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Gradual Change or Punctuated Equilibrium? Reconsidering Patterns of Health in Later-Life

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Abstract

This paper examines the curious mismatch between the supposition of gradual, continuous change embedded in common health trajectory models and a pattern of punctuated stability that is captured in the nationally-representative and widely-used Health and Retirement Study. Inspired by an insight from evolutionary biology, our analysis contrasts the conclusions drawn from mixed regression methods (growth curve models and latent class growth analysis) designed to capture trajectories in repeated-measure data with methods (multistate life tables and sequence analysis) designed to describe discrete states and transition patterns. Although a gradually increasing number of functional limitations is consistent with prevailing notions of health decline, our findings suggest that later life functional health, as captured in survey data, is more aptly characterized as a punctuated equilibrium: long-term stability that is irregularly interrupted by changes in health status or mortality. We conclude by discussing the implications of a punctuated equilibrium model for studies of health and aging.

Key words: health, aging, longitudinal analysis, trajectory

Introduction

Stability and change are fundamental concepts in studies of individual development across the lifespan and population trajectories over time (Baltes and Nesselroade, 1979, George, 2009). While some attributes remain constant as persons age, others – including health – may be profoundly altered. In the popular and scholarly imaginations, change attracts more attention than stability. The desire to study change has inspired the ongoing collection of longitudinal data and the development of statistical methodologies that use repeated-measure observations to determine what is constant and what changes, to describe how change unfolds, and to explain why change takes place.

Changes in health, as in other characteristics, may occur suddenly or unfold steadily as persons age. We show that an intuitively appealing, biologically compelling, and analytically tractable assumption of gradualism is built into several influential statistical models used to describe longitudinal health trajectories. Inspired by a classical insight from evolutionary biology, however, we ask whether the discrete survey data on which such analyses rely are in fact consistent with a gradualist model or whether they may be more aptly characterized via a punctuated equilibrium model: a pattern of long-term stability that is irregularly interrupted by changes in health status.

Gradualism vs. Punctuated Equilibrium: In Search of a Guiding Metaphor

In a seminal 1972 paper, paleontologists Niles Eldredge and Stephen Jay Gould proposed a new framework for understanding the historical development of new species. The prevailing model held that speciation unfolded gradually, as a "slow and steady transformation of entire populations" (84). Eldredge and Gould (1972) argued instead that a model of punctuated equilibrium – long-term stasis occasionally disrupted by "rapid and episodic events" – is a more accurate description of evolutionary change as documented in the fossil record. This approach highlighted the predominance of long spans of time without variation in key features rather than the progressive unfolding of change. Change does take place "rather often in the fullness of time" – but it tends to be a rare deviation from a previously stable trend, rather than a continuous incremental process.

Eldredge and Gould's argument was based not on new data, but rather on the reconsideration of existing evidence. The gradualist model had regarded discontinuities in the fossil record as missing data in an otherwise smooth trajectory. In contrast, the punctuated equilibrium perspective interpreted breaks in the fossil record as real disruptions to the status quo – reflecting a messy, non-deterministic historical process that interweaves stability and disruption. Using the contrast between gradualism and punctuated equilibrium as a guiding metaphor, we highlight the mismatch between the supposition of gradual, continuous change embedded in health trajectory models and the pattern of punctuated stability that is captured in population-based health survey data.

Gradualism is an intuitively appealing framework for health analysts because many physiological changes probably do occur in a continuous incremental fashion sub-clinically (Ben-Shlomo and Kuh, 2002). Gradualism also has appealing statistical properties, because it can be modeled using standard functional forms that trace smooth patterns of change. Scientific hypotheses consistent with gradualist assumptions generate clear expectations about the nature of health change in aging populations, and these hypotheses can be tested against the available data and used in predictive models. For all of these reasons, the most prominent analytic approaches in longitudinal health research aim to capture underlying trajectories of continuous health changes.

However, the major studies following aging cohorts collect data in discrete increments. The Health and Retirement Study, for example, interviews respondents over 2-year intervals. More frequent assessments would likely capture more detailed health changes, though research suggests that rather than simply filling in a pattern of gradual health decline finer-grained data (both in terms of time intervals and specificity of health measurements) would or uncover brief spells of debilitation and recovery that are less consistent with assumptions of smooth incremental changes (Wolf and Gill, 2009).

The punctuated equilibrium framework provides a more literal reading of the fossil record than gradualism, and it also presents a compelling metaphor for the lived health experiences of many individuals, who may not consciously track their health until they experience a sudden change in it – either due to an acute event or when a particular underlying health condition passes a clinical threshold. Discrete survey data – like the paleontological fossil record in Eldredge and Gould's analysis – may thus be relatively well suited for capturing overall stability in health and recording primarily those shifts in health that are significant enough to establish a new homeostasis.

It is important to note here that the punctuated equilibrium framework is not necessarily in conflict with the gradualist one: it simply reads the available evidence on a different time scale. While gradualism is concerned with the incremental, continuous changes that ultimately differentiate species or health statuses, punctuated equilibrium describes discrete changes on a time scale that matches the data collection schedule. Thus, the fundamental mechanism of change could indeed be gradual (as assumed in statistical models used to analyze longitudinal data), but only those changes that cross the threshold of observation at survey time are recorded in the data. This perspective raises questions about the widespread notion that longitudinal data and models allow researchers to accurately depict health in later life as a process of gradual decline. This notion may be problematic not because health does not change gradually – indeed, it very likely does do so in many cases – but rather because clinical records and survey measures capture static snapshots that may not form smooth trajectories, creating a potential mismatch between the data and the methods used to analyze them.

Modeling Longitudinal Change

Researchers across the social, behavioral, and health sciences use longitudinal (time-series) data to identify both intraindividual and interindividual changes: that is, they examine the timing, direction, and magnitude of within-person changes as well as the ways in which patterns of individual change vary across persons in a population (Nesselroade, 1991, George, 2009). Longitudinal data allow the construction of trajectories that reflect the sequencing of distinct events of interest, or, more commonly, identify patterns of stability and change in repeated measures. A variety of methods are available for analyzing temporally ordered elements, and they vary in the extent to which they consider trajectories as discrete step-wise processes or, alternatively, continuous whole units (Abbott, 1995).

