. (2013). *The great escape: Health, wealth, and the origins of inequality*. Princeton University Press.

Desai, S., Barik, D., & Choudhuri, P. (2021). Dynamics of poverty in india. *India Human Development Survey Working Paper*.

Desai, S., Barik, D., Choudhuri, P., Chouhan, B., Sharma, O. P., Sharma, S., & Tiwari, D. K. (2025). Rethinking social safety nets in a changing society: Evidence from the india human development survey. *[Journal]*, *21*(1), 96–136.

Desai, S., & Dubey, A. (2011). Caste in 21st century india: Competing narratives. *Economic and Political Weekly*, *46*(11), 40–49.

Desai, S., & Vanneman, R. (2018). *India human development survey-ii (ihds-ii), 2011–12*. Inter-university Consortium for Political; Social Research.

Deshpande, A. (2011). *The grammar of caste: Economic discrimination in contemporary india*. Oxford University Press.

DiPrete, T. A., & Eirich, G. M. (2006). Cumulative advantage as a mechanism for inequality: A review of theoretical and empirical developments. *Annual Review of Sociology*, *32*(1), 271–297.

Douglas, M. (2003). *Purity and danger: An analysis of concept of pollution and taboo*. Routledge.

Dumont, L. (1980). *Homo hierarchicus: The caste system and its implications*. University of Chicago Press.

Dwyer-Lindgren, L., Bertozzi-Villa, A., Stubbs, R. W., Morozoff, C., Mackenbach, J. P., Van Lenthe, F. J., Mokdad, A. H., & Murray, C. J. (2017). Inequalities in life expectancy among us counties, 1980 to 2014: Temporal trends and key drivers. *JAMA internal medicine*, *177*(7), 1003–1011.

Dynes, R. R. (2002). *The importance of social capital in disaster response*. Disaster Research Center.

Ehsan, A., Klaas, H. S., Bastianen, A., & Spini, D. (2019). Social capital and health: A systematic review of systematic reviews. *SSM—Population Health*, *8*, 100425.

Elder, G. H., Johnson, M. K., & Crosnoe, R. (2003). *The emergence and development of life course theory*. Springer.

Elo, I. T., & Preston, S. H. (1992). Effects of early-life conditions on adult mortality: A review. *Population Index*, 186–212.

Ferrucci, L., Guralnik, J. M., Simonsick, E., Salive, M. E., Corti, C., & Langlois, J. (1996). Progressive versus catastrophic disability: A longitudinal view of the disablement process. *The Journals of Gerontology Series A: Biological Sciences and Medical Sciences*, *51*(3), M123–M130.

Fogel, R. W. (2004). Health, nutrition, and economic growth. *Economic Development and Cultural Change*, *52*(3), 643–658.

for Population Sciences (IIPS), I. I., & ICF. (2017). *National family health survey (nfhs-4), 2015–16: India*. IIPS.

for Population Sciences (IIPS), I. I., & International, M. (2007). *National family health survey (nfhs-3), 2005–06: India*. IIPS.

for Population Sciences (IIPS), I. I., & Macro, O. (2000). *National family health survey (nfhs-2), 1998–99: India*. IIPS.

Freedman, V. A., Martin, L. G., & Schoeni, R. F. (2002). Recent trends in disability and functioning among older adults in the united states: A systematic review. *JAMA*, *288*(24), 3137–3146.

Fussell, E., Sastry, N., & VanLandingham, M. (2010). Race, socioeconomic status, and return migration to new orleans after hurricane katrina. *Population and Environment*, *31*(1–3), 20–42.

Geronimus, A. T., Hicken, M., Keene, D., & Bound, J. (2006). "weathering" and age patterns of allostatic load scores among blacks and whites in the united states. *American Journal of Public Health*, *96*(5), 826–833.

Ghosh, J. (2022). *India and the covid-19 crisis: Fault lines and fractures*. Cambridge University Press.

Ghurye, G. S. (1969). *Caste and race in india*. Popular Prakashan.

Gupta, A., & Sudharsanan, N. (2022). Large and persistent life expectancy disparities between india's social groups. *Population and Development Review*, *48*(3), 863–882.

Gupta, D. (2000). *Interrogating caste: Understanding hierarchy and difference in indian society*. Penguin Books.

