Center for Demography and Ecology

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Andrew Halpern-Manners
John Robert Warren
James Raymo
D. Adam Nicholson

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Andrew Halpern-Manners
Indiana University

John Robert Warren
University of Minnesota

James Raymo
University of Wisconsin-Madison

D. Adam Nicholson
Indiana University

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Abstract

Motivated by theoretical and empirical research in life course sociology, we examine relationships between trajectories of work and family roles across the life course and five measures of economic well-being in later adulthood. Using data from the Wisconsin Longitudinal Study (WLS), we first identify latent trajectories of work and family roles between late adolescence and age 65. We then model economic well-being (at age 65) as a function of these trajectories and contemporaneously measured indicators of older adults' work, family, and health statuses. Our central finding is that trajectories of work and family experiences across the life course have direct effects on later-life economic well-being, as well as indirect effects that operate through more proximate measures of work, family, and other characteristics. We argue that these findings have important implications for how social scientists conceptualize and model the relationship between later-life economic outcomes and people's work and family experiences.

The Impact of Work and Family Life Histories on Economic Well-Being at Older Ages

Americans' work and family lives have become increasingly complicated over the last quarter century. Declining employment security (Beck 2000; Farber 2010; Hacker 2008; Kalleberg 2000), growing exposure to "bad jobs" (Findlay, Kalleberg, and Warhurst 2013; Kalleberg 2011; Kalleberg 2009; Mishel, Bernstein, and Allegreto 2007; Presser 2005; Raymo et al. 2011), and increases in divorce, cohabitation, and stepfamily formation (Bianchi and Milkie 2010; Bumpass and Lu 2000; Cherlin 2009; Kennedy and Ruggles 2014; Seltzer 2000) have all contributed to greater variability in work and family experiences across the life course. Together, these changes have produced a "new narrative" surrounding work and family life (Hollister 2011), in which long-term stability (e.g., continuous work for a single employer or a smooth, unidirectional progression from being single, to getting married, to having children, to being an "empty nester") has been replaced by more frequent transitions, shorter-term arrangements, and considerably more intra-individual life-course complexity.

This shift presents a challenge for researchers who are interested in studying the relationship between individuals' work and family experiences and their well-being during later adulthood. Due to the limited availability of detailed life history data, researchers are often forced to rely on static cross-sectional measures (e.g., employment status at a certain age or marital status at a particular point in time) or blunt summary indicators (e.g., "ever divorced" or "total number of jobs held") to characterize what are often very complicated biographies, both at work and at home. Although these analyses are of considerable scientific value, they typically lack information concerning the timing, duration, and sequencing of adults' work and family roles (Han and Moen 1999; Mayer 2010; Pearlin et al. 2005; Umberson, Pudrovska, and Reczek 2010). This empirical "blind spot" could have serious consequences, especially given increasing variation in the structure, stability, and patterning of people's working careers and family lives.

In this article, we start from the premise that variation in later-life outcomes should be understood as a consequence of heterogeneity in earlier-life factors and that these earlier-life factors influence later-life outcomes through complex, temporally organized pathways that are typically not well understood. To understand well-being at a given age it is therefore not enough to know about people's circumstances *at that age*; one must also consider longer-term trajectories in the labor market, at home, and in other social domains. To evaluate the merits of this argument, we examine the relationship between long-term trajectories of work and family experiences and individuals' economic outcomes during later adulthood. Our primary objective is to determine how lifelong patterns of work and family experiences combine to influence people's economic resources at older ages—and what kinds of data are needed to model these processes properly. We believe that the answers to these questions have important implications for life course theory and research.

Background

Heterogeneity in economic well-being at older ages has received considerable scholarly and policy attention in recent years. Studies have shown that income inequality among Americans over the age of 65 is increasing (Burtless 2009; O'Rand 1996; Smeeding 2006; Smith 1997), and that many older adults are not financially prepared for life after retirement (Malone et al. 2010; Munnell and Quinby 2009; Ozawa and Tseng 2000; Sass, Monk, and Haverstick 2010). Projections now indicate that as much as 35% of the early baby boom cohort (individuals born between 1946-1954) will not be able to maintain their pre-retirement standard of living, even if they work full time until age 65 (Munnell, Golub-Sass, and Webb 2007). Over the last decade, social scientists have linked these trends to the shift toward greater individual responsibility for financing the retirement years (Hacker 2008; Munnell and Sass 2008), the growing importance of financial literacy (Lusardi and Mitchell 2011), and the increasing need for long-term financial planning (Ekerdt 2004).

At the same time that Americans are required to assume more responsibility for their financial security, the labor market and family contexts in which individuals' lives unfold have undergone profound changes. Since the early 1970s, the labor market has been characterized by reductions in job security, wage security, and access to benefits (Hacker 2008). Kalleberg (2009) argues that layoffs have become a basic component of employers' restructuring strategies and that precarious employment has spread from unskilled, less-educated segments of the labor force to all sectors of the economy. Involuntary job loss is a widely-used indicator of employment insecurity (Brand, Levy, and Gallo 2008), and recent research shows that the proportion of employees who experience involuntary job loss in a given three-year period has fluctuated between 9% and 13% since the 1980s (Farber 2005). Estimates from the Bureau of Labor Statistics indicate that more than 30 million involuntary job losses occurred between the early 1980s and 2004 (Kalleberg 2009).

Family life has also become more differentiated over this period. Rates of marital dissolution have increased dramatically, with the sharpest increase in divorce rates occurring among men and women born between 1936 and 1945 (Hughes and O'Rand 2004). Although divorce tends to reduce economic well-being in later life, especially for women, the impact of divorce on economic well-being depends on a number of factors, including age at divorce, gender, number of children, and work history (O'Rand and Henretta 1999). Variation in age at first childbirth has also increased in recent decades (Hughes and O'Rand 2004), with implications for the timing and duration of childrearing responsibilities (Martin 2000; Smock and Greenland 2010). Taken as a whole, these dramatic changes in family behavior and family structure have resulted in increasing variation across the life course in marital status, the number of marriages, and the presence of children in the household (Cherlin 2009)—all of which are well-documented correlates of economic well-being (see, e.g., Hao 1996; Smock, Manning, and Gupta 1999)

Theories of cumulative advantage and the life course

The combination of increasing individual responsibility for financial preparation for old age and growing diversity and instability in work and family lives has spurred efforts to understand the ways in which experiences *across the life course* contribute to within-cohort variation in economic resources at older ages. The theory of cumulative advantage posits that differences in individuals' well-being are compounded over time to generate larger differentials at later points in the life course (see, e.g., Dannefer 1987; DiPrete and Eirich 2006; Willson, Shuey, and Elder 2007). Initial individual differences—by race, gender, or socioeconomic status—give rise to unique (and often unequal) opportunity structures and life pathways, which serve to further differentiate individuals as they age. The linkage of individual lives to historical events (e.g. wars, economic downturns) and institutional arrangements (e.g. employment, family) produces individual biographies that heighten intra-cohort heterogeneity in financial resources, health, and other important later-life outcomes.

This basic theoretical perspective is embedded within the more general life course framework. Life course research recognizes that individuals' past experiences have enduring consequences for their later-life outcomes (Elder, Johnson, and Crosnoe 2004). Throughout their lives, individuals occupy particular roles or statuses—e.g., as workers, spouses, or parents. Trajectories refer to the sequences of these roles or statuses within specific social pathways, such as employment or family life (Elder et al. 2004; Elder 1985). Trajectories vary depending on (1) the particular statuses of which they are composed, (2) the duration of time spent in each status, and (3) the timing and frequency of transitions between statuses. According to cumulative advantage theory, individuals experience a unique temporal ordering of roles and statuses as they age, which produce trajectories that are increasingly dissimilar from other members of their cohort. Differentiation in these trajectories contributes to heterogeneity in well-being at older ages (DiPrete and Eirich 2006).

The application of these ideas to the study of later-life economic outcomes is straightforward. Based on DiPrete and Eirich's (2006) "path-dependent" model of cumulative advantage, one would expect to see differences in financial well-being between two individuals whose work and family statuses at time t (e.g., married, employed, parent, holder of a well-paying job, etc.) are identical, but whose *prior history* of these characteristics (in all periods leading up to time t) differs in meaningful ways. Under this model, individuals' past experiences (at work and at home) not only influence their future experiences (at work and at home), but also have direct effects on their later-life economic outcomes. The causal pathways implied by this model are depicted in Figure 1, with arrows linking individuals' prior work and family circumstances to their current work and family circumstances ($A \rightarrow A'$), their current work and family circumstances to their current financial well-being ($A' \rightarrow Y$), and their prior work and family circumstances to their current financial well-being ($A \rightarrow Y$).