One early approach to the analysis of change over age was the use of multistate (or increment-decrement) life tables (Namboodiri and Suchindran, 1987). The multistate life table models change as a Markov-process, a method that allows the calculation of transition probabilities across a finite number of predefined discrete states. The method allows exit and re-entry into the same state and accounts for the competing risk of mortality.[1] Other early statistical approaches to longitudinal data involved reducing repeated measures into summary indicators of change (also known as end-point analysis). Each of these methods approaches longitudinal changes as differences between discrete

[1]Event-history methods, also known as duration (time-to-event) methods, hazard methods, and failure or survival analysis, expanded on the life table approach to model the timing of particular transitions between states, often by building in smooth gradualist assumptions about the shape of the underlying hazard function.

states, and has been widely employed in a variety of social science and public health applications.

Over the past three decades, mixed effects regression models have become the most prominent statistical approach to longitudinal data. These methods allow researchers to reduce their reliance on constructed discrete categories and instead model trajectories via continuous distribution functions that characterize patterns of change across ages (see Lynch and Taylor (2016) for a review). One major framework that guides contemporary longitudinal analyses is based on the assumption that individuals come from a single population, and that therefore, a single parametric trajectory can adequately summarize their pattern of change over time. Known as growth curves within the multilevel or hierarchical linear models literature (Raudenbush and Bryk, 2002) or latent growth curves in the structural equation models literature (Bollen and Curran, 2006), these models estimate an average trajectory along with parameters that capture individual heterogeneity. While the specific parameters defining the average trajectory may vary, growth curves by definition assume that changes occur at a constant or constantly increasing rate, and their parameter estimates specify the pace of gradual change.

Another prominent framework challenges the assumption that populations can be well characterized using a single average trajectory with random effects, and instead suggests that populations comprise meaningful classes of individuals who follow distinct trajectories (Jung and Wickrama, 2008). Latent class growth analysis (LCGA) assume multiple classes, each internally homogeneous (Nagin, 2005). The more computationally intensive approach of growth mixture models (GMM) relaxes the assumption of within-class homogeneity and models heterogeneity within distinct latent classes of trajectories (Muthén and Asparouhov, 2008). Both of these group-based latent-class approaches use mixtures of probability distributions and a multinomial modeling strategy to identify unique clusters of trajectories that aim to more explicitly capture interindiviudal differences in intraindividual trajectories, and have consequently proved increasingly popular with analysts working within the life course perspective.

The parametric assumptions built into class-based models produce relatively smooth and gradually unfolding trajectories, even when applied to health data that is observed at discrete time periods. Despite concerns about the accuracy of classification results and uncertainty about model fit (Warren et al., 2015), latent class models and their growth curve counterpart remain appealing to researchers because of their capacity to portray a coherent pattern of longitudinal change.

When estimated via a full-information maximum likelihood approach, these models also have the advantage of employing all available information, including on persons who provide incomplete information due to intermittent missingness or early drop out. Notably, however, this method does not fully address the potential bias that results from the compositional impacts of non-random and likely health-related missing data (Jackson et al., 2017).

Sequence analysis is a separate methodological tradition that originated in studies of protein and DNA strings and was imported into the social science (Abbott and Tsay, 2000, Billari, 2001). This method approaches ordered series of discrete events or states as whole analytic units, and can characterize linear progression as well as more complex patterns that allow for contingency, chance occurrences, and interdependence among states (Abbott, 1995). Contemporary sequence analyses generate typologies – clusters of cases with similar trajectories – as well as measures summarizing the diversity and complexity of observed patterns (Gabadinho et al., 2011, Barban and Billari, 2012). They are thus flexible enough to accommodate both gradual trajectories and punctuated patterns of change.

Below, we compare and contrast the conclusions drawn from growth curve models, latent class growth analysis, multistate life tables, and sequence analysis applied to repeated measures of functional health in a nationally representative longitudinal survey. In considering whether the data are consistent with a model of gradual change or a less predictable punctuated equilibrium pattern, we document how observed patterns of intra-individual change become aggregated into different population trajectories depending on the analytic method. We examine the extent to which different methods acknowledge and represent inter-individual heterogeneity in intra-individual change and explore each method's implications for inferences about patterns of health in later life.

Changes in Health Across the Life Course

Health is a complex multifaceted construct that encompasses subclinical and manifest components. In the absence of a single comprehensive measure, health surveys collect information about chronic diseases, adverse events, functional limitations, disability, and self-rated health at multiple time points, and longitudinal models allow researchers to describe the onset, timing, severity, and rate of changes in these variables (George, 2009, Wolf, 2016). Intuitively, we talk about patterns of health decline in later life, while empirically we measure changes in health as the accumulation of negative outcomes.

The life course perspective encourages researchers to consider health in relation to accumulated exposures to advantage and disadvantage that differentiate individuals or groups over time (Dannefer, 2003, Ferraro and Shippee, 2009). More specifically, dynamic interactions between structures and processes of social stratification, individual social position, personal traits, and contingent events are theorized to generate inequality in social and economic measures and in health.

Empirical research has tested this broad life course hypothesis by exploring early social and economic disadvantage in relation to specific adult health outcomes (Hayward and Gorman, 2004, Ferraro et al., 2016). A growing number of studies have employed growth curve models to describe trajectories of health in later life (Haas, 2008, Shuey and Willson, 2008, Quiñones et al., 2011, Warner and Brown, 2011, Brown et al., 2012) and many have adopted latent class growth analysis or growth mixture models to describe heterogeneity across individuals in the direction and pace of health changes in later life (Liang et al., 2010b, Taylor and Lynch, 2011, Gill et al., 2010, Wickrama et al., 2012, Han et al., 2013). These trajectory studies have described patterns in self-rated and functional health, as well as the in the accumulation of limitations in activities of daily living and markers of frailty. They have also highlighted differences across groups and tested hypotheses about the extent to which exposure to disadvantage – e.g. economic hardship and discrimination based on race/ethnicity or gender – sorts individuals into differential health decline patterns.