Guralnik, J. M., Ferrucci, L., Simonsick, E. M., Salive, M. E., & Wallace, R. B. (1995). Lower-extremity function in persons over the age of 70 years as a predictor of subsequent disability. *New England Journal of Medicine*, *332*(9), 556–562.

Gutin, I., & Hummer, R. A. (2021). Social inequality and the future of us life expectancy. *Annual Review of Sociology*, *47*(1), 501–520.

Hayward, M. D., & Gorman, B. K. (2004). The long arm of childhood: The influence of early-life social conditions on men's mortality. *Demography*, *41*(1), 87–107.

Hayward, M. D., & Heron, M. (1999). Racial inequality in active life among adult americans. *Demography*, *36*(1), 77–91.

Hendi, A. S. (2024). Where does the black–white life expectancy gap come from? the deadly consequences of residential segregation. *Population and Development Review*, *50*(2), 403–436.

Hosseinpoor, A. R., Bergen, N., Barros, A. J., Wong, K. L., Boerma, T., & Victora, C. G. (2016). Monitoring subnational regional inequalities in health: Measurement approaches and challenges. *International journal for equity in health*, *15*(1), 18.

Hummer, R. A., & Chinn, J. J. (2011). Race/ethnicity and us adult mortality: Progress, prospects, and new analyses. *Du Bois Review: Social Science Research on Race*, *8*(1), 5–24.

IIPS & IFC. (2021). *National family health survey (nfhs-5), 2019–21: India*. International Institute for Population Sciences.

Jackson, H., & Engelman, M. (2022). Deaths, disparities, and cumulative (dis)advantage: How social inequities produce an impairment paradox in later life. *The Journals of Gerontology: Series A*, *77*(2), 392–401.

Jodhka, S. S. (2007). Caste and democracy: Assertion and identity among dalits in rural punjab. *Contributions to Indian Sociology*, *41*(3), 321–354.

Jodhka, S. S. (2017). Caste in contemporary india. *Annual Review of Sociology*, *43*(1), 391–410.

Johnston, B. F., & Mellor, J. W. (1961). The role of agriculture in economic development. *The American Economic Review*, *51*(4), 566–593.

Kawachi, I., & Kennedy, B. P. (1999). Income inequality and health: Pathways and mechanisms. *Health Services Research*, *34*(1 Pt 2), 215–227.

Khalid, N., Behrman, J., Hannum, E., & Thapa, A. (2024). Floods and children's education in rural india. *RSF: The Russell Sage Foundation Journal of the Social Sciences*, *10*(1), 230–254.

Kirk, D. (1996). Demographic transition theory. *Population Studies*, *50*(3), 361–387.

Kriebel-Gasparro, A. (2022). Climate change: Effects on the older adult. *The Journal for Nurse Practitioners*, *18*(4), 372–376.

Kumar, P., Mangla, S., & Kundu, S. (2022). Inequalities in overweight and obesity among reproductive age group women in india: Evidence from national family health survey (2015–16). *BMC women's health*, *22*(1), 205.

Kumari, M., & Mohanty, S. K. (2020). Caste, religion and regional differentials in life expectancy at birth in india: Cross-sectional estimates from recent national family health survey. *BMJ Open*, *10*(8), e035392.

Lin, N. (1999). Social networks and status attainment. *Annual Review of Sociology*, *25*(1), 467–487.

Lin, N. (2000). Inequality in social capital. *Contemporary Sociology*, *29*(6), 785–795.

Lin, N. (2017). Building a network theory of social capital. *Social Capital*, 3–28.

Link, B. G., & Phelan, J. (1995). Social conditions as fundamental causes of disease. *Journal of Health and Social Behavior*, 80–94.

Link, B. G., & Phelan, J. C. (2009). The social shaping of health and smoking. *Drug and Alcohol Dependence*, *104*(S1), S6–S10.

Lynch, J., Smith, G. D., Harper, S. A., Hillemeier, M., Ross, N., Kaplan, G. A., & Wolfson, M. (2004). Is income inequality a determinant of population health? part 1. a systematic review. *The Milbank Quarterly*, *82*(1), 5–99.

Madani Hosseini, M., Zargoush, M., & Ghazalbash, S. (2024). Climate crisis risks to elderly health: Strategies for effective promotion and response. *Health Promotion International*, *39*(2), daae031.

Malik, M. A. (2020). *Functional disability among older adults in india*. IHDS Working Paper.