To make this model more concrete, consider the relationship between employment instability and later-life net worth. In most cases, unstable work patterns during mid-life—characterized by experiences of dismissal, part-time work, working in "bad" jobs, and/or frequent employer changes—will limit the ability to accumulate assets (Gangl 2006). These disruptions could, in turn, place constraints on a person's future financial resources—a direct effect stemming from a gap in employment and an associated loss in earnings and investment ($A \rightarrow Y$). If they are sufficiently severe, these disruptions could also have collateral consequences for important downstream variables ($A \rightarrow A'$). Marriage (Amato and Beattie 2011), health (Young 2012), and future work behaviors (Gangl 2005) have all been linked to employment instability—and could all have an influence on later-life outcomes ($A' \rightarrow Y$). The end result is a combination of direct and indirect effects, with future work, family, and health-related variables serving as the primary mediators.

[FIGURE 1 ABOUT HERE]

Although this conceptual model may seem intuitive, it has rarely been subjected to direct empirical testing. Instead, scholars have typically focused on estimating the relationship between A' and Y, with little attention to direct ($A \rightarrow Y$) and indirect ($A \rightarrow A' \rightarrow Y$) effects emanating from individuals' prior work and family roles (A).[1] Examples include Farkas and O'Rand's (1998) study of

[1] Most researchers recognize—at least on a conceptual level—that it would be preferable to model data on the entirety of the life course (i.e., $A' \rightarrow Y$, $A \rightarrow Y$, and $A \rightarrow A' \rightarrow Y$). The problem is that the necessary data typically do not exist—and even when they do exist, it is often unclear which methods should be used to analyze them (Warren et al. 2013). In this paper, we consider a variety of estimation strategies and data types in an effort to provide clarification on these issues.

employment status and pension receipt among older women; Yabiku's (2000) study of marriage, parenthood, and job benefits; Lum and Lightfoot's (2003) study of health and later-life retirement savings; and Gustman and Juster's (1996) study of marital status and income. In all of these analyses, the implicit (but generally untested) assumption is that personal biographies (with respect to employment histories, workplace opportunities and exposures, marital histories, parenthood, and so on) are irrelevant once more proximate indicators of people's work and family circumstances (i.e., A') are taken into account.

As a strategy for identifying factors that contribute to variation in financial well-being at older ages, we worry that this approach may obscure important variation in individuals' prior work and family experiences. Even among older adults who are all married, who all have children, and who all work full time, there will be differences with respect to when they married; whether and when they divorced or were widowed and then remarried; when they had children; the age at which they first worked full time; how many jobs they ever lost involuntarily; how many jobs they held across their careers; how the characteristics and/or quality of their jobs varied over time; and so on. According to the life course perspective and to theories of cumulative advantage (see, e.g., Dannefer 2003; DiPrete and Eirich 2006; O'Rand and Henretta 1999), this heterogeneity in lived experiences should matter for people's later-life economic outcomes regardless of their work and family circumstances at the time that their economic outcomes are assessed.

To convincingly test this hypothesis, one must have access to finely-grained data that include detailed information about people's past work and family experiences. As we noted earlier, this requirement presents a steep hurdle. Because the collection of detailed life histories is timeconsuming and expensive, many sources of data on older adults' financial well-being offer an incomplete record of their work and family biographies. Helpful summary measures (e.g., number of years in the labor force or number of jobs held) can be constructed using nationally-representative surveys like the Health and Retirement Study (HRS), but these data generally do not offer the level of detail that would be required to characterize the full longitudinal sequencing, timing, structure, and context of older adults' work and family roles. Despite well-developed *theory* about the importance of life-long trajectories at work and at home, *actual measures* that capture the richness and complexity of people's lived experiences remain very difficult to produce.[2]

In this article, we address this limitation using nearly 50 years' worth of detailed life history data that were collected as a part of the Wisconsin Longitudinal Study (WLS). Drawing on the life-course perspective and the conceptual framework outlined by DiPrete and Eirich (2006), we specify a model of later-life economic outcomes that allows for complex direct and indirect effects stemming from individuals' previous work and family circumstances (i.e., $A \rightarrow Y$, and $A \rightarrow A' \rightarrow Y$). Our approach—

[2] One area where detailed trajectories of respondents' life experiences have been constructed is in the literature on marital status (see, e.g., Addo and Lichter 2013; Tamborini, Iam, and Whitman 2009). Results from this research suggest that people's sequences of marital statuses *are* associated with inequality in later-life financial well-being, and that these effects persist after controlling for summary measures of current or past marital status. This finding is consistent with our central hypothesis that economic well-being at older ages is the cumulative result of a lifetime's worth of experiences in the labor market, the family, and other social contexts.

which we describe in substantially more detail below—allows us to (1) characterize the timing, duration, and sequencing of individuals' experiences in the labor market and at home; and (2) evaluate life course ideas about the ways in which heterogeneity in later-life outcomes are related to people's long-term trajectories of work and family experiences. In carrying out these analyses, we seek to provide new and important information about the *lifelong* processes that contribute to economic inequality among older adults.

Data and methods

In this section, we provide a detailed description of our data and measures. We then go on to describe the methodological approach that we use to (1) concatenate people's long-term history of work and family experiences into a limited number of qualitatively distinct trajectory groups; and (2) relate these trajectories to respondents' later-life economic outcomes.

Data

The Wisconsin Longitudinal Study (WLS) is a long-term study of a random sample of 10,317 men and women who graduated from Wisconsin high schools in 1957 (Sewell et al. 2004). WLS "graduates" were interviewed in 1957, 1975, 1992, 2004, and 2011; and spouses of the original respondent were interviewed in 2004. The WLS graduate sample is broadly representative of white, non-Hispanic Americans who have completed at least a high school education—a group that includes approximately two-thirds of all Americans belonging to this particular cohort (Hauser 2005). Response rates to WLS telephone and mail surveys have been consistently high. Responses were obtained from 88% of surviving graduates' parents in 1964 and from 90% of surviving graduates in

1975. In 1993, 87% of surviving graduates responded to the telephone survey and 71% responded to the mail survey. In 2004, 78% of surviving graduates responded to the telephone survey and 76% responded to the mail survey.[3]

The 1975 through 2004 WLS telephone surveys collected detailed information on marriage, childbearing, and most of the jobs that respondents ever held, allowing us to construct work and family histories in greater detail than in previous studies. In 1993 and 2004, the WLS telephone surveys obtained essentially complete employment histories for graduates covering the period 1975 through 2004 (or ages 36 through 65). The 1975, 1993, and 2004 telephone surveys obtained complete

[3] We found some evidence of differential attrition when examining respondents' baseline characteristics. To adjust for these differences, we generated predicted probabilities of attrition and then used these probabilities to re-weight the data. This procedure is known as inverse propensity weighting (Robins, Rotnitzky, and Zhao 1994). To create the necessary weights, we fit a logistic regression model predicting attrition, where attrition was expressed as a function of the baseline characteristics whose means or proportions were significantly different between those who were in-sample in 2004 and those who were not. We then took the inverse of the predicted probability and used it to obtain weighted estimates. The characteristics that we included in our model of attrition were cognitive ability (Henmon-Nelson Test of Mental Ability scores), SES (Duncan's SEI for father's 1957 occupation), farm origins, parents' income (from tax records), and attractiveness (measured using yearbook photos). For more information about these variables see Hauser (2009).

marital histories through 2004 (or age 65). Rich information on health, work, and family circumstances collected in the 2004 survey allows us to construct a comprehensive set of established temporally proximate correlates of economic well-being (A' in Figure 1), as observed at or around age 65. Finally, the WLS collected multiple measures of economic well-being in 2004 (Y in Figure 1), including personal and household income, savings, net worth, and home equity (as we describe in more detail below). All measures are available for male and female respondents.

Our analyses are initially restricted to the 3,249 male and 3,785 female graduates who responded to the 1993 and 2004 telephone surveys; without this restriction we cannot observe complete trajectories of work and family roles. We then removed respondents whose birth year was not ascertained (and who may not have been a member of the modal birth cohort) and whose life history data were completely missing (n = 18). Our final analytic sample of 7,016 individuals includes about 78% of the 9,030 graduates who survived to 2004, nearly a half century after they were first enrolled in the WLS. To ease the impact of item-level missing data, we multiply imputed missing values using chained equations in Stata, where the number of imputed data sets equaled 10. Following von Hippel's (2007) recommendations, we included observations with missing values on the dependent variables during imputation but deleted them prior to estimating our substantive models. This leads to some minor variation across models with respect to sample size (as shown below).