Although cumulative (dis)advantage and inequality theories recognizes that risks may increase both gradually as well as sporadically or non-linearly, most empirical analyses nonetheless treat health change as gradual and steady. Thus, although estimated trajectories vary in baseline profiles and in whether the pattern of change is depicted as linear, geometric, or exponential (DiPrete and Eirich, 2006), all results reflect the assumption of gradual continuous change.

A separate line of research has employed multistate life tables to estimate the expected duration in states of health, illness, and disability (Crimmins et al., 1994, 2009, Hayward et al., 2014). These studies found that increased longevity comprises years lived in good health and in disability, and that the distribution of years in different health states varies by socioeconomic status. Multistate models capture stability in health over time and incorporate mortality as a competing risk to varied levels of limitation. Although discrete multistate models provide an incomplete approximation of the continuous process thought to underlie health changes, they nonetheless offer a compelling counterpoint to the gradualist regression models – one that is consistent with the nature of survey data and compatible with a punctuated equilibrium model.

Finally, although sequence analysis is frequently used in life course research exploring patterns of marriage and fertility, education and employment, and criminal or deviant behavior (Billari, 2001), it is less commonly applied to health patterns. While an early example identified typologies of health that differ in the timing, order, and direction of change (Clipp et al., 1992), more recent sequence analyses in the health sciences have focused on genetic markers. Nonetheless, sequence analysis offers a promising way to disentangle patterns of intraindividual changes from the model assumptions and compositional changes that shape aggregate trajectories.

Here, we compare patterns of functional limitation in later life produced by gradualist and discrete analytic techniques and consider their implications for conclusions about population health patterns. We show that models that assume continuous incremental change may be at odds with data that record general stability irregularly punctuated by relatively sudden change.

Data and Methods

Data

We illustrate the contrast between the gradualist and punctuated equilibrium perspectives using data from the Health and Retirement Study (HRS), a nationally-representative longitudinal survey of community-dwelling middle-aged and older Americans (Juster and Suzman, 1995) that is a leading source of information about health and well-being in later life. The HRS is particularly well suited for our purpose because of its longitudinal nature and because researchers across the social and public health sciences have relied on it extensively to describe patterns of health in later life. We use 11 waves of data covering the period 1994-2014. Our analytic sample includes members of the main HRS cohort born between 1931-1941, whose follow-up period encompasses the ages when health problems typically manifest and escalate.[2]

Our analysis is based on 10,198 members of the HRS cohort. Of respondents in the initial sample, 3,505 (34%) died during the follow-up period, and 1,781 (17%) left the survey prior to the

[2]The original sample was recruited in 1992 and our descriptive analysis considers all 12 rounds of data (1992-2014) as information on chronic conditions is available for 1992

final wave. The full 10,198 cohort members contribute at least some information to the descriptive analysis and sequence analysis. This data allows us to fully quantify the impact of attrition, mortality, and temporary missingness. The sample size for each analysis described below varies somewhat depending on how each methods handles temporary missingness and attrition. The 9,706 individuals who have at least one measure of functional limitations are included in the latent growth curve, latent class growth analysis, and multi-state models. In models that analyze change, we restrict the analytic sample to 9,141 persons who had health outcomes observed during at least two survey rounds.[3]

Key Variables

Our outcome is the sum (0-12) of functional limitations at survey rounds 2-12. Functional limitations are measured via three sub-scales of mobility (walking several blocks, walking one block, walking across the room, climbing several flights of stairs and climbing one flight of stairs), large muscle functioning (sitting for two hours, getting up from a chair, stooping or kneeling or crouching, and pushing or pulling a large object), and fine motor skills (picking up a dime, eating, and dressing). For all items, 0=no difficulty; 1=difficulty, and higher sums indicate more limitation.

Of the health measures available in the Health and Retirement Study, the sum of functional limitations is arguably the best suited to capture gradual change in health over time as it contains a large number of items that measure a mix of mild and severe limitations which individuals can develop or recover from over time. Functional limitations are conceptually situated between chronic conditions and ADL limitations (Verbrugge and Jette, 1994), and prior studies using the HRS data have found that functional limitations gradually accumulate across survey rounds, both for the study cohort as a whole and for specific sub-populations (Haas, 2008, Liang et al., 2010b,a, Brown et al., 2012). Functional limitation are more likely than other commonly-used measures of health, including the number of chronic conditions or the number of limitations in activities of daily living (ADLs) to fit the gradualist paradigm. Chronic conditions, while common, accumulate more slowly than functional limitations, and often require formal diagnosis by a physician with little prospect for recovery. Limitations in ADLs, on the other hand, are relatively rare and encompass only a few

[3] In supplementary analyses (available upon request), we examine how different excluded members of the HRS cohort are from those retained in the change analysis.

(5) indicators of severe disability, leaving little opportunity to capture substantial progression or recovery.

Our analyses focus on patterns of functional health and do not adjust for covariates in order to compare inferences across longitudinal techniques.

Methods

We began by fitting an **unconditional growth curve model** for repeated measures of functional limitations. The model includes a fixed effect representing a mean trajectory across all individuals in the sample, and a random effect representing the variance of individual trajectories around the group mean. We tested linear and quadratic specifications and the best fitting model was chosen using a combination of CFI, TLI, and RMSEA fit statistics (Raudenbush and Bryk, 2002).

Next, we modeled trajectories of functional limitations with **latent class growth analysis (LCGA)**, an approach that identifies qualitatively distinct trajectories of functional limitation onset and accumulation within a population and classifies individuals into the best-fitting category (Nagin, 2005). Following suggested practice (Jung and Wickrama, 2008), we determined the best fitting model based on the smallest sample-adjusted BIC value combined with a significant Lo, Mendell, and Rubin likelihood ratio test.

To evaluate the gradualistic assumptions built into the above models, we conducted a **descriptive analysis** to estimate: i) the percent of the sample that experiences increasing limitations; ii) the percent of the sample with a constant (or consistently missing) number of functional limitations; and iii) the percent of the sample that experiences decreasing limitations. These quantities were estimated comparing the first and last observed rounds as well as over the total duration of the study.

