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Indirect Measurement of Intersectionality Using Data from the Understanding America Study

by Richard E. Chard, David Rogofsky, Cherice Jefferies, and Francisco Perez-Arce*

This article introduces a quantitative measure of intersectionality. Intersectionality is the examination of an individual's overlapping identities—for example, one's sex and race and ethnicity—and the relative privileges or barriers that a society perceives for or attaches to a given intersectional identity. We use data from the Understanding America Study (UAS) to construct a Sociopolitical Power Scale (SPPS) that measures societal perceptions of relative power among intersectional identities, and we test whether perceptions of intersectional identities differ from those of single-characteristic identities. UAS questions cover relative political and societal power between men and women and between racial and ethnic groups but not between intersectional identities. We therefore explore differences between men and women in the SPPS within racial and ethnic groups and racial and ethnic differences in the SPPS between men and women. We find some significant differences between intersectional and single-characteristic identities.

Introduction

In this article, we show how we created a tool that social scientists across disciplines can use to study intersectionality and structural barriers. Intersectionality is the concept that an individual has multiple overlapping identities, such as sex and race and ethnicity, which can be subject to discrimination both individually and in combination. These identities are often associated with existing structural barriers, such as those encountered by Black people and women. For example, a Black woman has a merged identity as both a woman and a Black person that differs from her societally perceived identity as a member of either group singly.

We focus on people's perceptions about overall societal attitudes toward people in particular demographic groups rather than the perspectives of individuals about their own intersectional identities. We explore how intersectionality can amplify the discrimination experienced by certain groups. We also examine how discrimination, as measured by societal attitudes toward marginalized groups, can create structural barriers for those groups. Although the full breadth of the latter examination is beyond the scope of this article, social scientists can apply our measure of comparative sociopolitical power to their various fields of expertise to model the relationship between intersectionality and discrimination.

Defining "Structural Barriers"

Simms and others (2015, 4) define structural barriers as "obstacles that collectively affect a group disproportionately and perpetuate or maintain stark disparities in outcomes." Hong and others (2021, 31) define structural barriers in the context of a job search as "the condition that no matter how good the person's

Selected Abbreviations

GM	General Motors
PCA	principal component analysis
SPPS	Sociopolitical Power Scale
UAS	Understanding America Study

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qualifications may be, elements within the social and economic structures make it difficult for the person to obtain employment. These elements include secondary labor market; racial discrimination; immigrant status; gender discrimination; lack of jobs; transportation; neighborhood/location; and general structural factors." Hong and others also examine how those factors affect the administration of income support programs, which is directly relevant to the Social Security Administration in its role of administering the Supplemental Security Income program.

History of the Study of Intersectionality

Among the origins of the concept of intersectionality is a 1976 case heard in U.S. District Court for the Eastern District of Missouri, *DeGraffenreid v. General Motors Assembly Division*. Five Black women who had been fired by General Motors (GM) brought a discrimination lawsuit against their former employer. The plaintiffs argued that they were discriminated against because they were *both* Black and women, not solely because they were Black and not solely because they were women: They acknowledged that GM hired Black men and White women. Ultimately, the judge denied that argument, writing that "the initial issue in this lawsuit is whether the plaintiffs are seeking relief from racial discrimination, or sex-based discrimination. The plaintiffs allege that they are suing on behalf of Black women, and that therefore this lawsuit attempts to combine two causes of action into a new special sub-category, namely, a combination of racial and sex-based discrimination." The court decided that there was no protected class to be found at the intersection of the two identities and ruled in favor of GM. At the time this case was being adjudicated, a theory of intersectionality was arising organically among the Black feminist community (for example, Smith 1983).

Crenshaw (1989) coined the term *intersectionality* in a law review article revisiting *DeGraffenreid v. GM* to explore systemic racism in general and its effects against Black women in particular. Crenshaw argued that it was impossible to separate the identity of being Black from the identity of being a woman. Instead, the two identities create a new intersectional identity, in which the discrimination associated with being Black and the discrimination associated with being a woman are amplified by their coexistence. Crenshaw (1991) identified three forms of intersectionality: representational, political, and structural. Representational intersectionality refers to the way intersectional identities are portrayed in culture and media. Political intersectionality refers to the way that an intersectional identity can combine two or more marginalized groups for whom some political objectives may be at cross-purposes. Structural intersectionality refers to the way various institutions perpetuate or eliminate the barriers faced by people with marginalized intersecting identities. Intersectionality describes the effects of multiple existing structural barriers in combination (Hong and others 2021), as the *DeGraffenreid* plaintiffs attempted to argue: They faced the structural employment barriers that women faced coupled with the structural employment barriers that Black people faced. That combination amplified the structural barriers that they would have faced had they been either Black men or White women.

Although we aim to create a measure of all forms of intersectionality, we see our model of structural intersectionality as most useful to the Social Security Administration and other government agencies in efforts to prevent discrimination in their hiring and employee development policies[1] and in administering their programs. Since Crenshaw (1991), numerous studies have used *intersectionality* to describe the unique combinations of challenges faced by people with particular sex-and-race identities across various realms, including politics (Hancock 2007; Holvino 2010), education (McCall 2005; Jones 2003), health care (Kelly 2009; Viruell-Fuentes, Miranda, and Abdulrahim 2012), and economics (Ladson-Billings and Tate 1995). Hong and others (2021) focused on labor dynamics and used data from a small sample (388 respondents) to construct a Perceived Employment Barrier Scale. Yet all those studies tend to focus on one particular aspect of intersectionality, while our measure is meant to model multiple elements and provide a comprehensive quantitative measure of intersectionality that social scientists can use to examine empirically how intersectional identities affect access to social services, societal power, and government benefits.

In our research, we explore whether a measure of intersectional identities can be created using a novel indirect regression approach applied to survey data on societal perceptions of different groups' social and political power. We seek to understand how the simultaneity of race or ethnicity and sex affect different groups' social standings and power in society by creating a quantitative metric we call the Sociopolitical

Power Scale (SPPS). Although our examination is purely methodological, we propose ways that the SPPS could be used in models measuring social groups' interactions with government agencies and programs.

Data and Methods

We use data from the Understanding America Study (UAS), a nationally representative survey fielded by the University of Southern California's Center for Economic and Social Research, to construct the SPPS. UAS survey 135, titled "Health Insurance, Politics, and Social Attitudes and Values" and fielded May–June 2018, included a Social Construction module containing a series of questions addressing perceptions of population groups' relative societal and political power.