Measuring economic well-being at older ages (Y)

Economic well-being (or Y) is a multi-dimensional construct that can be measured in a variety of ways (see, e.g., Angel, Jiménez, and Angel 2007; Haveman et al. 2003; Kahn and Pearlin 2006;

Sorokina, Webb, and Muldoon 2008; van der Klaauw and Wolpin 2008). In an effort to capture as many different aspects of economic well-being as possible, and in order to allow for the possibility that different economic outcomes exhibit different relationships to respondents' work and family experiences, we examined five commonly-used indicators of financial security—all of which were collected as a part of the 2004 phone survey when most respondents were 64. Independent reports obtained through the 2004 survey of WLS spouses suggest that the reliability of our measures is relatively high (e.g., the correlation between graduates' and spouses' answers to identically worded questions about home equity was $r = 0.74$). Below, we describe the five measures that we use in our analysis, and in Table 1 we provide basic descriptive statistics for each variable.

[TABLE 1 ABOUT HERE]

Our first measure of economic well-being is respondents' net worth; this variable reflects the total market value of respondents' home(s), other real estate, farms, vehicle(s), savings, and investments, minus any debt owed on those assets. We express net worth in logged dollars; for the small number of respondents with negative or zero net worth, we assigned a value of $1 before taking the log. Our second measure, home equity, is based on a series of items that assess whether respondents own their own homes, how much the home is worth, and how much they owe on their homes; respondents who did not own their homes are assumed to have $0 in home equity. Our third measure provides information about respondents' savings and investments, which include checking, savings, and money market funds; certificates of deposit and government savings bonds; treasury bills, stocks, bonds, and mutual funds; and other assets. As with net worth, we express home equity and savings and investment assets in log dollars (after adding a small constant for respondents with

$0 in home equity).

Our fourth and fifth measures of economic well-being provide information about respondents' personal and household income, respectively. Household income includes wages, farm income, interest income, social security benefits, pensions, public assistance, other government programs, child support, alimony, and other sources of income for all members of respondents' households (to adjust for differences in household size, we divide household income by the square root of household size and re-express in logged dollars). Personal income is the total amount that respondents received from the various sources listed above, and is also expressed in log dollars. The descriptive statistics shown in Table 1 suggest that, on average, women earn less than men and have lower net worth; that men tend to live in homes with a higher net value; and that women's later-life financial outcomes are somewhat more variable (as indicated by larger standard deviations). These descriptive patterns are generally consistent with prior research (see, e.g., Bernasek and Shwiff 2001).

Proximate predictors of economic well-being (A´)

Our models predicting economic well-being include several measures of respondents' labor force and family circumstances as observed at age 64—these indicators can be thought of as *A´* in Figure 1. Measures of labor force conditions include employment status (employed or not employed); retirement status (partially retired, completely retired, or not retired); whether respondents' current or most recent employer offered them pension benefits and/or health insurance; and the prestige of respondents' current or last occupation (measured in terms of occupational earnings).[4] Measures of family circumstances at age 64 include number of children; an indicator of whether respondents have any long-term activity-limiting health condition; a measure of respondents' self-assessed overall health (excellent, good, or otherwise); an indicator of marital status (married or not married); an indicator of spouses' employment status (employed, not employed, or not married); and an indicator of spouses' overall health (excellent, very good, fair/poor/very poor, or not married). Descriptive statistics for each of these variables can be found in Table 2.

[TABLE 2 ABOUT HERE]

Identifying trajectories of work and family experiences (A)

We characterize respondents' work and family experiences (or *A*) in two ways: first, we model work- and marital-history data using three different statistical approaches that (1) estimate the number of latent trajectories in the population; (2) assign individuals to one of these trajectories using a probabilistic approach; and (3) quantify uncertainty in both (1) and (2). Second, we use work- and marital-history data to construct comparatively simple summary measures. Both types of measures are based on data collected in the 1975 through 2004 telephone surveys. The resulting work history data reflect employment circumstances at six month intervals from 1975 (age 36) through 2004; the

[4] Occupational earnings is defined as the percentage of people in a given occupation who reported hourly wages of at least $14.30 in the 1990 census. See Warren, Sheridan, and Hauser (1998) for more information.

resulting marital history data characterize marital status at six month intervals from 1955 (age 16) through 2004. Using each method, we model trajectories of employment status (i.e., employed or not); occupational standing (i.e., whether respondents' occupations were in the bottom quartile of the occupational earnings distribution); pension and health insurance availability (i.e., whether respondents' employers offered these benefits); and marital status (i.e., married or not).[5]

Our statistical approaches to operationalizing trajectories of work and marital roles include latent class analysis (see, e.g., Clogg 1995), latent class growth models (see, e.g., Nagin 2005), and growth mixture models (see, e.g., Muthén 2004).[6] Using each method, and separately for each type of trajectory, we begin by estimating models that specify 1, 2, …, *k* trajectory groups. Based on a combination of formal (BIC, AIC, and LMR-LRT) and informal (size of the smallest group, and the distinctiveness of the trajectory shapes) criteria, we identify the best-fitting model and infer the appropriate number of trajectory groups; the results of each model also identify the latent trajectory that best describes each individual's observed experiences. Our decision to use multiple methodologies was informed by Warren et al.'s (2013) work, which suggests that different estimators can sometimes produce different results with respect to the number, shape, and composition of latent trajectory classes. Information on model fit—presented separately for men and women and for each of the three methods that we employ—can be found in Appendix Tables A1a-c (online).

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[5] The cutoff that we used to define low occupational standing—i.e., whether respondents' were in the bottom quartile of the occupational earnings distribution—is gender- and year-specific.

[6] See the technical appendix for more information about these methods.

For reasons that we describe below, we also use work- and family-history data to construct a series of simpler summary measures. Our work measures—which describe the period 1975 (usually age 36) through 2004—include number of years employed; whether respondents ever worked at a job that offered pension benefits; whether respondents ever worked at a job that offered health insurance benefits; and whether respondents ever lost a job involuntarily. Our family measures—which describe the period between 1955 (usually age 16) and 2004—include number of times married; age at first marriage; and whether respondents were ever divorced or widowed. The measures of age at first marriage and age at parenthood are categorical, and express whether respondents made those transitions at the modal sex-specific ages (as opposed to making those transitions earlier or later than the average WLS respondent). These measures—which are summarized in Table 3—are meant to approximate the kinds of variables that can be constructed using simple retrospective reports.

[TABLE 3 ABOUT HERE]

Testing for direct ($A \rightarrow Y$) and indirect effects ($A \rightarrow A' \rightarrow Y$)

Life course theory and theories of cumulative advantage both suggest that individuals' prior work and family experiences should have an influence on their later-life well-being—even after controlling for more proximate, point-in-time predictors. To test this hypothesis we fit a series of multiple mediator models (Breen, Karlson, and Holm 2013), where the key independent variables (A) are our trajectory-based measures; where the mediators (A') are our contemporaneously-measured work, family, and health status indicators; and where the outcomes (Y) are the five economic variables that we described earlier. All models were fit separately by gender to allow for the possibility that the processes in question operate differently for men and women. The specific parameters that we estimate are (1) the total effect of A on Y, (2) the direct effect of A on Y, and (3) the indirect effect of A on Y through A'. If theories of cumulative advantage hold, we would expect to see statistically significant values for each of these three quantities. That is, people's past work and family experiences should have both direct and indirect effects on their later-life economic outcomes.

We fit our multiple mediator models using the user-written *khb* routine in Stata. The routine—which can flexibly estimate models with linear or non-linear outcomes, and which can accommodate continuous and/or categorical mediators—allows researchers to decompose the total effects associated with a given variable (or set of variables) into direct and indirect effects (see Breen, Karlson, and Holm 2013). The decomposition is accomplished by comparing the coefficients obtained from a "reduced model" (without mediators) to a fully specified model (with mediators). The coefficients obtained from the reduced model provide an estimate of the total effects associated with the variables of interest (i.e., respondents' trajectories of work and family experiences); the coefficients obtained from the full model provide an estimate of the direct effects; and differences between these two sets of coefficients provide an estimate of the indirect effects (i.e., the effects that are transmitted via more proximate indicators of respondents' work and family circumstances). See Breen, Karlson, and Holm (2013) and Kohler, Karlson, and Holm (2011) for more details.

Comparing sophisticated trajectory-based measures to simpler summary indicators

The theoretical framework outlined earlier also predicts that the temporal properties of people's experiences (e.g., the amount of time they spent in a "good" job or the age at which they entered the labor force) should bear directly on their financial situation later in life. One corollary of this hypothesis is that detailed trajectory-based indicators—that characterize the full longitudinal patterning of people's experiences—should provide additional information above and beyond what is contained in simpler summary measures, which are easily collected and commonly available in retrospective surveys but do not fully capture the temporal properties of adults' work and family roles. This corollary can be tested by comparing the results obtained from models that include trajectory-based indicators to the results of models that include less-detailed characterizations of respondents' work and family experiences. If the trajectory-based indicators provide additional explanatory power, we can infer that detailed life history data (and methods that are capable of harnessing such data) are needed to effectively model heterogeneity in later-life economic well-being. This finding would provide further support for the life course perspective, and would underscore the value of prospective studies that collect detailed information on work and family experiences across respondents' life course.