Malik, M. A. (2022). Functional disability among older adults in india: A gender perspective. *PLOS ONE*, *17*(9), e0273659.

Marmot, M. (2004). *The status syndrome: How social standing affects our health and longevity*. Times Books.

Marmot, M. (2006). Health in an unequal world. *The Lancet*, *368*(9552), 2081–2094.

Masters, R. K., Hummer, R. A., & Powers, D. A. (2012). Educational differences in us adult mortality: A cohort perspective. *American Sociological Review*, *77*(4), 548–572.

Masters, W. A., Hall, A., Martinez, E. M., Shi, P., Singh, G., Webb, P., & Mozaffarian, D. (2016). The nutrition transition and agricultural transformation: A preston curve approach. *Agricultural Economics*, *47*(S1), 97–114.

Matthewman, S. (2016). *Disasters, risks and revelation: Making sense of our times*. Springer.

McKenna, Z. J., Foster, J., Atkins, W. C., Belval, L. N., Watso, J. C., Jarrard, C. P., Orth, B. D., & Crandall, C. G. (2023). Age alters the thermoregulatory responses to extreme heat exposure with accompanying activities of daily living. *Journal of Applied Physiology*.

Meshram, I., Balakrishna, N., Bhaskar, V., Laxmaiah, A., Brahmam, G., & Arlappa, N. (2025). Trends in body mass index, nutrient intake and nutritional status of rural adults in india: National nutrition monitoring bureau survey findings (1975–2012). *BMC Public Health*, *25*(1), 2929.

Meyer, M. A. (2017). Social capital in disaster research. In *Handbook of disaster research* (pp. 263–286). Springer.

Miech, R., Pampel, F., Kim, J., & Rogers, R. G. (2011). The enduring association between education and mortality: The role of widening and narrowing disparities. *American Sociological Review*, *76*(6), 913–934.

Mishra, A. K., & Singh, V. P. (2010). A review of drought concepts. *Journal of Hydrology*, *391*(1–2), 202–216.

Mishra, V. (2020a). India's projected aged population (65+), projected life expectancy at birth and insecurities faced by aged population. *Ageing International*, *45*(1), 72–84.

Mishra, V. (2020b). India's projected aged population (65+), projected life expectancy at birth and insecurities faced by aged population. *Ageing International*, *45*(1), 72–84.

Monteiro, C. A., Conde, W. L., Lu, B., & Popkin, B. M. (2004). Obesity and inequities in health in the developing world. *International Journal of Obesity*, *28*(9), 1181–1186.

Montez, J. K., & Hayward, M. D. (2014). Cumulative childhood adversity, educational attainment, and active life expectancy among us adults. *Demography*, *51*(2), 413–435.

Montgomery, A. L., Ram, U., Kumar, R., & Jha, P. (2014). Maternal mortality in india: Causes and healthcare service use based on a nationally representative survey. *PLOS ONE*, *9*(1), e83331.

Mood, C. (2010). Logistic regression: Why we cannot do what we think we can do, and what we can do about it. *European Sociological Review*, *26*(1), 67–82.

Muckenhuber, J., Stronegger, W. J., & Freidl, W. (2013). Social capital affects the health of older people more strongly than that of younger people. *Ageing & Society*, *33*(5), 853–870.

Mujumdar, M., Bhaskar, P., Ramarao, M., Uppara, U., Goswami, M., Borgaonkar, H., Chakraborty, S., Ram, S., Mishra, V., & Rajeevan, M. (2020). Droughts and floods. In *Assessment of climate change over the indian region* (pp. 117–141). Springer.

Munshi, K. (2019). Caste and the indian economy. *Journal of Economic Literature*, *57*(4), 781–834.

Murray, C. J. L., Kulkarni, S. C., Michaud, C., Tomijima, N., Bulzacchelli, M. T., Iandiorio, T. J., & Ezzati, M. (2006). Eight americas: Investigating mortality disparities across races, counties, and race-counties in the united states. *PLoS medicine*, *3*(9), e260.

Nagamine, Y., Fujiwara, T., Tani, Y., Murayama, H., Tabuchi, T., Kondo, K., & Kawachi, I. (2020). Gender difference in the association between subjective socioeconomic mobility across life

course and mortality at older ages: Results from the jages longitudinal study. *Journal of Epidemiology*, *30*(11), 497–502.