The UAS is an internet-based panel survey administered to participants aged 18 or older. UAS surveys cover a wide array of topics, including demographic and socioeconomic characteristics, political affiliation, financial literacy, and personality type.[2] If needed, participants are provided a tablet and internet connection. UAS 135 had 4,679 respondents among the 6,154 UAS panel participants at the time, providing a 76 percent response rate.[3]

Demographic Information

Table 1 shows summary demographic characteristics of the UAS 135 respondents. Women outnumbered men, 57 percent to 43 percent. The majority of respondents (72 percent) were non-Hispanic White, while 8 percent were non-Hispanic Black and 11 percent were Hispanic (any race). Respondents' average years of education (14.5) included some years after a high school diploma, and the mean household income was almost $65,000.

In the following subsections, we provide a description of the method we used to create the SPPS, along with an analysis of that method and a discussion of the applicability of the scale and its possible uses and extensions.

Table 1.
Summary characteristics of UAS 135 respondents (unweighted): May–June 2018

Characteristic	Total
Number of respondents	4,679
Percentage who are—	
Women	57
Men	43
White (non-Hispanic)	72
Black (non-Hispanic)	8
Hispanic (any race)	11
Mean—	
Age	50.3
Years of education	14.5
Household income ($)	64,823

SOURCE: Authors' calculations based on UAS data.

SPPS Theory and Method

We aim to demonstrate the amplification of discrimination (or privilege) that Crenshaw (1989) identified so that it can be integrated into empirical social science research. The theoretical origins of the SPPS come from the psychosocial theory of social constructions, or the examination of the creation and endurance of stereotypes. Berger and Luckmann (1967) framed social constructions as the process by which beliefs and perceptions about groups of people become institutionalized such that the collective belief endures and becomes a dominant perception that is thus internalized by members of the groups that are the subject of these perceptions. For example, the societal perception of the experience being a Black woman reinforces the actual experience of being a Black woman. This in turn fortifies the societal perception of Black women, which differs from the societal perceptions both of Black people overall and of women overall. This exemplifies what Crenshaw (1989) calls the amplification of identities.

The SPPS combines the perceptions of societal power and political power into a scalar measure to help us better understand how those factors influence individuals' interactions with government agencies and programs. Although the possible combinations of intersectional identities may number in the hundreds, we simplify this analysis by focusing on the intersection of sex and race or ethnicity and limiting the latter to four groups: non-Hispanic White, non-Hispanic Black, non-Hispanic Asian, and Hispanic (any race).[4] We test whether the SPPS results for a single-characteristic identity (such as being a Black person) differ from an intersectional identity (such as being a Black woman).

Constructing the SPPS

We use the responses to three UAS 135 questions to collect data on the perceived societal and political power of 13 population groups: men; women; White, Black, Hispanic, and Asian people; residents of suburban, urban, and rural areas; immigrants with a visa;

immigrants without a visa; aged people; and people with a disability. The survey questions listed the groups in random order. We tested the questions using exploratory factor analysis in the STATA statistical software and determined that they were scalable—that is, amenable to inclusion in a scale. We also confirmed that the questions were loaded on a limited number of common factors, meaning that they are related by an underlying concept.

The three questions are listed below:

- **Political power.** "Please rate the following groups of U.S. residents in terms of their political power, that is, how much politicians and lawmakers care about what the group wants." Response options consist of *very low* (1), *low* (2), *moderate* (3), *high* (4), and *very high* (5).
- **Societal power.** "Please rate the following groups of U.S. residents in terms of their level of societal power. By societal power we mean the ability that members of those groups have to get things done within U.S. society." Response options consist of *very low* (1), *low* (2), *moderate* (3), *high* (4), and *very high* (5).
- **Social construction.** "Thinking about those groups of U.S. residents in terms of how U.S. society generally views them, would you say the view is mostly negative, positive or somewhere in between?" Response options consist of *negative* (1), *somewhat negative* (2), *neither positive nor negative* (3), *somewhat positive* (4), and *positive* (5).

We used principal component analysis (PCA) of the SPPS' components—political power, societal power, and social construction—to ensure that they are different measures of an underlying concept and are thereby not biased by collinearity or correlation. PCA is an appropriate method of factor analysis because it looks for similarities in measures that have no prior theoretical structuring or grouping of observations (Bartholomew and others 2008; Jolliffe 2002). Chard, Rogofsky, and Yoong (2017) used PCA for their scalar measures and in constructing the weighted scale they used to analyze financial behavior and to create their Retirement Planning Index. We use PCA to test the independence of the political and societal power measures and to give insight into how they may be scaled together to create the SPPS. If the measures capture the same underlying concept, then we can expect a factor analysis to show that the components load on a small number of factors. If instead they capture different concepts, then we should see the opposite, loading on many factors with no single factor explaining most of the variance (Bartholomew and others 2008; Jolliffe 2002).[5]

Table 2 shows the correlations among the responses to each of the three survey questions with respect to women. All of the correlation coefficients of the three questions lie between 0.5 and 0.6, suggesting that there is a substantial correlation. However, the correlations are not above the level (0.8) at which adding the second or third question would be of no analytical value.

Next, we created a scree plot of the eigenvalues for the three components (survey questions) for each of the 13 population groups (Chart 1). The scree plots indicate whether the information in the three questions could be summarized in a single index variable to represent sociopolitical power, or whether adding a second variable (second component) would provide significantly more information. An eigenvalue lower than 1 is commonly a clear indicator that the given component does not contain sufficient additional information to warrant attention.[6] The scree plots for the 13 population groups look very similar. In each case, the eigenvalues for the first component are close to 2, while the eigenvalues for the second and third