Results

Before addressing our two main research questions, we first summarize the results we obtained from our three methods of generating discrete and qualitatively distinct work and family trajectories. Table 4 presents the distribution of the sample with respect to trajectory group membership, separately by sex and method, with trajectory groups ordered from highest to lowest prevalence. Each trajectory has been given a qualitative label that describes its basic shape (e.g., "Consistently employed", "Late entry", "Intermittent/no employment," "Retired in early 60s"); the relative size of each trajectory is provided in the columns adjacent to the labels.[7] Reassuringly, there appears to be little variation across estimators with respect to the number of estimated trajectory groups. The only inconsistencies that we observed were for our measure of marital status (our preferred LCGA identified three trajectories for women as opposed to four). There were no inconsistencies across estimators for the bad jobs, employment status, health insurance, or pension variables. Each of these measures produced four latent trajectories, regardless of the estimation strategy that we used.

[TABLE 4 ABOUT HERE]

A closer inspection of the percentages presented in Table 4 reveals some interesting patterns. According to the results, the modal experience for both women and men involved marrying in their mid-20s, working full-time throughout mid-adulthood, having access to employer-provided health and pension benefits, and spending very little time in what we classify as "bad jobs". These can all be considered fairly stable (and easy to summarize) trajectories, given how few changes people made across ages with respect to work and family roles. In contrast, we also found evidence of more complicated trajectory groups (especially among women). These included a late marriage and multiple marriage group; an early retirement group; a group that moved out of bad jobs; a group that moved into them; a group that lost benefits; a group that gained benefits; and, among women only, a group that delayed entry into the labor market until middle adulthood. In the remainder of our analysis, we turn our attention to the relationship between these diverse—and often complicated—life pathways and respondents' economic well-being at older ages.

[7] Group sizes are based on the estimated posterior probabilities of group membership.

The relationship between long-term trajectories and later-life outcomes

Our first research question is whether detailed trajectories of work and family experiences are related to economic outcomes in later adulthood even after we control for work, family and other circumstances as measured at the time that respondents' financial outcomes are observed (i.e., at age 65). As mentioned above, we sought to answer this question by estimating the total, direct, and indirect effects associated with older adults' long-term work and family experiences (using a series of multiple mediator models). Results from these analyses are presented in Table 5, separately by gender, outcome, and trajectory-generating method. To facilitate interpretation, each cell provides a *p*-value corresponding to an *F*-test of the hypothesis that the trajectory-based indicators have jointly significant (direct, total, or indirect) effects on the economic outcome in question. Bolded *p*-values are less than or equal to 0.05.

[TABLE 5 ABOUT HERE]

Overall, the results appear to be consistent for men and women, similar across financial outcomes, and (mostly) robust to our choice of trajectory-based estimation strategy. In nearly every case, we found that respondents' trajectories of work and family experiences have significant total, direct, and indirect effects on their later-life financial well-being. This implies that our trajectory-based measures are predictive of older adults' economic outcomes (i.e., past experiences matter); that the effects persist after controlling for more proximate predictors of those same outcomes (i.e., past experiences have *lagged* effects on adults' later life well-being); and that the total effects associated with past work and family experiences are partially, but not completely, transmitted through more proximate channels (i.e., past experiences have effects that ripple through the life course, influencing subsequent statuses, and, in turn, later life well-being). We take this as important evidence of the long-term influence of life trajectories that has been posited, but not empirically validated, in previous research on processes of cumulative advantage.

[TABLE 6 ABOUT HERE]

To give a better sense for how trajectories of work and family experience are related to later-life economic outcomes, Table 6 provides results from models predicting (logged) net worth when trajectories are identified using latent class growth models; detailed results for other outcomes and/or trajectory-based estimators are available upon request. The coefficients pertaining to the proximate predictors—which are not shown in the table, but which are available in the online appendix—are mostly unsurprising: people who had good jobs, who were in excellent or very good health, and whose spouses were in excellent or very good health tended to have higher net worth at age 65, all else equal. The coefficients pertaining to the trajectory-based indicators are also unsurprising: after adjusting for proximate predictors, we observed significant and negative effects for respondents who had a weak or intermittent attachment to the labor force, whose jobs were in the bottom quartile of the occupational earnings distribution, who did not receive pension benefits (or who only received such benefits later in life), and who married multiple times or remained unmarried throughout the majority of their adult life.

Trajectory-based measures versus simpler summary indicators

Our second empirical question is whether statistically sophisticated measures of work and family trajectories predict later-life economic well-being better than simpler summary indicators. To answer this question, we compare the model fit obtained from models that include summary indicators and proximate variables to the model fit obtained when we include summary indicators, proximate variables, *and* trajectory-based measures. Because the first set of models is nested within the second, we can evaluate their relative performance using a Wald test. The null hypothesis for the test is that the inclusion of the trajectory-based measures provides no additional explanatory power (i.e., the joint effect of the trajectory measures is not significant net of the summary indicators and proximate variables). If we are able to reject this hypothesis, it would imply that the timing, duration, and/or sequencing of respondents' work and family experiences—which are not captured by summary measures and proximate variables, but which are captured by our trajectory-based indicators—have important consequences for our understanding of later-life well-being.

[TABLE 7 ABOUT HERE]

Results from these model comparisons are provided in Table 7. As with our previous findings, we provide *p*-values indicating whether our trajectory-based measures are jointly significant after adjusting for the other variables in the model. Taken together, the results suggest that finely-grained life-history data—and trajectory-based methods that are able to exploit those data—*are* required to effectively model the relationship between work and family experiences and economic outcomes at older ages. Regardless of the method we used, or the financial outcomes we examined, we found that the inclusion of trajectory-based measures improved our ability to explain respondents' later-life well-being (14 out of the 24 hypothesis tests that we conducted produced significant results at the $p < 0.05$ level; and 18 out of 24 were significant at the $p < 0.10$ level). These findings are consistent with empirical predictions derived from the life course perspective: knowing something about the temporal characteristics of people's work and family experiences allows for a better and more refined model of important later-life variables.

Discussion

According to theories of cumulative advantage (see, e.g., Crystal and Waehrer 1996; Dannefer 2003; DiPrete and Eirich 2006; O'Rand 1996; Willson et al. 2007), variation in economic well-being, health, and other later-life outcomes is (at least in part) the product of people's *long-term* exposure to various work and family roles. How much time people spend in different work and family roles, their longitudinal sequencing and timing, how and when they transition between them, their qualitative attributes, and whether and when they experience unanticipated "turning points" all combine to shape later life well-being. A central empirical premise of this perspective is that life course trajectories of work and family roles should matter for later-life well-being, and that the effects associated with these trajectories should operate both directly and indirectly via more proximate predictors. Unfortunately, a lack of suitable data has constrained researchers' ability to test this perspective in a way that does justice to its conceptual and theoretical promise.

To address these issues, we examined two related research questions using rich longitudinal data from a long-term study of men and women who are now entering their retirement years. In the first part of our analysis, we asked whether adults' lifelong *trajectories* of work and family experiences are independently related to their later-life financial outcomes. The answer to this question was a decided "yes." Consistent with theoretical expectations, we found a significant and robust relationship between our trajectory-based measures of adults' work and family experiences and several dimensions of later-life economic well-being. Our results suggest that these effects operate both directly *and* indirectly, with proximate indicators of work, family, and other circumstances serving as mediating variables. These findings were insensitive to the trajectory-based estimation strategies that we used (latent class analysis, latent class growth models, and growth mixture models), and held for each of the financial outcomes that we examined.

In the second part of our analysis, we asked whether statistically sophisticated measures of work and family trajectories—typically based on expensive, prospectively-collected longitudinal data—do more to predict later-life well-being than simpler summary measures of work and family histories, which might be based on more conventional (and easier to obtain) retrospective reports. The answer to this question was also "yes." For most of the models that we estimated, we found that the inclusion of trajectory-based measures improved our ability to predict economic outcomes—even after controlling for point-in-time variables *and* broad summary measures. Our interpretation of this finding is that simpler summary measures—things like number of years worked, whether the respondent ever received pension or health insurance benefits, whether the respondent ever lost a job involuntarily, and whether the respondent was ever divorced or widowed—fail to capture key dimensions of life course pathways that matter for financial well-being later in life.