We then estimated a **multi-state model** (Namboodiri and Suchindran, 1987) that calculates the probability of transitions across five states: i) 0-1 limitations; ii) 2-5 limitations; iii) 6-12 limitations, iv) temporarily missing (i.e. missing data but not attrition); and v) lost to follow up (including respondents who died and who dropped out of the study). The Markov-process model allows recovery and the only absorbing state is loss to follow up (see**Figure 1**). Model fit is evaluated using the likelihood ratio test, AIC, and difference between observed and model predicted values. The best fitting model assumes the probability of transitioning across states is constant between survey rounds 2-6, 6-9, and 9-12. Sensitivity analyses varied the functional limitation cutpoints used to classify individuals into particular health states, and our results appear robust to varying the specification of the states.

Finally, we conducted a **sequence analysis** (Gabadinho et al., 2011) to identify, describe, and visualize the most commonly observed patterns of functional limitation. Since the first analyses showed the high prevalence of static trajectories (i.e. ones where no change is experienced prior to drop out), we conducted a second sequence analysis restricted to those who experienced any increase in functional limitations.

Across analyses, no imputation was performed. Missing data is handled in the latent growth curve and latent class growth analysis using full information maximum likelihood (FIML). FIML keeps cases in the sample until the time of attrition allowing them to contribute all available information to estimated trajectories. However, FIML is designed for situations where data is missing at random, while for this sample we strongly suspect that attrition and dropout are related to health selection and decidedly missing not at random (Jackson et al. 2017).

In the multi-state models, temporary missingness is treated as a discrete state and individuals may transition between having any number of functional limitations to the missing state and later return to the sample. This estimation treats missingness as informative and allows us to empirically quantify the likelihood that individuals in various health states will leave and return to the sample. Subject dropout and mortality are treated as an absorbing state.

Finally, in the sequence analysis, all members of the sample are included in an initial analysis that quantifies the frequency of all health patterns. This analysis distinguishes between three types of missingness: temporary missingness, attrition, and mortality, explicitly showing the contribution of different types of missing data to the cohort's health experiences.

Analyses were conducted using the statistical packages Stata, R, and Mplus 7.11 (Muthén and Muthén, 2013). A more detailed description of each method's implementation is available in the Appendix.

Results

Consistent with prior analyses in the HRS, our unconditional growth curve model (**Figure 2**) generates a curvilinear trajectory in which functional limitations accumulate gradually over the course of the study. While the full model results in **Table 1** suggest substantial heterogeneity around the average population trajectory parameters, the main conclusion affirms common assumptions about the pattern of increasing limitations in later life.[4] However, as subsequent analyses suggest, this gradual accumulation is partially driven by the model's parameters and the relatively small proportion of individuals who experience a change in health at any particular time in the study.

The trajectory classes identified by the LCGA model divides the HRS cohort into four subgroups with qualitatively distinct health trajectories (**Figure 3**). Class A (approximately 65% of the sample) is characterized by few limitations at the beginning of the study, and a slow, gradual accumulation of limitations across survey rounds. Class B displays a relatively fast pace of limitation accumulation. Individuals in Class C begin the study with a higher number of limitations (4), and slowly accumulate limitations thereafter. Those in Class D begin with a high number of limitations (8), and remain relatively constant at that level with some slight evidence of a health recovery at later rounds. Prior research casts some doubts about the accuracy of class identification (Warren et al., 2015, Jackson et al., 2017), partially because heterogeneity within classes and compositional change due to selective mortality and attrition may bias the parameters shaping each groups trajectory. Still, the relative flatness of most class trajectories (with the striking exception of Class B) in Figure 3 relative to the mean trajectory estimated in Figure 2 suggests that many respondents experience stability in functional health over time, and that the steeper accumulation in the LGC is at least partially an artifact of population composition. That said, with the exception of Class D, which depicts a slight recovery, the trajectories depicted in Figure 3 are also characterized by a pattern of steady accumulation over time.[5]

Subsequent analyses further indicate that a trajectory of gradually increasing limitations is far from universal. **Table 1** summarizes results from a simple descriptive analysis. Panel 1 in the table confirms the overall health declines for this sample: the average number of chronic conditions,

[4]Criteria for selecting best fitting model are shown in Appendix Table A1.
[5]Criteria for selecting best fitting model are shown in Appendix Table A2.

functional limitations, and ADL limitations is higher at the last survey round than at the first.[6] Panel 2 describes the proportion of the sample whose health changes between the first and last survey rounds observed. While 59% of the sample reports more functional limitations at the last survey round than they did at the first round, nearly 25% experiences no change in functional limitations and 16% experience a decrease in limitations between the first and last round observed. A similar analysis of change in chronic conditions and activities of daily living reinforces the idea that the pattern of later-life health is more heterogeneous than a single trajectory of decline: 20% of the sample reports no change in the number of chronic conditions between the first and last rounds observed, and a striking 73% report no change in ADL limitations between the first and last round observed.

However, changes in sample health are somewhat more common than the prior analysis suggests. As panel 3 in Table 1 shows, although only 59% of the sample saw increased functional limitations between their first and last observations, 79% experienced an increase at some point during the survey. Similarly, while 24% of the sample had more limitations in ADLs at the last round of the survey than at the first, 37% had an increase in ADL limitations over the observation period. These findings suggest a non-trivial proportion of the sample recovers after experiencing a health decline.

The pattern of within-individual change in health suggests that a gradual increase in limitations is not very common. As summarized in panel 4, on average across survey rounds, an individual experiences no change in chronic conditions, functional limitations, or ADL limitations in ADLs more commonly than an increase or decrease. An individual is expected to experience 2.47 increases in functional limitations, 2.75 occasions when their number of functional limitations does not change, and 1.94 decreases in functional limitations. Together, these findings suggest that although the mean number of functional limitations (as well as ADL limitations and chronic conditions) increases between the first and last rounds of observation, this population-level change reflects the experiences of only a small subset of the sample.[7] Declining health is not a universal experience nor does it appear to work in the progressive fashion often assumed by gradualist models. Perhaps

[6] We define last survey round as the last round a person is observed and the first survey round as the first round observed. People with only one survey round observed are excluded from this analysis, which reduces the representativeness of the sample and deflates the proportion with constant health over time.