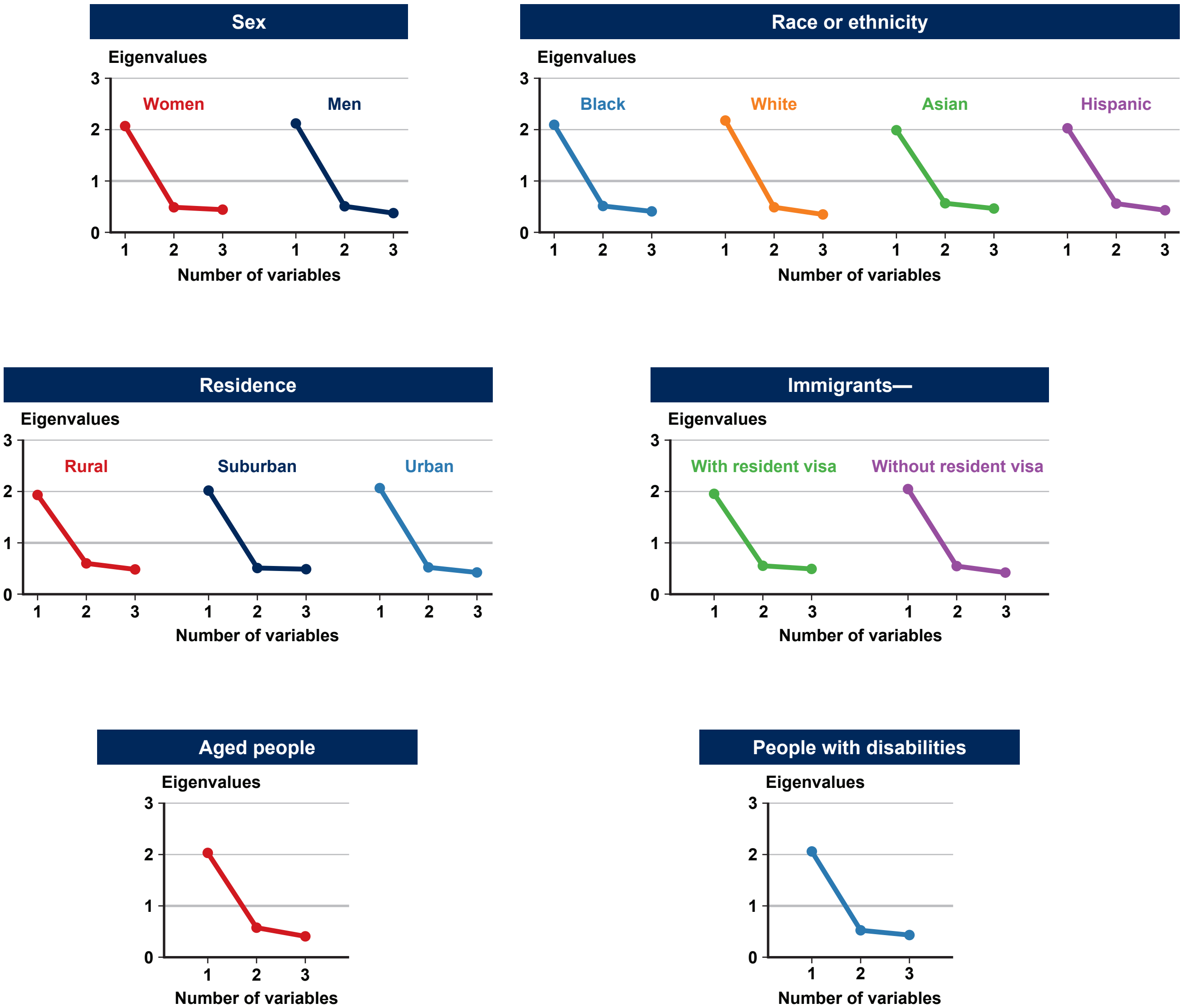
Table 2.
Perceived societal attitudes toward women: Correlations among responses to UAS 135 questions

Question	Societal power	Social construction	Political power
Societal power	1.0000	. . .	. . .
Social construction	0.5164	1.0000	. . .
Political power	0.5554	0.5320	1.0000

SOURCE: Authors' calculations based on UAS data.

NOTE: . . . = not applicable.

Chart 1.
Viability of using one, two, or three index variables in constructing a measure of sociopolitical power: Scree plot analysis of survey results on each of 13 subject population groups



SOURCE: Authors' calculations based on UAS data.

components are well below 1. That result confirms that we can use a single index to represent the sociopolitical power of each of the groups.

Next, we analyze the PCA results for weighting of each factor (survey question), shown in Table 3, for each of the 13 groups we studied. In the example of women, the weights are similar: 0.578 for societal power, 0.570 for social construction, and 0.584 for political power. These weights indicate the relative contribution of the responses to each of these questions in the overall perceptions of the sociopolitical power of women as a group.

Across all 13 groups, the weights for each of the three questions are very similar. Within any group, the most dissimilar weights are those for the societal power question (0.595) and the social construction question (0.553) for people with a rural residence (a difference of 0.042, or about 7.6 percent of the weight for the social construction question). This result indicates that people perceive a difference between the societal power of rural residents (how powerful they are as a group) and their social construction (how society views them as a group).

Table 4 shows descriptive statistics on the SPPS scores. Possible SPPS scores range from 1 (lowest) to 5 (highest). The unweighted results support existing concepts of intersectionality. For example, men have a higher SPPS score (that is, more perceived sociopolitical power) than women, and White people have a significantly higher SPPS score than people of another race or ethnicity. Black people and women, the identities that intersect in Crenshaw (1989), have some of the lowest SPPS scores. The weighted results are fundamentally similar. For instance, the weighted mean SPPS score for White people is higher than the unweighted mean SPPS score, but only by 0.02.

Table 3.
Factor analysis results for three questions, by population group

Group	Societal power	Social construction	Political power
Sex			
Women	0.578	0.570	0.584
Men	0.588	0.553	0.590
Race or ethnicity			
White	0.590	0.553	0.588
Black	0.587	0.558	0.587
Asian	0.592	0.558	0.582
Hispanic	0.592	0.552	0.587
Residence			
Rural	0.595	0.553	0.584
Suburban	0.582	0.575	0.576
Urban	0.590	0.559	0.582
Immigrants—			
With resident visa	0.589	0.568	0.575
Without resident visa	0.591	0.553	0.587
Aged people	0.594	0.543	0.594
People with disabilities	0.581	0.561	0.590

SOURCE: Authors' calculations based on UAS data.

Table 4.
Descriptive statistics for SPPS scores (unweighted and weighted)

	Unweighted			Weighted	
Characteristic	SPPS median	SPPS mean	Standard deviation	SPPS mean	Standard deviation
Sex					
Women	3.33	3.19	0.77	3.18	0.78
Men	4.00	3.81	0.87	3.79	0.90
Race or ethnicity					
White	4.66	3.79	0.89	3.81	0.91
Black	2.66	2.69	0.86	2.67	0.88
Asian	3.00	2.77	0.72	2.76	0.72
Hispanic	2.33	2.77	0.72	2.48	0.80

SOURCE: Authors' calculations based on UAS data.

NOTE: SPPS scores for all groups range from 1 (lowest) to 5 (highest).

Measuring Intersectional Identities Using the SPPS

The survey questions do not cover intersectional identities so we cannot directly compute SPPS scores for those identities as we can for the 13 population groups examined in UAS 135. Instead, we use an indirect approach that begins with conducting regression analyses to test whether there are differences between men and women, and between racial and ethnic groups, in the perceived sociopolitical power of their own group.[7] To accomplish this, we first analyze differences between male and female respondents in the perceived sociopolitical power of their own racial or ethnic group. For instance, we examine whether Black women perceive lower sociopolitical power for Black people than Black men do and whether Hispanic women perceive lower sociopolitical power for Hispanic people than Hispanic men do. Next, we conduct similar analyses of female respondents' perceptions of women's sociopolitical power across racial and ethnic groups. For instance, we examine whether Black and Hispanic women perceive lower sociopolitical power for women than White women do.