We believe that these findings have important theoretical implications. Our results suggest that people's work and family experiences have consequences that reverberate across the life course, impacting their future experiences, and ultimately shaping their circumstances as older adults. One can think of this chain of events as a non-Markovian process. Work and family experiences early in life set that stage for work and family experiences later in life, but they also have lagged effects on later-life well-being. This result is consistent with theories of cumulative advantage (DiPrete and Eirich 2006), which suggest that earlier advantages and disadvantages accumulate with time, interacting with unexpected life events (e.g., divorce, job loss) to produce increasing within-cohort variation with respect to financial well-being, health, and other adult outcomes (see, e.g., Dannefer 2003; Ferraro and Shippee 2009; Garbarski 2014; Giudici and Pallas 2014; O'Rand and Hamil-Luker 2005; Petersen et al. 2011; Willson et al. 2007).

Our results also have important practical implications. Researchers and funding agencies are currently making major investments in large-scale longitudinal studies. At the same time, methods for developing complex measures of trajectories are proliferating (Warren et al. 2013). This is despite a lack of sound evidence about whether trajectories matter (for financial outcomes) net of proximal measures; a lack of consensus about how to model trajectory data; and a lack of information about whether simpler summary measures might serve as well as more advanced trajectory-based indicators. Our findings should help to address these concerns. In our analyses, we showed that trajectories *do* matter, that simpler summary measures are *not* as informative as more sophisticated trajectory-based indicators, and that neither of these findings depend on which methods researchers use to model people's long-term work and family experiences. Social scientists who collect, analyze, and/or disseminate life history data should find these results encouraging.

Conclusion

Economic well-being during the retirement years is increasingly dependent upon people's own planning and resources. This policy shift—toward increased individual responsibility—has taken place within the context of growing heterogeneity in people's working careers and family lives. Within the past 50 years, Americans have experienced fundamental changes in the structure of the labor market, in employment relationships, in women's labor force participation rates, and in rates of marital dissolution. These changes have important consequences for how researchers think about and model the relationship between later-life well-being and people's longer-term work and family experiences. Our research shows that economic well-being among older Americans is best understood as the product of a lifetime of accumulated experiences in the two most important social roles that most people occupy: their families and their jobs. We take this as strong evidence in support of the life course perspective and theories of cumulative advantage.

Technical appendix

In recent years, many researchers have turned to finite mixture models as a way to model change within people over time (Halpern-Manners, Warren, and Brand 2009; McLeod and Fettes 2007; Mustillo, Hendrix, and Schafer 2012; Petts 2009; Wagmiller et al. 2006; Zimmer et al. 2012). Latent class analysis (LCA), latent class growth analysis (LCGA), and growth mixture models (GMMs) are three different types of finite mixture model (Clogg 1995; Muthén 2004). In all three cases, individuals are assigned to latent trajectory groups on the basis of their observed experiences or behaviors.[8] Each trajectory group represents a qualitatively distinct latent subpopulation within the data, composed of individuals with relatively similar measurements on some age-sequenced variable (e.g., employment status or marital status or job quality). GMMs allow for residual variation within these trajectory groups (i.e., within-class heterogeneity or random effects), whereas LCA and LCGA assume homogeneity conditional on trajectory group membership.

In these models, the number of underlying trajectories, their shape, their prevalence within the population, and the assignment of individuals to them are *all* inferred from the data; see Nagin (2005), Muthén (2004), and Bollen and Curran (2006) for technical details and relevant formulas. Models with increasing numbers of trajectory classes are typically fit in an iterative fashion. The "preferred model" is then determined using a combination of formal and informal criteria. In many applications, researchers base decisions about the number of trajectories on measures of model fit (e.g., BIC, AIC,

[8] Posterior probabilities are used for assignment purposes. These probabilities provide the likelihood that an individual belongs to a particular class given their observed sequence of measurements.

and/or the Lo-Mendell-Rubin Likelihood Ratio Test), the share of cases assigned to the smallest trajectory group, interpretability, the distinctiveness of the trajectories, and model convergence (see, e.g., Henselmans et al. 2010; Marcell et al. 2011). We followed a similar approach in our analysis, relying on a blend of formal and informal criteria to identify our preferred specifications. Fit statistics for each of the models that we estimated can be found in Appendix Tables A1a-A1c (online).

A key concern when estimating finite mixture models is the presence of local maxima (Hipp and Bauer 2006; McLachlan and Peel 2000). Likelihood functions for mixture models are exceedingly complex (e.g., not always concave), which can sometimes lead to false solutions and/or non-convergence problems. In an effort to guard against these possibilities, we randomly generated at least 400 sets of starting values for every LCGA, LCA, and GMM that we estimated, using the automated STARTS routine available in recent versions of Mplus (Muthén and Muthén 2010). We then optimized the 100 best sets, as identified by a comparison of the log-likelihoods. Our final estimates were obtained from model estimates in which the highest log-likelihood was replicated at least once, suggesting that the global maximum likelihood solution was successfully reached. If the best log-likelihood was *not* replicated, we increased the number of start values to 1,000 and the number of second-stage optimizations to 250, and then re-estimated the model. Similar approaches have been used" in other substantive applications (see, e.g., McLeod and Fettes 2007).

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Table 1. Financial Outcomes in 2004 Used as Dependent Variables

	Men						Women					
	N	Avg	(sd)	Min	Max	Dist	N	Avg	(sd)	Min	Max	Dist
Financial Circumstances in 2004 ($ln)												
Household Net Worth	3,191	12.55	(2.72)	0.00	16.30		3,725	11.76	(3.27)	0.00	16.30	
Household Income	3,207	10.05	(2.71)	0.00	13.47		3,742	9.33	(3.18)	0.00	13.47	
Personal Wage & Salary Income	3,206	9.98	(2.84)	0.00	13.22		3,741	8.73	(3.26)	0.00	13.22	
Net Value of Home	3,186	10.58	(3.94)	0.00	14.22		3,721	9.64	(4.72)	0.00	14.22	

Note: WLS sample restricted to graduates who responded to the 1975, 1993, and 2004 telephone surveys. All estimates are weighted to account for non-random sample attrition. See text for variable descriptions.

Table 2. Current Labor Force, Family, and Other Circumstances in 2004

	Men (N = 3,238)					Women (N = 3,778)				
	Mean	(SD)	Min	Max	Dist.	Mean	(SD)	Min	Max	Dist.
Labor Force Circumstances in 2004										
Currently Employed (1=Yes)	0.51		0.00	1.00		0.41		0.00	1.00	
Retired: Completely (1=Yes)	0.46		0.00	1.00		0.52		0.00	1.00	
Retired: Partly (1=Yes)	0.27		0.00	1.00		0.19		0.00	1.00	
Retired: Not at All (1=Yes)	0.27		0.00	1.00		0.28		0.00	1.00	
Pension Plan on Current/Last Job (1=Yes)	0.50		0.00	1.00		0.43		0.00	1.00	
Health Insurance at Current/Last Job (1=Yes)	0.53		0.00	1.00		0.42		0.00	1.00	
Occupation Earnings of Current/Last Job	38.84	(20.21)	4.49	87.60		24.56	(18.12)	3.70	82.90	
Family Circumstances in 2004										
Current Spouse: None (1=Yes)	0.14		0.00	1.00		0.27		0.00	1.00	
Current Spouse: Not Employed (1=Yes)	0.47		0.00	1.00		0.45		0.00	1.00	
Current Spouse: Employed (1=Yes)	0.39		0.00	1.00		0.28		0.00	1.00	
Current Spouse: Excellent/Good Health (1=Yes)	0.74		0.00	1.00		0.59		0.00	1.00	
Current Spouse: Fair/Poor/Very Poor Health (1=Yes)	0.12		0.00	1.00		0.13		0.00	1.00	
Number of Children	2.92	(1.64)	0.00	10.00		3.13	(1.77)	0.00	10.00	
Health in 2004										
Self-Assessed Health (1=Good, Fair, or Poor)	0.36		0.00	1.00		0.35		0.00	1.00	
Activity Limiting Condition (1=Yes)	0.25		0.00	1.00		0.27		0.00	1.00	

Note : WLS sample restricted to graduates who responded to the 1975, 1993, and 2004 telephone surveys. Distributions of continuous variables are shown in the "Dist." column. Missing values imputed using chained equations in Stata. All estimates are weighted to account for non-random sample attrition. See text for variable descriptions.