Nagarkar, A., Kulkarni, A., Bhagat, A., & Bhattacharya, S. (2020). Assessment of functional disability among elderly in rural pune. *Indian Journal of Community Health*, *32*(2), 362–368.

Nations, U. (2022). *World population prospects 2022*.

Newman, A. B., Simonsick, E. M., Naydeck, B. L., Boudreau, R. M., Kritchevsky, S. B., Nevitt, M. C., Pahor, M., Satterfield, S., Brach, J. S., & Studenski, S. A. (2006). Association of long-distance corridor walk performance with mortality, cardiovascular disease, mobility limitation, and disability. *JAMA*, *295*(17), 2018–2026.

Nguyen, P. H., Scott, S., Headey, D., Singh, N., Tran, L. M., Menon, P., & Ruel, M. T. (2021). The double burden of malnutrition in india: Trends and inequalities (2006–2016). *Plos one*, *16*(2), e0247856.

O'Rand, A. M. (1996). The precious and the precocious: Understanding cumulative disadvantage and cumulative advantage over the life course. *The Gerontologist*, *36*(2), 230–238.

Paarlberg, R. L. (2011). *Governing the dietary transition: Linking agriculture, nutrition, and health*. International Food Policy Research Institute.

Pampel, F. C., & Denney, J. T. (2011). Cross-national sources of health inequality: Education and tobacco use in the world health survey. *Demography*, *48*(2), 653–674.

Panagariya, A., & Mukim, M. (2014). A comprehensive analysis of poverty in india. *Asian Development Review*, *31*(1), 1–52.

Patil, S., et al. (2025). Social capital, noncommunicable diseases, and functional disability in india. *Journal of Aging and Health*.

Paul, R., & Rashmi. (2022). Risk factors and clustering of mortality among older adults in the india human development survey. *Scientific Reports*, *12*(1), 6644.

Paul, R., Srivastava, S., Muhammad, T., & Rashmi, R. (2021). Determinants of acquired disability and recovery from disability in indian older adults. *BMC Geriatrics*, *21*(1), 426.

Peek, L., Wachtendorf, T., & Meyer, M. A. (2021). Sociology of disasters. *Handbook of Environmental Sociology*, 219–241.

Pengpid, S., & Peltzer, K. (2019). Prevalence and correlates of underweight and overweight/obesity among women in india: Results from the national family health survey 2015–2016. *Diabetes, Metabolic Syndrome and Obesity*, *12*, 647–653.

Phelan, J. C., Link, B. G., & Tehranifar, P. (2010). Social conditions as fundamental causes of health inequalities: Theory, evidence, and policy implications. *Journal of Health and Social Behavior*, *51*(S), S28–S40.

Planning Commission, G. o. I. (2009). *Report of the expert group to review the methodology for estimation of poverty* (tech. rep.) (Chaired by S. D. Tendulkar). Planning Commission, Government of India. New Delhi.

Planning Commission, G. o. I. (2013). *Press note on poverty estimates, 2011–12* (tech. rep.). Planning Commission, Government of India. New Delhi.

Po, J. Y. T., & Subramanian, S. V. (2011). Mortality burden and socioeconomic status in india. *PLOS ONE*, *6*(2), e16844.

Pool, L. R., Burgard, S. A., Needham, B. L., Elliott, M. R., Langa, K. M., & Mendes de Leon, C. F. (2018). Association of a negative wealth shock with all-cause mortality in middle-aged and older adults in the united states. *JAMA*, *319*(13), 1341–1350.

Popkin, B. M. (1994). The nutrition transition in low-income countries: An emerging crisis. *Nutrition Reviews*, *52*(9), 285–298.

Popkin, B. M. (2002). The dynamics of the dietary transition in the developing world. In *The nutrition transition* (pp. 111–128). Elsevier.

Powers, D., & Xie, Y. (2008). *Statistical methods for categorical data analysis*. Emerald Group Publishing.

Preston, S. H. (1975). The changing relation between mortality and level of economic development. *Population Studies*, *29*(2), 231–248.

Pruchno, R., Wilson-Genderson, M., Heid, A. R., & Cartwright, F. P. (2020). Type of disaster exposure affects functional limitations of older people 6 years later. *The Journals of Gerontology: Series A*, *75*(11), 2139–2146.