Table 5 shows the results of our regression analysis of the relationship between sex and the perceived sociopolitical power for each respondent's own racial or ethnic group. Results for each racial and ethnic group are shown with and without control variables (age, education, and household income). In both cases, the dummy variable indicates the independent variable of interest: a female respondent.[8] The coefficients for the SPPS score for Black people are negative, showing that Black women perceive lower sociopolitical power for Black people than Black men do. The *p*-values of a test comparing the results for Black respondents to those for White people are both 0.05 or less. Similarly, Hispanic women perceive lower sociopolitical power for Hispanic people than Hispanic men do. We do not find such differences between the views of Asian men and women, and White women perceive slightly higher sociopolitical power for White people than White men do.

Table 6 shows the results of a regression analysis relating Black, Asian, and Hispanic women's perceptions of the sociopolitical power of women overall against White women's perceptions of the sociopolitical power of women overall. This sample includes only female respondents. As in Table 5, results are shown with and without control variables (age, education, and household income). The coefficient for SPPS scores of White female respondents relative to those of Black women (without control variables) is positive and significant. This indicates that White women perceive higher sociopolitical power for women overall than Black women do.[9] Hispanic women also perceive lower sociopolitical power for women than

Table 5.
Regression analysis of the perceived sociopolitical power of one's own racial or ethnic group: Views of women relative to those of men

Variable	White: Without control variables	White: With control variables	Black: Without control variables	Black: With control variables	Asian: Without control variables	Asian: With control variables	Hispanic: Without control variables	Hispanic: With control variables
Women	0.038	0.076**	-0.165	-0.162	-0.030	-0.009	-0.200***	-0.202***
Standard error	-0.030	-0.030	-0.107	-0.108	-0.108	-0.106	-0.076	-0.077
p-value [a]	. . .	. . .	0.050	<0.010	0.300	0.150	<0.010	<0.010
Number of respondents	3,371	3,364	379	379	145	145	525	523
R^2	0.000	0.049	0.006	0.029	0.001	0.080	0.013	0.022

SOURCE: Authors' calculations based on UAS data.

NOTES: The dependent variable is the SPPS score for each racial or ethnic group. The independent variable of interest is the respondent's sex (female). The control variables are age, education level, and household income.

. . . = not applicable; * = statistically significant at the 0.10 level; ** = statistically significant at the 0.05 level; *** = statistically significant at the 0.01 level.

a. Indicator of equality of the coefficient for female respondents of the given racial or ethnic group with the corresponding regression (that is, with or without controls) for White people.

Table 6.
Regression analysis of women's perceptions of the sociopolitical power of women: Views of White women relative to those of Black, Asian, and Hispanic women

Variable	Black		Asian		Hispanic	
	Without control variables	With control variables	Without control variables	With control variables	Without control variables	With control variables
White	0.190***	0.082	-0.057	-0.035	0.192***	0.086*
Standard error	-0.050	-0.051	-0.082	-0.082	-0.044	-0.046
Number of respondents	2,110	2,106	1,940	1,936	2,186	2,180
R^2	0.007	0.039	0.000	0.049	0.009	0.050

SOURCE: Authors' calculations based on UAS data.

NOTES: The dependent variable is the SPPS score for women as viewed by Black, Asian, and Hispanic women. The independent variable of interest is the female respondent's race (White). Control variables are age, education level, and household income.

* = statistically significant at the 0.10 level; ** = statistically significant at the 0.05 level; *** = statistically significant at the 0.01 level.

White women do. There are no significant differences between the views of White and Asian women. Tables 5 and 6 together show that Black women have lower perceptions of Black people's sociopolitical power than Black men have, and lower perceptions of women's sociopolitical power than White women have. Likewise, Hispanic women perceive lower sociopolitical power for Hispanic people than Hispanic men do, and lower sociopolitical power for women than White women do.

To summarize our results, we find that UAS 135 respondents, empaneled as a representative sample of the American population, have the following perceptions:

1. Sociopolitical power differs significantly by race, ethnicity, and sex. For example, Black and Hispanic people are generally perceived as having less sociopolitical power than White people and women are seen as having less sociopolitical power than men.
2. Black and Hispanic women perceive lower sociopolitical power for their own race or ethnicity than their male counterparts perceive.
3. Black and Hispanic women perceive lower sociopolitical power for women than White women perceive.

These findings support the concept of intersectionality and underscore the issues that were discussed in Black feminist literature as the theory of intersectionality was being developed. The concepts that we measure with the SPPS may support efforts to improve political efficacy for certain groups.[10]

Conclusion

Overall, we have accomplished our goal of using an indirect approach to quantitatively assess intersectionality using survey data that combine factual elements (race, ethnicity, and sex) with attitudinal elements (perceptions of political and societal power). We combine those elements to empirically model intersectional identities. Further, our quantitative measures support the idea of the amplification of discrimination and privilege that Crenshaw (1989) discussed. Our results also complement Hong and others (2021, 47), who found that "elements of race and gender discrimination are given significant attention as co-occurring structural barriers."

Limitations

The sample size for the UAS 135 Social Construction module was not large enough to allow us to examine intersectional identities at more than two levels (sex; race or ethnicity). However, as the UAS sample size increases, we envision the possibility of applying this method to study a third layer of identity, such as age, disability status, or another characteristic.

A second limitation is that the data we capture are from a single point in time, but they are influenced by a mosaic of societal forces that have come together over the years to create those perceptions. Those intrinsic factors include historic barriers that helped to create the situation the *DeGraffenreid* plaintiffs called to light and that continue to shape political and societal views today. Despite those limitations, we envision researchers using our SPPS, along with additional intersectional dimensions such as age, place of residence, disability status, and educational attainment, to see if any of those variables further amplify or decrease disparity in the SPPS.

Future Research

The SPPS can be useful for research on a variety of topics, many of which are particularly relevant to Social Security researchers. For example, it can be combined with the diverse data collected by the UAS, ranging from respondent retirement preparedness to policy preferences and experiences with government agencies.

We would like to see the SPPS applied to study people with disabilities (and disability program beneficiaries in particular). We would also like to see the SPPS used to evaluate the public's experiences with the Social Security Administration, perhaps by expanding on previous research on people's preferred channels of receiving program information, to identify any potential structural barriers that limit use of any of those channels. The SPPS could also be used to study the myriad issues related to employment such as the declining availability of private pensions, and to examine wealth accumulation for retirement, building (for example) on work by Kijakazi, Smith, and Runes (2019).