Table 3. Summary Measures of Labor Force and Family Experiences through 2004

	Men (*N* = 3,248)					Women (*N* = 3,785)				
	Avg	(sd)	Min	Max	Dist.	Avg	(sd)	Min	Max	Dist.
Summary Measures of Labor Force Experiences through 2004										
Years Employed, 1975 to 2004	26.48	(4.48)	0.00	31.00		21.52	(8.47)	0.00	31.00	
Number of Employer Spells, 1975 to 2004	3.71	(2.36)	0.00	26.00		3.60	(2.41)	0.00	23.00	
Ever Offered Health Insurance on Job (1=Yes)	0.92		0.00	1.00		0.72		0.00	1.00	
Ever Offered Pension on Job (1=Yes)	0.88		0.00	1.00		0.69		0.00	1.00	
Ever Lost a Job Involuntarily (1=Yes)	0.15		0.00	1.00		0.15		0.00	1.00	
Summary Measures of Family Experiences through 2004										
Number of Times Married through 2004	1.22	(0.59)	0.00	4.00		1.17	(0.54)	0.00	4.00	
Age at First Marriage: Never Married (1=Yes)	0.04		0.00	1.00		0.04		0.00	1.00	
Age at First Marriage: Younger than Mode (1=Yes)	0.16		0.00	1.00		0.13		0.00	1.00	
Age at First Marriage: Modal Ages (1=Yes)	0.40		0.00	1.00		0.48		0.00	1.00	
Age at First Marriage: Older than Mode (1=Yes)	0.41		0.00	1.00		0.35		0.00	1.00	
Ever Divorced (1=Yes)	0.25		0.00	1.00		0.24		0.00	1.00	
Ever Widowed (1=Yes)	0.05		0.00	1.00		0.14		0.00	1.00	
Age at First Child: No Children (1=Yes)	0.07		0.00	1.00		0.07		0.00	1.00	
Age at First Child: Younger than Mode (1=Yes)	0.15		0.00	1.00		0.12		0.00	1.00	
Age at First Child: Modal Ages (1=Yes)	0.31		0.00	1.00		0.37		0.00	1.00	
Age at First Child: Older than Mode (1=Yes)	0.47		0.00	1.00		0.44		0.00	1.00	

Note: WLS sample restricted to graduates who responded to the 1975, 1993, and 2004 telephone surveys. Missing values imputed using chained equations in Stata. Distributions of continuous variables are shown in the "Dist." column. All estimates are weighted to account for non-random sample attrition. See text for variable descriptions.

Table 4. Distribution of Respondents Across Trajectory Groups, by Estimation Strategy and Gender

	Men			Women		
Type of trajectory	Latent Class Analysis	Latent Class Growth Models	Growth Mixture Models	Latent Class Analysis	Latent Class Growth Models	Growth Mixture Models
Employment status						
Consistently employed	51.9%	51.7%	49.2%	43.5%	42.4%	30.2%
Retired in early 60s	28.2%	27.6%	24.6%	25.2%	25.3%	23.7%
Retired in mid 50s	14.4%	14.2%	17.0%	–	–	–
Intermittent/no employment	5.5%	6.4%	9.1%	15.1%	14.7%	29.2%
Late entry	–	–	–	16.2%	17.6%	16.8%
Job quality						
Never held a bad job	60.5%	60.3%	52.7%	55.3%	55.1%	54.3%
Always held a bad job	17.4%	17.6%	20.5%	16.0%	16.7%	19.7%
Transitioned into a bad job	13.2%	13.7%	13.8%	14.3%	13.6%	13.2%
Transitioned out of a bad job	9.0%	8.4%	13.0%	14.4%	14.6%	12.7%
Health insurance benefits						
Received insurance until 60s	32.8%	53.7%	42.1%	33.1%	34.5%	23.3%
Received insurance until 50s	28.6%	25.8%	27.6%	19.2%	18.3%	25.0%
Intermittent	24.4%	10.3%	16.7%	–	–	–
Never received insurance	14.1%	10.2%	13.6%	30.5%	29.8%	34.3%
Transitioned into a job w/ coverage	–	–	–	17.1%	17.4%	17.4%
Pension benefits						
Received benefits until 60s	42.8%	43.8%	50.4%	27.5%	28.6%	23.8%
Received benefits until 50s	26.9%	26.0%	23.9%	19.0%	18.3%	24.7%
Never received benefits	17.1%	16.9%	14.7%	35.1%	34.3%	35.2%
Intermittent	13.2%	13.3%	11.0%	–	–	–
Transitioned into a job w/ coverage	–	–	–	18.4%	18.8%	16.2%
Marital status						
Marriage in early to mid-20s	54.2%	48.9%	47.0%	59.4%	62.7%	63.5%
Marriage after age 30	27.4%	25.2%	25.7%	17.8%	22.5%	11.1%
Multiple marriages	12.7%	16.6%	17.4%	14.6%	–	12.3%
Divorce with no remarriage	5.7%	9.2%	10.0%	8.2%	14.8%	13.1%

Note: WLS sample restricted to graduates who responded to the 1975, 1993, and 2004 telephone surveys. Job quality was measured using quartiles of the occupational earnings distribution; jobs in the bottom quartile were considered to be "bad" (see, e.g., Raymo et al. 2011). See text for a description of the methods we used to infer the most appropriate number of latent trajectories and trajectory group membership.

Table 5. *P* -values from Hypothesis Tests of the Total, Direct, and Indirect Effects of Respondents' Past Work and Family Experiences

	Men			Women		
Outcome in 2004	Latent Class Analysis	Latent Class Growth Models	Growth Mixture Models	Latent Class Analysis	Latent Class Growth Models	Growth Mixture Models
Household Net Worth ($ln)						
Total effect of trajectories	**< 0.01**	**< 0.01**	**< 0.01**	**< 0.01**	**< 0.01**	**< 0.01**
Direct effect of trajectories	**0.01**	**0.02**	**0.02**	**< 0.01**	**< 0.01**	**< 0.01**
Indirect effect of trajectories (via proximate measures)	**0.00**	**< 0.01**	**< 0.01**	**0.01**	**< 0.01**	**< 0.01**
Household Income ($ln)						
Total effect of trajectories	**< 0.01**	**< 0.01**	**< 0.01**	**< 0.01**	**< 0.01**	**< 0.01**
Direct effect of trajectories	**0.02**	0.13	**0.03**	**0.02**	**0.02**	0.05
Indirect effect of trajectories (via proximate measures)	**0.01**	**< 0.01**	**< 0.01**	0.25	0.16	**0.01**
Personal Wage & Salary Income ($ln)						
Total effect of trajectories	**< 0.01**	**< 0.01**	**< 0.01**	**< 0.01**	**< 0.01**	**< 0.01**
Direct effect of trajectories	**< 0.01**	**0.01**	**0.01**	**< 0.01**	**< 0.01**	**< 0.01**
Indirect effect of trajectories (via proximate measures)	**0.02**	**0.03**	**< 0.01**	**< 0.01**	**< 0.01**	**< 0.01**
Net Value of Home ($ln)						
Total effect of trajectories	**< 0.01**	**< 0.01**	**< 0.01**	**< 0.01**	**< 0.01**	**< 0.01**
Direct effect of trajectories	**0.01**	**0.01**	**0.01**	**< 0.01**	**< 0.01**	**< 0.01**
Indirect effect of trajectories (via proximate measures)	**< 0.01**	**< 0.01**	**< 0.01**	**0.04**	**0.01**	0.09

Note: WLS sample restricted to graduates who responded to the 1975, 1993, and 2004 telephone surveys. Missing values on exogenous variables were imputed using chained equations in Stata. *P* -values for the indirect effects were calculated using the procedures described by Breen et al. (2013). Proximate measures include indicators of respondents' work, family, and other circumstances as measured contemporaneously with the dependent variable in 2004. Bolded *p* -values are less than or equal to 0.05. All estimates are weighted to account for non-random sample attrition. See text for more details.

Table 6. Detailed Estimates from Models Predicting Respondents' Net Worth at Age 65

	Men		Women	
Type of work/family trajectory	b	(s.e.)	b	(s.e.)
Employment status trajectories				
Consistently employed	[Reference Group]		[Reference Group]	
Retired in early 60s	-0.22	(0.12)	-0.08	(0.13)
Retired in mid 50s	-0.00	(0.18)	–	–
Intermittent/no employment	**-0.53**	**(0.26)**	-0.10	(0.25)
Late entry	–	–	-0.08	(0.16)
"Bad job" trajectories				
Never held a bad job	[Reference Group]		[Reference Group]	
Always held a bad job	**-0.84**	**(0.15)**	**-0.96**	**(0.17)**
Transitioned into a bad job	**-0.76**	**(0.16)**	**-0.75**	**(0.16)**
Transitioned out of a bad job	-0.32	(0.15)	-0.32	(0.15)
Health insurance trajectories				
Received insurance until 60s	[Reference Group]		[Reference Group]	
Received insurance until 50s	0.26	(0.20)	0.04	(0.22)
Intermittent	0.06	(0.21)	–	–
Never received insurance	0.19	(0.33)	-0.17	(0.23)
Transitioned into a job with insurance	–	–	0.29	(0.19)
Pension benefits trajectories				
Received benefits until 60s	[Reference Group]		[Reference Group]	
Received benefits until 50s	-0.34	(0.18)	-0.03	(0.22)
Never received benefits	**-0.68**	**(0.25)**	-0.42	(0.22)
Intermittent	-0.32	(0.20)	–	–
Transitioned into a job with pension benefits	–	–	**-0.43**	**(0.20)**
Marital status trajectories				
Marriage in early to mid-20s	[Reference Group]		[Reference Group]	
Marriage after age 30	0.04	(0.12)	-0.20	(0.12)
Multiple marriages	**-0.33**	**(0.15)**	–	–
Divorce with no remarriage	**-1.03**	**(0.21)**	**-1.38**	**(0.17)**
Constant	**13.19**	**(0.11)**	**12.63**	**(0.11)**

Note: Indicators of trajectory group membership were obtained from LCGA models; results for other models are available upon request. Bolded coefficients have p -values that are less than or equal to 0.05. All estimates are weighted to account for non-random sample attrition. See text for further details.