[7] supplemental analysis (Appendix Table A3) calculates the number of individuals who, starting from baseline (round 2), experience successive increases in functional limitations. No individual experienced an increase in functional limitations at each follow-up survey round and less than 1% of the sample experienced more than three successive increases in functional limitations.

most importantly, people, on average, spend more time not changing than they do changing.

Results from the best-fitting[8] multistate model (see **Table 3**) confirm that with the exception of transitions to and from a missing state, the most common pattern across survey rounds is stasis, remaining in the same health status. For example, individuals who had 0-1 functional limitations at survey Round 2 are estimated to have a 74% chance of remaining in that state at the next round. Notably, the model also suggests a non-trivial risk of recovery. At round 9, people with 6-12 functional limitations had a 17% chance of transitioning to having between 2-5 limitations at survey round 10. Consistent with our descriptive analysis, results from the multistate model suggest that a linear accumulation of functional limitations is in fact quite rare. Even at the final survey rounds, the probability of progressively moving from health class 1 (0 to 1 limitations) to health class 2 (2 to 5 Limitations) to health class 3 (6 to 12 limitations) is only 3.74%.

Finally, our sequence analysis identified the most common functional limitation patterns for individual members of the HRS cohort. The line width in each panel of **figures 3 and 4** is weighted by the number of cases who follow the particular trajectory. Sequences are shown on separate panels because they are otherwise indistinguishable from each other, as most involve shifts between the state of no limitations and missing values (mortality, attrition, or temporary missingness). Notably, no single pattern characterizes more than 2% of the sample, and none of the 12 most common trajectories in **figures 3** involve a gradual accumulation of functional limitation. Instead, they highlight stability over time, and the role of selective mortality or attrition. While increases in functional limitations do occur, they are relatively rare and occur at varying times.

When the analysis is restricted to individuals who experience any increase in functional limitations over time (n=7,235), the results in **figure 4** further reinforce the conclusion that functional health over time is better described as a punctuated equilibrium than a gradual accumulation of limitations. The 12 most common sequences show that an increase in limitations happens relatively rarely across survey rounds, occurs at varying times, and most often consists of the addition of one limitation between a given set of rounds, rather than a gradual, continuous accumulation.

Although examples of continuous accumulation do exist, they are less common than gradualist models lead us to expect. Instead, the trajectories produced by mixed regression methods are driven by parametric assumptions and compositional changes in the sample. The average population

[8] Criteria for selecting best fitting model are shown in Appendix Table A4.

(or subpopulation) trajectory does not accurately represent the longitudinal experience of most individuals.

Discussion

In longitudinal studies of health, researchers choose how to aggregate individual records of change and stability into summaries of population level. The chosen model reflects a theory about health and aging as well as a perspective on heterogeneity in the population being analyzed. It also influences the inferences that can be drawn from the data. We have argued that there is a disconnect between recorded individual health histories and the trajectory models that aim to characterize longitudinal health changes in populations. Expectations about smooth patterns of gradual change – while intuitively and analytically appealing – may simply not fit the survey data record.

Later-Life Health: Modeled and Observed Patterns

By design, mixed regression parametric models characterize the longitudinal pattern of health among older adults via continuous linear or quadratic trajectories. Results from our latent growth curve and latent class growth analysis are consistent with this literature, showing a slow, gradual accumulation of functional limitations for members of the HRS cohort overall, and within subgroups distinguished by their initial level of limitations and the pace of subsequent accumulation.

Researchers have cautioned against equating the predicted smooth trajectories with the complex dynamics that trajectories imperfectly measure, or reifying latent trajectory classes without acknowledging within-group heterogeneity and the competing risks of mortality and drop out (Lynch and Taylor, 2016, Warren et al., 2015, Wolf, 2016, Zimmer et al., 2012). Still, these models have remained popular because their assumptions are biologically plausible and intuitively appealing, and their statistical properties facilitate the testing of hypotheses as well as the prediction of population health patterns.

However, descriptive, multistate, and sequence analyses all cast doubt on the gradualist assumptions embedded in trajectory models. Our descriptive analysis shows that a pattern of increasing limitations is far from universal in this sample of older adults, and stasis rather than change is the most common occurrence. The multistate and sequence analyses reinforce these conclusions: both suggest that even though change is common in the sample overall, for individuals it occurs only rarely, at irregular times and intervals, and in a non-linear fashion.

While the more discrete analyses do not impose the same parametric assumptions as the mixed regression models, they too have drawbacks. Computational and data constraints require that individuals with different numbers of functional limitations be pooled into relatively few groups for the multistate analysis. While our results are robust to alternative specification of states, it is possible that an individual experienced a health change between survey rounds without transitioning between model states. The multistate model also flattens the temporal dimension of change, focusing on the occurrence of transitions rather than their timing. Although this aspect of the model involves the loss of some detail, it allows analysts to avoid assuming a consistent pattern of gradual change across individuals and time. In contrast, the sequence analysis preserves the full richness of the data but at the expense of parsimony. With over 8000 distinct sequences, it is difficult to distill findings into generalizable conclusions about population health. Still, this difficulty in reducing the data is itself informative.

Our results highlight stasis as a major characteristic of longitudinal health patterns, with most people experiencing no observed changes most of the time, even though in the sample as a whole, change occurs frequently. The analysis also highlights the diverse nature of change, with increases and declines happening at different times and intervals, yielding no single typical trajectory or clear set of naturally-clustering sequence patterns. Notably, functional limitation are more likely than other commonly-used measures of health – including the number of chronic conditions or the number of ADL limitations – to fit the gradualist assumption, and yet they do not. Our findings suggest that conventional survey follow-up is not well suited for capturing gradual changes in health that may be occurring.

The impact of temporary missingness, attrition, and mortality on inferences should be noted. A majority of the sample is lost to attrition or mortality, raising questions about the potentially-biasing impact of nonrandom compositional changes on the estimated population trajectories. This problem is particularly acute in the case of the LCGA, because it produces considerable uncertainty in the assignment of individuals into latent class (Jackson et al., 2017). The high prevalence of missing data also complicates the interpretation of our descriptive, multistate, and sequence analyses. Across analyses, we do not impute but instead allow the missingness to be potentially informative. It is, however possible that some temporary missingness is random or due to illness followed by complete recovery. Individuals who drop out may experience a greater accumulation of functional limitations than those observed throughout the study, suggesting that analyses may underestimate the prevalence and severity of functional limitations.