We envision the SPPS being used to determine how the COVID-19 pandemic's effects were distributed among different groups, and incorporated into studies on topics such as homeownership and incarceration, where systemic racism is known to be a persistent historical factor.[11] Again, although the SPPS is a snapshot measure of cumulative systemic barriers, it can illuminate how those historical factors have affected different groups in modern America.

Notes

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[1] The Equal Employment Opportunity Commission (2006) states that Title VII of the Civil Rights Act specifically protects against intersectional discrimination.

[2] Alattar, Messel, and Rogofsky (2018) provide additional information on UAS methodology, and Chard and others (2020) present a detailed discussion of social construction, comparing the social construction of multiple target populations.

[3] With its random and unbiased sample, the UAS enables researchers to make estimations about larger populations. Survey sampling and inferential statistics are important tools for social scientists because it is often too difficult or expensive to collect data from a whole population of interest.

[4] Hereafter, when we refer to the White, Black, and Asian groups, "non-Hispanic" should be assumed. Likewise, Hispanic people can be assumed to be of any race.

[5] We also conducted a subsequent PCA with varimax rotation. Varimax rotation is used to maximize the variance of the squared loadings of a factor (column) on all the variables (rows) in a factor matrix, which causes differentiating of the original variables by a factor thereby making it easier to identify each variable with a single factor (Russell 2002).

[6] Eigenvalues reflect the coefficients of eigenvectors, which give the various magnitudes of the axes of those vectors. They are the calculated lines passing through the observed data, which indicate their covariance. The eigenvectors are then ranked in order of their eigenvalues, with higher numbers indicating greater significance.

[7] Our indirect approach limits the risk of creating social desirability bias because it does not nudge respondents to think about intersectionality. In seminal research on equality, Chong (1993, 869) observes: "Since respondents tend to answer questions off the tops of their heads, it is easy to see how survey results can be biased by altering the wording, format, or context of the survey questions. By making certain cues in the question more prominent than others, we can affect which frames of reference respondents will use to base their opinions. For example, respondents were regularly swayed during these interviews by the intimation or mention of honorific principles such as free speech, majority rule, or minority rights."

[8] We focus on female respondents in this analysis because, as separate regressions address the race-and-ethnicity component, using women's perceptions as our variable of interest allows us to examine that demographic intersection.

[9] The results are qualitatively similar when including controls but the magnitude is smaller and only marginally significant. The reduced coefficient when adding control variables may be explained by education mediating the relationship. Women with more education perceive higher sociopolitical power for women, and there are disparities in the education levels of White and Black women in the sample.

[10] Political efficacy is a political science concept that refers to citizens' trust in their ability to change the government and the belief that they can understand and influence political affairs.

[11] Although Social Security research might not focus on such topics, one could argue that both are germane to retirement in that periods of incarceration severely limit a person's ability to prepare for retirement and homeownership is a significant pathway to retirement wealth.

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A Competing Risks Analysis of Older Americans' Poverty Entry and Exit Patterns in the Health and Retirement Study

by Robert L. Clark, Annamaria Lusardi, and Olivia S. Mitchell*

We examine how older Americans' poverty entry and exit patterns are associated with survey sample attrition using a longitudinal data set for 2002–2018 from the Health and Retirement Study. We consider how sample attrition affects estimates of variables associated with poverty entry and exit, and we find that attrition bias is less apparent in models estimating poverty entry than in models of poverty exit. The effect of aging on poverty exit is smaller in competing risks models than in proportional risk models, and cross-model differences in race and ethnicity effects are not statistically significant. This indicates that long-term respondents were more likely to exit poverty than were those who attrited from the sample, implying a change in sample representativeness over time. Our research confirms the importance of understanding panel data attrition biases when examining older Americans' poverty vulnerability.

Introduction

Several studies have used survey data to trace American adults' poverty entry and exit patterns over time using longitudinal, or panel, data sets (for example, Duncan 1984; Bane and Ellwood 1986).[1] Although such analyses are valuable for studying peoples' exposure to poverty over several periods, they are also subject to sample attrition. For research aiming to measure the likelihood of poverty entry and exit in later life, when respondents with low income and/or disability may be more likely than younger respondents to die or otherwise leave the panel, sample attrition could be problematic.

This article examines the effect of sample attrition because of death or for other (unknown) reasons, which we refer to as loss to follow-up (LTF), on the estimated variables associated with poverty entry and exit. We analyzed data reported in the University of Michigan's Health and Retirement Study (HRS), a nationally representative panel data set of Americans aged 50 or older, by 11,549 households who responded to the 2002 HRS biennial core survey. Those respondents were then invited to reinterview every 2 years through 2018.[2] Some respondents died or left the panel study because of LTF, and such attrition may be associated with factors affecting poverty transition status in later life. If people who remain in the panel are better off (if they have higher incomes, for example, or are healthier) than their attriting counterparts, that could lead to lower measured poverty rates among the survivors than for the population from which the initial sample was drawn.

Selected Abbreviations

AHEAD	Asset and Health Dynamics of the Oldest Old
CODA	Children of the Depression
CPS	Current Population Survey
HRS	Health and Retirement Study
LTF	loss to follow-up

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Some analysts use proportional hazards models to evaluate the effects of various risk factors in panel surveys, yet those do not generally account for the possibility of nonrandom attrition over time. Accordingly, we examine both proportional hazards models and competing risks models that correct for nonrandom sample attrition. Our goal is to evaluate whether competing risks models produce different estimates of the variables associated with respondents' poverty transitions at older ages.[3]

In this article, we describe the methods we used to calculate older persons' poverty entry and exit rates. We then report our findings and discuss the results.

Methods

In this section, we describe the process used to collect HRS survey data, the reasons respondents may attrit from the survey, the statistical analysis we conducted to obtain the results, and the predictors and potential confounders we examined.

Data

The HRS survey protocol is detailed in HRS (2023b). HRS respondents are invited to be surveyed every 2 years either online or face-to-face, and all participants provide informed consent and receive small incentive payments. The data are housed at the University of Michigan's Survey Research Center and anonymized before analysts may access them.[4] Our analysis uses the RAND HRS Longitudinal File, which is "a cleaned, easy-to-use, and streamlined data product containing information from Core and Exit Interviews of the HRS, with derived variables covering a large range of topics" (Bugliari and others 2024). From this file, we gathered information on 11,549 households surveyed in 2002, the first year for which the RAND file includes a poverty status indicator. We tracked which households entered and which ones exited poverty between consecutive waves, 2 years apart, in the period 2002–2018.