Table 7. The Joint Significance of Trajectory-Based Measures in Models that Include Proximate Variables *and* Summary Indicators

	Men			Women		
Outcome in 2004 ($ln)	Latent Class Analysis	Latent Class Growth Models	Growth Mixture Models	Latent Class Analysis	Latent Class Growth Models	Growth Mixture Models
Household Net Worth	**0.02**	**0.01**	**< 0.01**	**< 0.01**	**< 0.01**	**< 0.01**
Household Income	0.15	0.32	0.49	**0.02**	0.06	0.27
Personal Wage/Salary Income	**0.02**	0.09	0.29	**0.01**	**0.03**	0.16
Net Value of Home	**< 0.01**	**< 0.01**	**< 0.01**	0.06	0.10	**0.01**

Note : WLS sample restricted to graduates who responded to the 1975, 1993, and 2004 telephone surveys. Missing values on exogenous variables imputed using chained equations in Stata. All models include summary measures of respondents' work and family histories as well as proximate measures of the work, family, and other circumstances (as observed in 2004). Bolded *p* -values are less than or equal to 0.05. All estimates are weighted to account for non-random sample attrition. See text for further details.

Table A1a. Fit Statistics by Model Specification, Gender, and Type of Work/Family Trajectory (LCA) [To be made available online]

	Men						Women					
	BIC	AIC	LMR	Entropy	Distinct	Size	BIC	AIC	LMR	Entropy	Distinct	Size
Employment status												
k = 1	108004.3	108004.3	–	–	■	■	246182.9	245809.1	–	–	■	■
k = 2	80968.9	80968.9	0.00	0.99	■	■	180998.0	180244.1	0.00	0.98	■	■
k = 3	70367.1	70367.1	0.00	0.99	■	■	157213.0	156079.0	0.00	0.98	■	■
k = 4	62267.5	62267.5	0.00	0.99	■	■	139044.7	137530.6	0.00	0.98	■	■
k = 5	59029.9	59029.9	0.00	0.99	□	■	130359.2	128465.1	0.00	0.98	□	□
Job quality												
k = 1	179098.7	178734.3	–	–	■	■	165596.0	165226.1	–	–	■	■
k = 2	86170.3	85435.4	0.00	0.99	■	■	93419.4	92673.4	0.00	0.98	■	■
k = 3	68541.3	67435.9	0.00	0.99	■	■	77056.6	75934.6	0.00	0.96	■	■
k = 4	56999.5	55523.6	0.00	0.99	■	■	64298.3	62800.2	0.00	0.96	■	■
k = 5	52182.6	50336.2	0.06	0.98	□	■	59449.7	57575.5	0.09	0.95	□	■
Health insurance												
k = 1	190714.8	190350.1	–	–	■	■	280784.9	280411.1	–	–	■	■
k = 2	133390.5	132655.0	0.00	0.99	■	■	180356.3	179602.5	0.00	0.99	■	■
k = 3	104616.7	103510.4	0.00	0.99	■	■	150087.5	148953.6	0.00	0.99	■	■
k = 4	93240.0	91762.9	0.00	0.99	■	■	128626.9	127112.9	0.00	0.98	■	■
k = 5	84131.0	82283.1	0.02	0.99	□	■	119423.1	117529.1	0.00	0.98	□	□
Pension benefits												
k = 1	220187.8	219823.1	–	–	■	■	276866.8	276493.0	–	–	■	■
k = 2	144156.0	143420.4	0.00	0.99	■	■	175945.7	175191.9	0.00	0.99	■	■
k = 3	116867.2	115760.9	0.00	0.99	■	■	142566.8	141432.8	0.00	0.99	■	■
k = 4	102139.7	100662.6	0.00	0.99	■	■	122146.6	120632.6	0.00	0.98	■	■
k = 5	92646.7	90798.7	0.42	0.98	□	■	113949.8	112055.8	0.56	0.98	□	□
Marital status												
k = 1	242874.2	242267.3	–	–	■	■	320220.2	319597.9	–	–	■	■
k = 2	159746.1	158526.1	0.00	1.00	■	■	198124.8	196873.9	0.00	1.00	■	■
k = 3	137632.7	135799.8	0.00	0.99	■	■	173563.7	171684.4	0.00	0.99	■	■
k = 4	123035.5	120589.6	0.00	0.99	■	■	154398.8	151890.9	0.00	0.99	■	■
k = 5	113527.4	110468.4	0.00	1.00	□	■	141495.1	138358.6	0.78	0.99	□	■

Note: Models with $k = 1, \ldots, 5$ trajectories were fit for each work/family charcteristic, separately by gender. The "LMR" column provides p -values from a Lo-Mendell-Rubin likelihood ratio test, comparing a model with k trajectories to a model with $k - 1$. The null hypothesis for the test is that the two models are equivalent. Filled boxes in the "Distinct" column indicate that trajectories identified by the model were substantively distinct; empty boxes indicate otherwise. We made these determinations by visually inspecting each of the trajectories. Filled boxes in the "Size" column indicate that the smallest of the resulting trajectory groups contained at least 5% of the sample, using posterior probabilities of group membership to make trajectory group assignments.

Table A1b. Fit Statistics by Model Specification, Gender, and Type of Work/Family Trajectory (LCGA) [To be made available online]

	Men						Women					
	BIC	AIC	LMR	Entropy	Distinct	Size	BIC	AIC	LMR	Entropy	Distinct	Size
Employment status												
$k = 1$	107756.3	107738.0	–	–	■	■	246107.9	246089.2	–	–	■	■
$k = 2$	81604.4	81561.8	0.00	0.96	■	■	180937.6	180893.9	0.00	0.98	■	■
$k = 3$	70409.8	70343.0	0.00	0.97	■	■	158064.6	157996.1	0.00	0.97	■	■
$k = 4$	62086.3	61995.1	0.00	0.98	■	■	140174.5	140081.0	0.00	0.97	■	■
$k = 5$	58822.8	58707.3	0.01	0.98	□	■	131808.9	131690.5	0.00	0.97	□	■
Job quality												
$k = 1$	178653.3	178635.0	–	–	■	■	165206.1	165187.6	–	–	■	■
$k = 2$	85794.2	85751.7	0.00	0.99	■	■	92735.6	92692.5	0.00	0.98	■	■
$k = 3$	68184.0	68117.2	0.00	0.99	■	■	77599.3	77531.5	0.00	0.96	■	■
$k = 4$	56228.5	56137.4	0.00	0.99	■	■	63986.1	63893.6	0.00	0.96	■	■
$k = 5$	51518.6	51403.2	0.32	0.98	□	□	59105.3	58988.1	0.21	0.95	□	■
Health insurance												
$k = 1$	191019.0	191000.7	–	–	■	■	281426.0	281407.3	–	–	■	■
$k = 2$	134368.1	134325.6	0.00	0.99	■	■	181782.6	181739.0	0.00	0.99	■	■
$k = 3$	106318.6	106251.7	0.00	0.99	■	■	152654.7	152586.1	0.00	0.99	■	■
$k = 4$	95968.7	95877.5	0.00	0.99	■	■	130451.0	130357.5	0.00	0.98	■	■
$k = 5$	86923.4	86807.9	0.59	0.98	□	□	121366.0	121247.6	0.11	0.97	□	■
Pension benefits												
$k = 1$	220608.6	220590.3	–	–	■	■	220608.6	220590.3	–	–	■	■
$k = 2$	146256.3	146213.8	0.00	0.99	■	■	146256.3	146213.8	0.00	0.99	■	■
$k = 3$	119539.0	119472.2	0.00	0.99	■	■	119539.0	119472.2	0.00	0.99	■	■
$k = 4$	104179.5	104088.4	0.00	0.99	■	■	104179.5	104088.4	0.00	0.99	■	■
$k = 5$	95843.9	95728.4	0.00	0.98	□	■	95843.9	95728.4	0.08	0.98	□	□
Marital status												
$k = 1$	258773.8	258755.6	–	–	■	■	347675.0	347656.3	–	–	■	■
$k = 2$	165121.4	165078.9	0.00	0.99	■	■	209433.3	209389.8	0.00	1.00	■	■
$k = 3$	141890.9	141824.1	0.00	0.98	■	■	177877.5	177809.1	0.00	0.99	■	■
$k = 4$	128224.4	128133.3	0.02	0.98	■	■	162922.9	162829.5	0.38	0.99	□	■
$k = 5$	118075.6	117960.2	0.12	0.98	□	□	147968.2	147849.9	0.98	0.99	□	□

Note: Models with $k = 1, \ldots, 5$ trajectories were fit for each work/family charcteristic, separately by gender. The "LMR" column provides p -values from a Lo-Mendell-Rubin likelihood ratio test, comparing a model with k trajectories to a model with $k - 1$. The null hypothesis for the test is that the two models are equivalent. Filled boxes in the "Distinct" column indicate that trajectories identified by the model were substantively distinct; empty boxes indicate otherwise. We made these determinations by visually inspecting each of the trajectories. Filled boxes in the "Size" column indicate that the smallest of the resulting trajectory groups contained at least 5% of the sample, using posterior probabilities of group membership to make trajectory group assignments.