Pudrovska, T., & Anikputa, B. (2014). Early-life socioeconomic status and mortality in later life: An integration of four life-course mechanisms. *Journals of Gerontology Series B: Psychological Sciences and Social Sciences*, *69*(3), 451–460.

Rendall, M. S. (2024). Acquisition of disability after age 50 following extreme urban coastal flooding events in india. *Population and Environment*, *46*(1), 5.

Richterman, A., Millien, C., Bair, E. F., Jerome, G., Suffrin, J. C. D., Behrman, J. R., & Thirumurthy, H. (2023). The effects of cash transfers on adult and child mortality in low- and middle-income countries. *Nature*, *618*(7965), 575–582.

Royston, P., & Parmar, M. K. (2002). Flexible parametric proportional-hazards and proportional-odds models for censored survival data, with application to prognostic modelling and estimation of treatment effects. *Statistics in medicine*, *21*(15), 2175–2197.

Rutstein, S. O., & Staveteig, S. (2014). *Making the demographic and health surveys wealth index comparable*. (Vol. 9). ICF International.

Sam, A. S., Padmaja, S. S., Kächele, H., Kumar, R., & Müller, K. (2020). Climate change, drought and rural communities: Understanding people's perceptions and adaptations in rural eastern india. *International Journal of Disaster Risk Reduction*, *44*, 101436.

Sedova, B., & Kalkuhl, M. (2020). Who are the climate migrants and where do they go? evidence from rural india. *World Development*, *129*, 104848.

Sengupta, A., Angeli, F., Syamala, T. S., Dagnelie, P. C., & Van Schayck, C. (2015). Overweight and obesity prevalence among indian women by place of residence and socio-economic status: Contrasting patterns from 'underweight states' and 'overweight states' of india. *Social science & medicine*, *138*, 161–169.

Shah, G. (2006). *Untouchability in rural india*. Sage Publications.

Silveira, I. H., Cortes, T. R., Bell, M. L., & Junger, W. L. (2023). Effects of heat waves on cardiovascular and respiratory mortality in rio de janeiro, brazil. *PLOS ONE*, *18*(3), e0283899.

Solon, G., Haider, S. J., & Wooldridge, J. M. (2015). What are we weighting for. *Journal of Human Resources*, *50*(2), 301–316.

Srinivas, M. N. (1962). *Caste in modern india and other essays*. Asia Publishing House.

Stanke, C., Kerac, M., Prudhomme, C., Medlock, J., & Murray, V. (2013). Health effects of drought: A systematic review of the evidence. *PLOS Currents Disasters*.

Story, W. T. (2014). Social capital and the utilization of maternal and child health services in india: A multilevel analysis. *Health & Place*, *28*, 73–84.

Story, W. T., & Carpiano, R. M. (2017). Household social capital and socioeconomic inequalities in child undernutrition in rural india. *Social Science & Medicine*, *181*, 112–121.

Subramanian, S. V., Ackerson, L. K., Subramanyam, M. A., & Wright, R. J. (2006). Domestic violence is associated with adult and childhood asthma prevalence in india. *International Journal of Epidemiology*, *36*(3), 569–579.

Subramanian, S. V., & Kawachi, I. (2004). Income inequality and health: What have we learned so far. *Epidemiologic Reviews*, *26*(1), 78–91.

Tamuly, D., & Mukhopadhyay, A. (2022). The impact of natural disasters on household consumption in rural india. *World Development*.

Tanji, F., Sugawara, Y., Tomata, Y., Watanabe, T., Sugiyama, K., Kaiho, Y., Tomita, H., & Tsuji, I. (2017). Psychological distress and the incident risk of functional disability in elderly survivors after the great east japan earthquake. *Journal of Affective Disorders*, *221*, 145–150.

Thoits, P. A. (2010). Stress and health: Major findings and policy implications. *Journal of Health and Social Behavior*, *51*(1 suppl), S41–S53.

Thorat, A., Vanneman, R., Desai, S., & Dubey, A. (2017). Escaping and falling into poverty in india today. *World Development*, *93*, 413–426.

Tipaldo, J. F., Balk, D., & Hunter, L. M. (2024). A framework for ageing and health vulnerabilities in a changing climate. *Nature Climate Change*, *14*(11), 1125–1135.