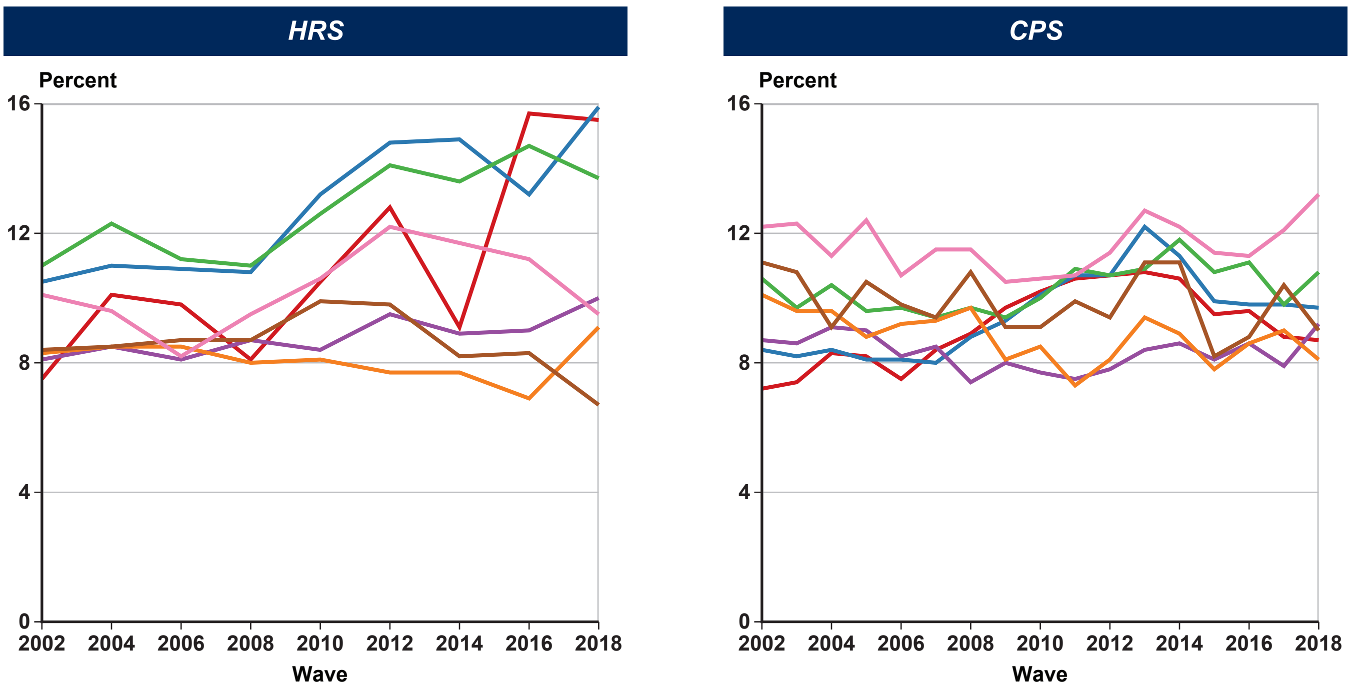
One advantage of using HRS data to examine poverty entry and exit patterns is the rich set of variables available in the database. The two main outcome variables for the older population we studied are (1) the hazard rate of entering poverty in wave t+1, having been nonpoor in wave t; and (2) the hazard rate of exiting poverty in wave t+1, having been poor in wave t. The RAND HRS file uses Census Bureau poverty thresholds and the family composition at the time of the interview to determine whether a household was in poverty in the previous year. Income comprises household labor earnings, pension benefits, Social Security income, disability program benefits, welfare benefits, withdrawals from deposit or individual retirement accounts, and income from self-employment, consulting, or any other source. Because the HRS is administered every 2 years, we can determine whether a household was poor or not at the time of each wave, but we cannot infer what the household's poverty status was between waves. Hence, the apparent poverty spells are actually consecutive reported occurrences across survey waves, which may or may not reflect continuous spells. This differs from many earlier studies on poverty, such as Card and Blank (2008), which used month-to-month Survey of Income and Program Participation data.

In addition to tracing respondents' poverty status over time, we also gathered 2002 HRS respondents' self-reported age, sex, race, ethnicity, education level, marital status, employment status, region of residence, number of marriages, and number of children younger than 18. We also included indicators for cohorts entering the sample at different times to assess whether cross-cohort patterns are statistically similar. We studied the Original HRS cohort (birth years 1931–1941), which was the first cohort surveyed, beginning in 1992; the Asset and Health Dynamics of the Oldest Old (AHEAD) cohort (birth years 1923 or earlier), first surveyed in 1993; and the Children of the Depression (CODA, birth years 1924–1930) and War Baby (birth years 1942–1947) cohorts, first surveyed in 1998.

Chart 1 compares 2002–2018 poverty rates for older Americans based on our HRS extract and the Current Population Survey (CPS) Annual Social and Economic Supplement. Poverty rates for older HRS and CPS respondents were generally consistent, ranging between about 7 percent and 16 percent. However, there were some differences. Among those aged 55–64, HRS respondents were slightly more likely to be poor (about 10–16 percent) than were CPS respondents (about 8–12 percent), although the HRS' relatively smaller sample sizes increase the standard error of its estimates and reduce the likelihood that estimated differences are statistically meaningful. In 2018, for persons aged 80 or older, the HRS poverty rate (9.5 percent) was lower than the CPS rate (13.2 percent); but again, the smaller HRS sample size suggests that this difference is not significant. Overall, we conclude that the two data sets provide relatively

Chart 1.

Comparison of 2002–2018 poverty rates of respondents aged 50 or older, by age and survey



SOURCE: Authors' calculations based on HRS and CPS data.

similar poverty status indicators by age in a given year. Yet, as we show in later sections, several other variables can influence poverty transitions.

Sample Attrition Definition

Respondents attrit from an HRS panel if they die or cannot be contacted by the survey team after substantial effort.[5] The University of Michigan maintains an HRS Tracker file that records known deaths based on the dates reported by a respondent's spouse, partner, or other knowledgeable person; imputed dates based on respondents' last date known alive; or the dates on which HRS staff learned that respondents were deceased. HRS staff also periodically consult the Centers for Disease Control and Prevention's National Death Index (NDI) to confirm dates of death, if applicable, for those who were not interviewed.[6] Table 1 shows the distribution of 2002–2018 HRS respondents by age, in each wave and overall. From 2002 to 2018, the share of respondents aged 80 or older increased from 19.4 percent to 46.2 percent. The median respondent age rose from about 60 in 2002 to about 70 in 2018 (not shown).