Table A1c. Fit Statistics by Model Specification, Gender, and Type of Work/Family Trajectory (GMMs) [To be made available online]

	Men						Women					
	BIC	AIC	LMR	Entropy	Distinct	Size	BIC	AIC	LMR	Entropy	Distinct	Size
Employment status												
k = 1	71432.4	71408.1	–	–	■	■	157517.3	157492.4	–	–	■	■
k = 2	54310.2	54261.6	0.00	0.93	■	■	123314.5	123264.7	0.00	0.87	■	■
k = 3	51631.2	51558.2	0.00	0.93	■	■	113104.2	113029.4	0.00	0.82	■	■
k = 4	52106.7	52009.4	0.00	0.93	■	■	105520.2	105420.5	0.00	0.81	■	■
k = 5	47372.7	47251.2	0.02	0.84	□	□	100454.1	100329.5	0.00	0.87	□	■
Job quality												
k = 1	66166.5	66142.2	–	–	■	■	73930.2	73905.5	–	–	■	■
k = 2	47660.4	47611.8	0.00	0.95	■	■	54795.6	54746.3	0.00	0.79	■	■
k = 3	41176.9	41104.0	0.00	0.93	■	■	48665.7	48591.7	0.00	0.80	■	■
k = 4	39352.1	39254.9	0.02	0.91	■	■	43760.4	43661.7	0.12	0.84	□	□
k = 5	36063.5	35942.1	0.31	0.85	□	■	40710.2	40586.9	0.02	0.73	□	□
Health insurance												
k = 1	111383.2	111358.9	–	–	■	■	156353.9	156329.0	–	–	■	■
k = 2	78153.4	78104.8	0.00	0.90	■	■	116037.2	115987.3	0.00	0.92	■	■
k = 3	96222.6	96149.7	0.01	0.98	■	□	101109.3	101034.5	0.00	0.87	■	■
k = 4	67152.1	67054.8	0.04	0.89	■	■	92837.2	92737.6	0.04	0.91	■	■
k = 5	64058.9	63937.4	0.08	0.88	□	□	88922.1	88797.5	0.10	0.89	□	■
Pension benefits												
k = 1	130045.5	130021.2	–	–	■	■	153865.0	153840.1	–	–	■	■
k = 2	86527.6	86478.9	0.00	0.93	■	■	111806.3	111756.4	0.03	0.94	■	■
k = 3	77035.1	76962.1	0.00	0.91	■	■	96832.5	96757.8	0.00	0.76	■	■
k = 4	74270.4	74173.2	0.00	0.90	■	■	88441.3	88341.6	0.00	0.93	■	■
k = 5	67695.3	67573.7	0.00	0.92	□	■	87778.9	87654.3	0.64	0.92	□	■
Marital status												
k = 1	154791.6	154767.3	–	–	■	■	217097.3	217072.4	–	–	■	■
k = 2	112341.9	112293.3	0.00	0.99	■	■	153784.1	153734.3	0.00	0.99	■	■
k = 3	99862.0	99789.1	0.00	0.98	■	■	130719.2	130644.5	0.00	0.98	■	■
k = 4	95692.2	95595.1	0.00	0.93	■	■	115571.1	115471.6	0.00	0.99	■	■
k = 5	90845.0	90723.6	0.09	0.93	□	■	110470.9	110346.4	0.52	0.93	□	■

Note: Models with k = 1, …, 5 trajectories were fit for each work/family charcteristic, separately by gender. The "LMR" column provides p -values from a Lo-Mendell-Rubin likelihood ratio test, comparing a model with k trajectories to a model with $k - 1$. The null hypothesis for the test is that the two models are equivalent. Filled boxes in the "Distinct" column indicate that trajectories identified by the model were substantively distinct; empty boxes indicate otherwise. We made these determinations by visually inspecting each of the trajectories. Filled boxes in the "Size" column indicate that the smallest of the resulting trajectory groups contained at least 5% of the sample, using posterior probabilities of group membership to make trajectory group assignments.

Table A2. Estimates from Models Predicting Respondents' Net Worth at Age 65 (Proximate Predictors) [To be made available online]

	Men		Women	
Proiximate variable (observed at age 65)	b	(s.e.)	b	(s.e.)
Labor Force Circumstances in 2004				
Not employed [Reference Group]	—	—	—	—
Currently Employed	0.39	(0.19)	0.27	(0.21)
Retired: Not at All [Reference Group]	—	—	—	—
Retired: Completely	0.01	(0.16)	**-0.45**	**(0.20)**
Retired: Partly	-0.18	(0.19)	-0.32	(0.22)
No pension [Reference Group]	—	—	—	—
Pension Plan on Current/Last Job	0.02	(0.16)	0.20	(0.18)
No Health Insurance [Reference Group]	—	—	—	—
Health Insurance at Current/Last Job	-0.01	(0.15)	-0.25	(0.16)
Occupation Earnings of Current/Last Job	**0.02**	**(0.00)**	**0.02**	**(0.00)**
Family Circumstances in 2004				
Current Spouse: Not married [Reference Group]	—	—	—	—
Current Spouse: Not Employed	-1.90	(1.19)	**-4.77**	**(2.25)**
Current Spouse: Employed	-1.90	(1.19)	-4.79	(2.25)
Current Spouse: Excellent/Good Health	**2.60**	**(1.18)**	**5.10**	**2.24**
Current Spouse: Fair/Poor/Very Poor Health	1.93	(1.18)	**4.84**	**2.25**
Number of Children	-0.04	(0.03)	-0.05	(0.03)
Health in 2004				
Self-Assessed Health: Excellent [Reference Group]	—	—	—	—
Self-Assessed Health: Good/Fair/Poor	**-0.35**	**(0.10)**	**-0.81**	**(0.12)**
No Activity Limiting Condition [Reference Group]	—	—	—	—
Activity Limiting Condition	-0.15	0.11	-0.21	0.13

Note: Models also include trajectory-based indicators obtained from LCGA; estimates for these measures are given in Table 6. Bolded coefficients have *p* -values that are less than or equal to 0.05. All estimates are weighted to account for non-random sample attrition. See text for further details.

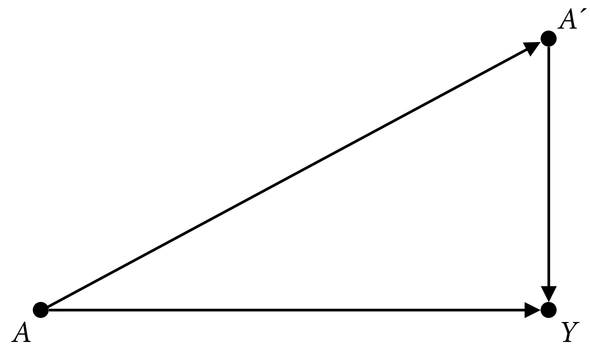

Figure 1. A simple two-period, path-dependent model of cumulative advantage. According to this model, financial well-being in period 2 (*Y*) is dependent on work and family circumstances in period 2 (A´) and work and family circumstances in period 1 (*A*). The arrows emanating from *A* indicate that prior work and family experiences have both direct ($A \rightarrow Y$) and indirect ($A \rightarrow A' \rightarrow Y$) effects on individuals' subsequent outcomes.

Center for Demography and Ecology
University of Wisconsin
1180 Observatory Drive Rm. 4412
Madison, WI 53706-1393
U.S.A.
608/262-2182
FAX 608/262-8400
comments to: jraymo@ssc.wisc.edu
requests to: cdepubs@ssc.wisc.edu