Coarse measures of health, regular two year intervals between periods of observed data, and irregular interruptions in the form of missing and censored data may all contribute to our finding that rather than the smooth change suggested by the gradualist assumptions, the standard survey data could be more aptly characterized as a punctuated equilibrium: long-term stability that is irregularly interrupted by singular, often small changes in health status or – frequently – mortality or attrition from the study.

Implications for Health and Aging Research

The punctuated equilibrium perspective presents challenges for those interested in examining health inequality across the life course. Empirical analyses aiming to link early and mid-life factors with the pace of later-life health declines have thus far relied on gradualist models, whose built-in assumptions facilitate the testing of cumulative disadvantage hypotheses. However, the notion of a constant or compounding health disadvantage for socially disadvantaged groups may appear to be refuted by our findings. While advantage and disadvantage may accumulate over the life course, there is no simple pattern of accumulation in functional limitations. If the gradual trajectory is not an accurate model for later life health patterns, using it to compare the longitudinal health patterns of subpopulations or test the association of such patterns with prior exposures becomes problematic, too.

For the HRS cohort and subpopulations defined by demographic and social characteristics, health does not appear to change in a gradual form (supplementary analyses available upon request). Several trajectory studies have indeed found that a variety of demographic and social characteristics are associated with baseline differences in health, but not with parameters describing the slope of change over time (e.g. Gueorguieva et al. (2009), Quiñones et al. (2011), Brown et al. (2012)). Such findings may be reflective of the problematic assumptions of gradualist models rather than a refutation of links between early exposures and later life health.

The earlier death of socially and economically disadvantaged persons (who might be expected to display some a cumulative health penalty) and the non-random nature of attrition in longitudinal surveys of health suggests that quantitative characterizations of health trajectories may underestimate the accumulation of poor health outcomes in disadvantaged populations (Jackson et al., 2017), contributing to an inaccurate impression of stable or narrowing gaps in health across groups.

To better understand health and inequalities in later life, researchers should pursue both better data and better methods. Larger data samples, more thorough follow-up for specific subgroups believed to have health disadvantages, and more nuanced measures of health and functioning are needed. The development of methods that can depict non-linearity in the progression of individual health while accounting for changes in population composition over time is another promising avenue for future research.

The notion that aging typically involves a gradual decline in health does not fit with currently available longitudinal survey data. Our analyses suggest that later-life health is better described as a punctuated equilibrium: general stability interrupted by sporadic change. Although human health unfolds on a different time scale than the speciation process studied by Eldredge and Gould (1972) and the translation of metaphors across disciplines may be fraught, a recasting of our analytic approach to health and aging is now warranted, as is the pursuit of new data and methods to test it. Although the punctuated equilibrium perspective reduces our ability to rely on gradualist models to depict and predict individual and population health patterns, the need to understand these patterns remains as strong as ever.

Figures

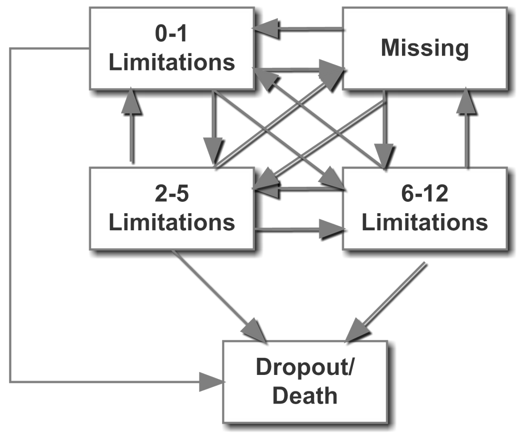

Figure 1: Multi-State Model

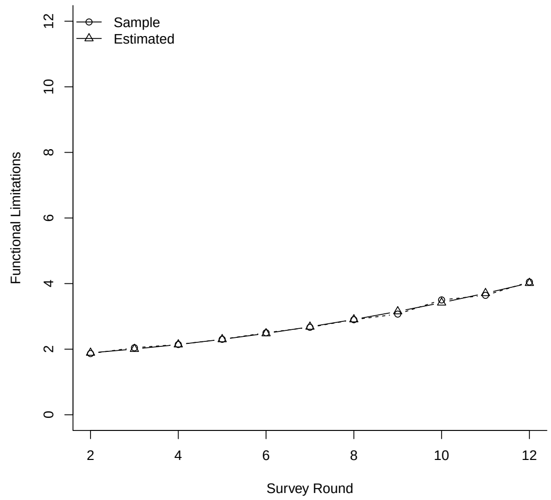

Figure 2: Latent Growth Curve with Quadratic Slope (n=9706)

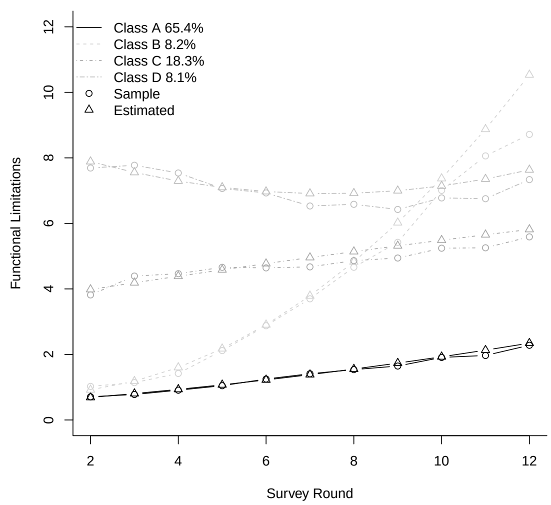

Figure 3: LCGA: Four Class Model with Quadratic Slope (n=9706)