Statistical Analysis

We first offer tabular and graphic depictions of poverty entry and exit patterns over the study period. Next, we employ a multivariate hazards model to evaluate the influences of our predictors on the key outcomes. That approach assumes that attrition is independent of poverty exit or reentry (Schober and Vetter 2021). Then, we report results from competing risks regression models, which we used to control for effects of several independent variables on survival time without assuming that death, LTF, poverty entrance, and poverty exit are independent events. Our goal is to determine whether the variables associated with poverty hazards in later life differ when we use a model that assumes random attrition.

Predictors and Potential Confounders

The primary sociodemographic variables we examine as predictors of poverty entry and exit consist of age, sex, race, ethnicity, education level, marital status, employment status, region of residence, HRS cohort, marital history, and number of dependent children in household.[7] Our first analysis measures those

Table 1.
Percentage distributions of 2002–2018 HRS respondents, by age and wave

Age	Wave									
	Total	2002	2004	2006	2008	2010	2012	2014	2016	2018
All	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
50–54	0.8	2.6	1.1	0.4	0.3	0.3	0.3	0.3	0.1	0.1
55–59	4.7	11.9	9.4	5.9	1.9	0.8	0.5	0.5	0.5	0.5
60–64	11.5	20.6	18.4	14.3	13.0	9.6	4.1	2.1	1.0	0.9
65–69	17.7	19.2	20.8	23.1	21.9	17.1	16.2	14.0	9.2	3.6
70–74	20.3	14.4	16.8	20.3	22.0	25.2	25.8	23.5	20.7	19.3
75–79	18.2	12.0	12.7	13.5	16.3	20.1	23.4	25.5	28.8	29.5
80–84	14.0	10.8	11.3	11.5	11.9	13.1	15.0	18.1	21.4	25.5
85–89	8.3	5.7	6.4	7.5	8.7	8.9	9.3	9.9	11.5	13.2
90 or older	4.4	2.9	3.1	3.5	3.9	4.9	5.4	6.2	6.7	7.5

SOURCE: Authors' calculations based on HRS data.

variables as of the 2002 HRS wave (which we call the "baseline"). In addition, because some of those control variables may vary over time, we provide an additional examination that considers the potential effects of such time-varying characteristics as changes in household headship, respondent and spouse health and employment status, marital status, and presence of dependent children.

Poverty Entry and Exit

Table 2 shows descriptive statistics for the HRS baseline respondents (those surveyed in 2002). The average age of all respondents was 69.8, similar to the average age of respondents in the subsamples that subsequently entered and exited poverty. The share of women among respondents entering poverty who were not poor at baseline was 54.1 percent, whereas the share of women among respondents exiting poverty was higher (73.4 percent). Among respondents entering poverty, 83.8 percent were White and 13.2 percent were Black, while 57.6 percent of those exiting poverty were White and 34.2 percent were Black. In addition, 6.5 percent of poverty entrants and 20.9 of those exiting poverty were Hispanic, while 93.5 percent of poverty entrants and 79.1 percent of those exiting poverty were non-Hispanic. Respondents with a high school education or higher constituted 75.9 percent of poverty entrants, but they constituted only 38.4 percent of the poverty exit subsample. Respondents working for pay accounted for 34.0 percent of the poverty entrant subsample, but they accounted for only 11.5 percent of those who exited poverty. Persons who were not working and reported a disability constituted 2.2 percent of poverty entrants, but they constituted 12.0 percent of those who exited poverty. Southerners made up 39.3 percent of those who entered poverty, but they accounted for 56.7 percent of those who exited poverty. The shares of each HRS cohort were similar among the entire sample and the two subsamples. The data suggest that respondents entering and exiting poverty were quite heterogeneous.

Table 3 documents poverty duration: how long, in terms of survey waves, HRS respondents' households remained in poverty. Almost 73 percent of the sample members were never in poverty in the period 2002–2018, and another 13.6 percent were poor in only a single wave. While the vast majority of the sample (86.5 percent) had no poverty experience or experienced poverty in only one wave, the remaining 13.5 percent of the sample experienced poverty in two or more waves, and 5.4 percent of the sample experienced poverty in four or more waves. Table 3 also shows the duration of respondents' longest poverty spells over the study period: 16.4 percent were poor for no longer than a single wave, yet 10.7 percent remained poor for two consecutive waves or more, a phenomenon referred to as "duration dependence" in the literature. The table shows heterogeneity in the chances that older Americans will enter and exit poverty, as well as duration dependence.

Table 2.
Descriptive statistics for baseline HRS respondents (2002 wave) who subsequently entered and exited poverty

Characteristic	Total	Poverty entry	Poverty exit
Number of respondents	11,549	10,293	1,256
Age (mean)	69.8	69.8	70.0
Age (standard deviation)	9.83	9.74	10.56
Percentage distribution by—			
Sex			
Women	56.2	54.1	73.4
Men	43.8	45.9	26.6
Race			
White	80.9	83.8	57.6
Black	15.5	13.2	34.2
Other [a]	3.5	3.0	8.0
Ethnicity			
Hispanic	8.0	6.5	20.9
Non-Hispanic	92.0	93.5	79.1
Education level			
Did not finish high school	28.2	24.1	61.5
High school graduate, no college	33.6	35.0	22.1
Some college or higher	38.2	40.9	16.3
Marital status			
Married	50.8	54.3	22.7
Other	49.2	45.7	77.3
Employment status			
Working for pay	31.5	34.0	11.5
Not working and reporting a disability	3.3	2.2	12.0
Unemployed, retired, or not in labor force	65.2	63.8	76.4
Region of residence			
West	17.2	17.7	12.7
Northeast	16.8	17.1	14.4
Midwest	24.6	25.7	15.5
South	41.2	39.3	56.7
HRS cohort			
AHEAD (born 1923 or earlier)	25.2	25.0	26.7
CODA (born 1924–1930)	11.6	11.9	9.8
HRS original (born 1931–1941)	51.2	51.3	51.0
War Baby (born 1942–1947)	12.0	11.9	12.5
Number of—			
Marriages (mean)	1.32	1.33	1.25
Marriages (standard deviation)	0.71	0.71	0.75
Children younger than 18 (mean)	0.05	0.04	0.07
Children younger than 18 (standard deviation)	0.28	0.27	0.36

SOURCE: Authors' calculations based on HRS data.

NOTE: Rounded components of percentage distributions do not necessarily sum to 100.0.

a. Consists primarily of respondents identifying as American Indian, Alaskan Native, Asian, or Pacific Islander.

Table 3.
Number and percentage distribution of HRS respondents by poverty experience, 2002–2018

Measure	Number of respondents	Percentage distribution
All	11,549	100.0
In poverty for—		
0 waves	8,419	72.9
1 wave	1,566	13.6
2 waves	586	5.1
3 waves	357	3.1
4 or more waves	621	5.4
Longest poverty spell		
0 waves	8,419	72.9
1 wave	1,895	16.4
2 waves	549	4.8
3 waves	257	2.2
4 or more waves	429	3.7

SOURCE: Authors' calculations based on HRS data.