Tomata, Y., Suzuki, Y., Kawado, M., Yamada, H., Murakami, Y., Mieno, M. N., Shibata, Y., Ojima, T., Hashimoto, S., & Tsuji, I. (2015). Long-term impact of the 2011 great east japan earthquake and tsunami on functional disability among older people. *Social Science & Medicine*, *147*, 296–299.

Uddin, J., Acharya, S., Valles, J., Baker, E. H., & Keith, V. M. (2020). Caste differences in hypertension among women in india: Diminishing health returns to socioeconomic status for lower caste groups. *Journal of Racial and Ethnic Health Disparities*, *7*, 987–995.

Vikram, K. (2018). Social capital and child nutrition in india: The moderating role of development. *Health & Place*, *50*, 42–51.

Vikram, K., Vanneman, R., & Desai, S. (2012). Linkages between maternal education and childhood immunization in india. *Social Science & Medicine*, *75*(2), 331–339.

Vins, H., Bell, J., Saha, S., & Hess, J. J. (2015). The mental health outcomes of drought: A systematic review and causal process diagram. *International Journal of Environmental Research and Public Health*, *12*(10), 13251–13275.

Viswanath, K., Randolph Steele, W., & Finnegan, J. R. (2006). Social capital and health: Civic engagement, community size, and recall of health messages. *American Journal of Public Health*, *96*(8), 1456–1461.

Vyas, S., Hathi, P., & Gupta, A. (2022). Social disadvantage, economic inequality, and life expectancy in nine indian states. *Proceedings of the National Academy of Sciences*, *119*(10), e2109226119.

Wallace, M., Hiam, L., & Aldridge, R. (2023). Elevated mortality among the second-generation (children of migrants) in europe: What is going wrong? a review. *British Medical Journal Bulletin*, *148*(1), 5–21.

Wang, H., et al. (2012). Age-specific and sex-specific mortality in 187 countries, 1970–2010. *The Lancet*, *380*(9859), 2071–2094.

Warner, D. F., & Hayward, M. D. (2006). Early-life origins of the race gap in men's mortality. *Journal of Health and Social Behavior*, *47*(3), 209–226.

Wilhite, D. A., & Glantz, M. H. (1985). Understanding the drought phenomenon: The role of definitions. *Water International*, *10*(3), 111–120.

Wilkinson, R., & Pickett, K. (2009). *The spirit level: Why more equal societies almost always do better*. Allen Lane.

Wilkinson, R. G. (1997). Socioeconomic determinants of health: Health inequalities: Relative or absolute material standards. *BMJ*, *314*(7080), 591.

Wilkinson, R. G. (2020). *The impact of inequality: How to make sick societies healthier*. Routledge.

Williamson, J. G. (1965). Regional inequality and the process of national development: A description of the patterns. *Economic development and cultural change*, *13*(4, Part 2), 1–84.

Willson, A. E., Shuey, K. M., & Elder, G. H. (2007). Cumulative advantage processes as mechanisms of inequality in life course health. *American Journal of Sociology*, *112*(6), 1886–1924.

Wind, T. R., & Komproe, I. H. (2012). The mechanisms that associate community social capital with post-disaster mental health: A multilevel model. *Social Science & Medicine*, *75*(9), 1715–1720.

Xue, Q.-L., Bandeen-Roche, K., Mielenz, T. J., Seplaki, C. L., Szanton, S. L., Thorpe, R. J., Kalyani, R. R., Chaves, P. H., Dam, T.-T. L., & Ornstein, K. (2012). Patterns of 12-year change in physical activity levels in community-dwelling older women: Can modest levels of physical activity help older women live longer? *American journal of epidemiology*, *176*(6), 534–543.

Xue, X., Reed, W. R., & Menclova, A. (2020). Social capital and health: A meta-analysis. *Journal of Health Economics*, *72*, 102317.

Zang, E., & Tian, M. (2025). Upward mobility context and health outcomes and behaviors during transition to adulthood: The intersectionality of race and sex. *Journal of Health and Social Behavior*, *66*(1), 18–37.

Zhang, J., & Centola, D. (2019). Social networks and health: New developments in diffusion, online and offline. *Annual Review of Sociology*, *45*(1), 91–109.

Zimmer, Z., Martin, L. G., Nagin, D. S., & Jones, B. L. (2012). Modeling disability trajectories and mortality of the oldest-old in China. *Demography*, *49*(1), 291–314.