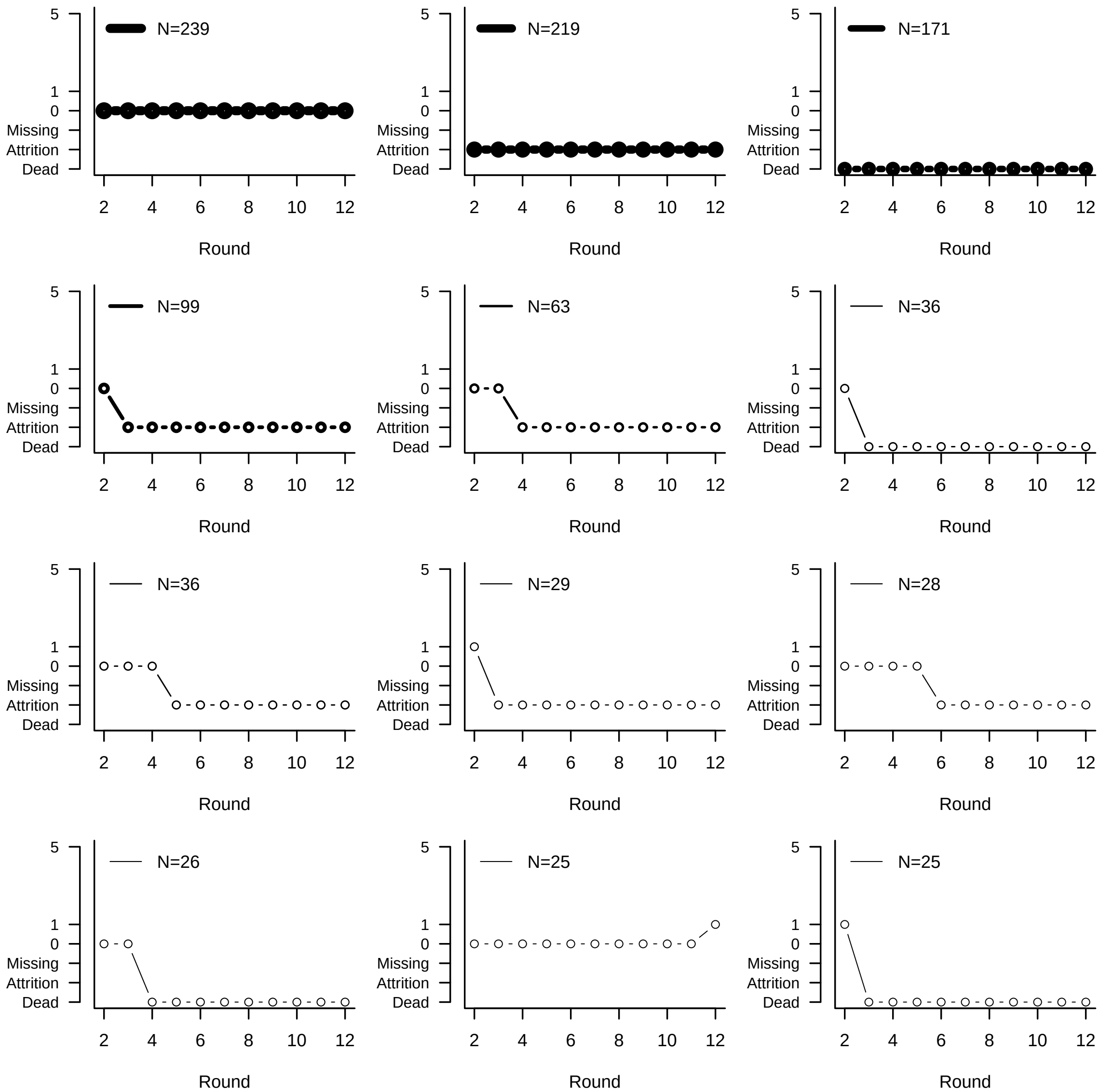

Figure 4: Sequence Analysis: Most Common Trajectories (n=10,198)

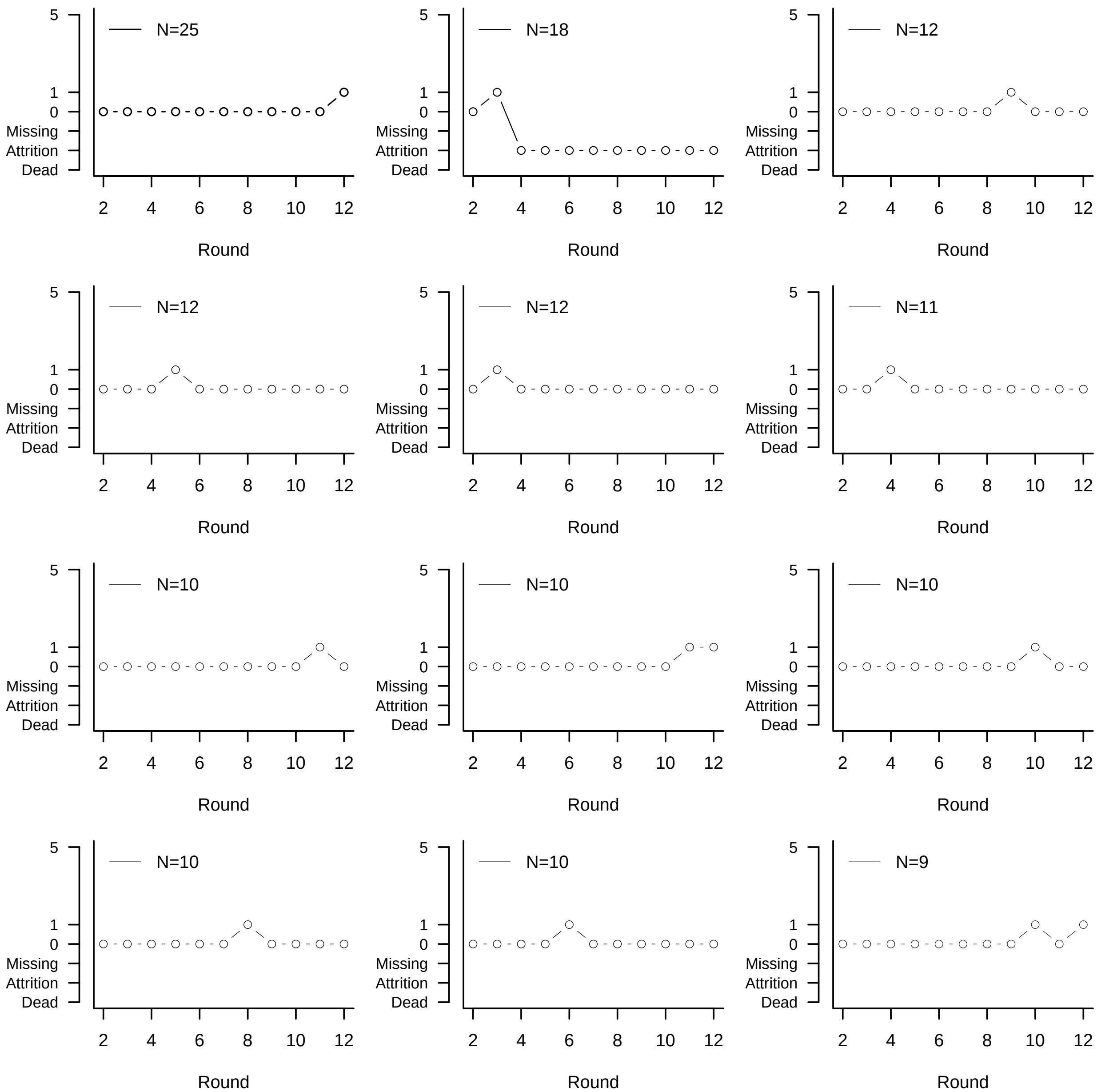

Figure 5: Sequence Analysis: Most Common Trajectories with Any Increase (n=7,235)

Tables

Parameter	
Linear Slope With Intercept	-0.14***
Quadratic Slope With Linear Slope	-0.02***
Quadaratic Slope With Intercept	0.005*
Mean	
Intercept	1.89***
Linear Slope	0.11***
Quadaratic Term	0.01***
Variance	
Intercept	4.86***
Linear Slope	0.26***
Quadratic Slope	0.00***
* P<.05 **P<.01 ***P<.001	

Table 1: Parameters from Best Fitting Latent Growth Curve with Quadratic Slope (n=9706)

Table 2: Descriptive Statistics on Chronic Conditions, Functional Limitations, and Limitations in ADLs

	(1)		
	Chronic Conditions	**Functional Limitations**	**Limitations in ADLs**
	N=9658	**N=9141**	**N=9143**
Panel 1			
Average Number at First Round Observed	1.05	1.85	0.14
Average Number at Last Round Observed	2.76	3.61	0.63
Minimum Number Observed	1.05	0.90	0.04
Maximum Number Observed	2.76	4.84	0.94
Panel 2			
Percent with Increase Between First and Last Round Observed	0.80	0.59	0.24
Percent with No Change Between First and Last Round Observed	0.20	0.25	0.73
Percent with Decrease Between First and Last Round Observed	–	0.16	0.03
Panel 3			
Percent with Any Increase Across Rounds Observed	0.80	0.79	0.37
Percent with No Change Across Rounds Observed	0.20	0.09	0.60
Percent with Any Decrease Across Rounds Observed	–	0.44	0.06
Panel 4			
Average Number of Increases Across Successive Survey Rounds	1.40	2.47	0.68
Average Number of Successive Survey Rounds with No Change	6.30	2.75	6.02
Average Number of Decreases Across Successive Survey Rounds	–	1.94	0.45

Table 3: Estimated Transition Probabilities from Best Fitting Multi-State Model N=9706

			Rounds 2 to 5		
	0 to 1 Limitations	2 to 5 Limitations	6 to 12 Limitations	Missing	Dropout/Died
0 to 1 Limitations	0.74	0.16	0.02	0.03	0.04
2 to 5 Limitations	0.25	0.55	0.13	0.03	0.06
6 to 12 Limitations	0.05	0.22	0.60	0.03	0.10
Missing	0.26	0.14	0.06	0.52	0.01
Dropout/Died	0	0	0	0	1
			Rounds 6 to 8		
	0 to 1 Limitations	2 to 5 Limitations	6 to 12 Limitations	Missing	Dropout/Died
0 to 1 Limitations	0.71	0.20	0.02	0.03	0.04
2 to 5 Limitations	0.21	0.58	0.14	0.02	0.05
6 to 12 Limitations	0.04	0.23	0.60	0.02	0.11
Missing	0.23	0.18	0.09	0.49	0.02
Dropout/Died	0	0	0	0	1
			Rounds 9 to 12		
	0 to 1 Limitations	2 to 5 Limitations	6 to 12 Limitations	Missing	Dropout/Died
0 to 1 Limitations	0.68	0.22	0.03	0.01	0.07
2 to 5 Limitations	0.17	0.56	0.17	0.01	0.09
6 to 12 Limitations	0.03	0.17	0.60	0.01	0.19
Missing	0.27	0.25	0.19	0.25	0.05
Dropout/Died	0	0	0	0	1

Appendix A: Tables

Table A1: Fit Statistics for Latent Growth Curve Models

Model	AIC	SABIC	RMSEA	CFI	TLI
Linear Latent Growth Curve	311461.707	311525.749	0.073	0.950	0.955
Quadratic Latent Growth Curve	309720.802	309800.855	0.051	0.977	0.978

Table A2: Fit Statistics for LCGA Analysis

Sample Adjusted BIC	
2 class linear	308003.334
2 class quadratic	306178.625
3 class linear	306664.58
3 class quadratic	304585.4
4 class linear	305882.043
4 class quadratic	303683.76
5 class linear	305273.165
5 class quadratic	–
6 class linear	–
6 class quadratic	–

Table A3: Prevalence of Gradually Increasing Functional Limitations

Successive Increase Through	Starting Sample Observed at Round 2
	N=8,825
Round 3	2,487
Round 4	504
Round 5	77
Round 6	12
Round 7	5
Round 8	1
Round 9	0

Table A4: AIC for Multi-State Models

Model	AIC
Transition Probabilities Constrained to be Constant Across Rounds	159407.1
Transition Probabilities Constrained to be Constant Between Rounds 2 to 5, 6 to 12	158736.4
Transition Probabilities Constrained to be Constant Between Rounds 2 to 5, 6 to 8, 9 to 12	158209.4

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