Modeling Poverty Entry and Exit Over Time

Chart 2 uses Kaplan-Meier survival curves to depict the time that passed until HRS respondents entered or exited poverty, conditional on remaining in the sample.[8] Panel A shows the cumulative probability that a respondent who was not poor in one wave entered poverty in subsequent waves, and Panel B shows the cumulative probability that a respondent who was poor in one wave later exited poverty.[9] A similar computation was conducted for each wave, and the cumulative distribution is shown by the red lines in Chart 2. Overall, the probability of entering poverty during 2002–2018 was far lower for older persons than their chances of exiting poverty once they had entered; this indicates the transitory nature of poverty for many older Americans.

Chart 2 also plots cumulative probabilities of poverty entry and exit, by wave, estimated using a competing risks model that allows for nonrandom attrition because of death and LTF. No other variables are included in these calculations. Interestingly, for poverty entry rates, the blue curve representing the competing risks model in Panel A lies below the Kaplan-Meier curve by 2 percentage points in 2004 and 12 percentage points in 2018. By contrast, poverty exit rates using the competing risks model were 17 percentage points lower than the Kaplan-Meier curve in 2004, but 32 percentage points lower in 2018.

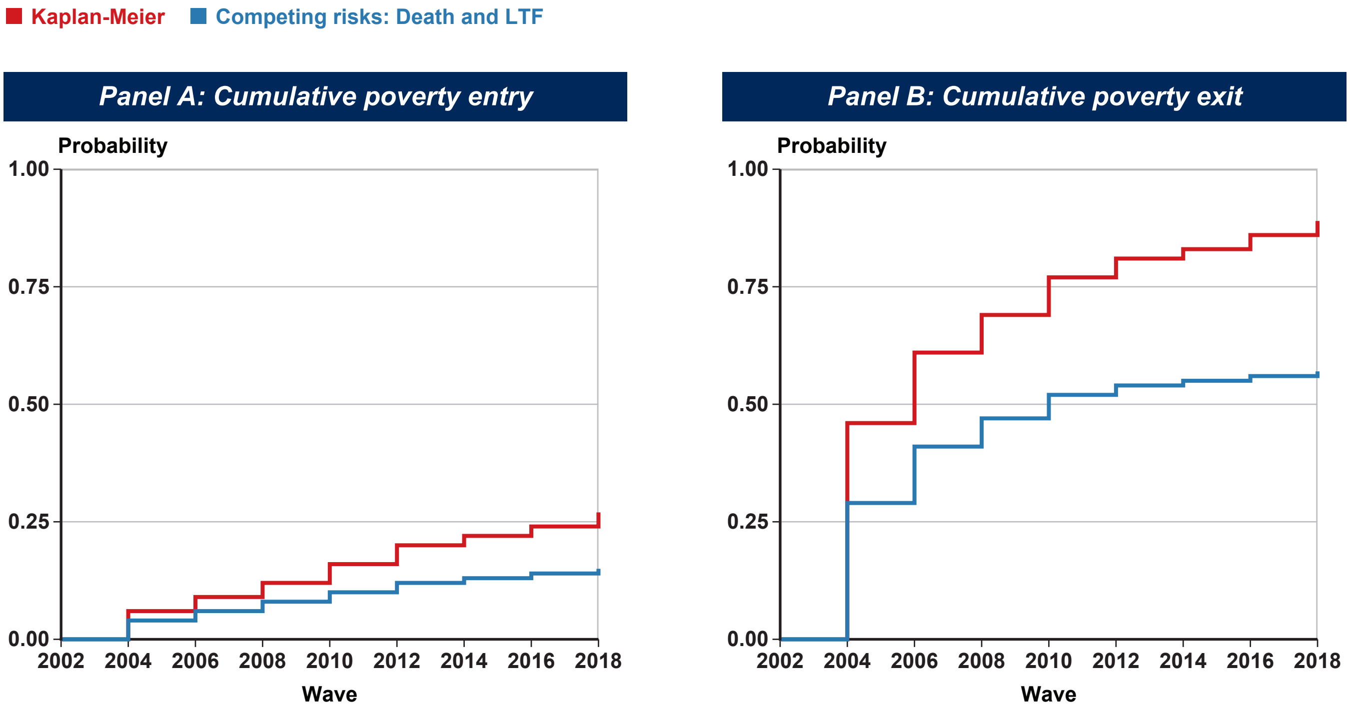
In sum, accounting for sample attrition in the longitudinal panel produces slightly lower poverty entry rates late in the study period, similarly lower poverty exit rates early in the period, and substantially lower poverty exit rates later in the period. This suggests that respondents who remain in the panel in the later part of the period are more likely to exit poverty than were those who attrited from the sample because of LTF or death, potentially indicating a change in the composition of the sample.

Multivariate Analysis Results

In contrast with simple survival curves, Table 4 presents multivariate model estimates that include baseline characteristics believed to be associated with poverty entry. Table 5 does the same for poverty exit. As we mentioned earlier, the variables include age, sex, race, ethnicity, education level, marital status, employment status, region of residence, HRS cohort, number of marriages, and number of dependent children in household. Both tables compare proportional hazards model results with results from a competing risks model. In addition, both tables show results for two separate specifications for each model: namely, *with* and *without* the effects of selected time-varying characteristics. The time-varying characteristics consist of the following occurrences between survey waves: a change in who is the head of household, poor health onset or an employment status change (own and spouse's), a marital status change, and the departure of dependent children. The tables show the adjusted hazard odds ratios for the proportional hazards model, the adjusted subhazard odds ratios for the competing risks model,[10] and the standard deviations (95 percent confidence intervals) for both models for each variable; an estimated odds ratio greater than 1 indicates a greater likelihood of entering or exiting poverty, while an odds ratio less than 1 indicates a lower likelihood.

For the poverty entry determinants in Table 4, we found that few of the age effects in the hazards model are statistically significant at the 5 percent level or better; only persons aged 90 or older are significantly more likely than those aged 50–54 to enter poverty when the time-varying characteristics are included. Interestingly, once time-varying characteristics are controlled in our preferred competing risks model—which incorporates nonrandom attrition because of death and LTF—none of the age coefficients are significant at the 5 percent level or better. Accordingly,

Chart 2.
Cumulative probability of poverty entry and exit, by wave



SOURCE: Authors' calculations based on HRS data and a competing risks model.

we see no evidence of differential age effects on the risk of poverty entry.

The likelihood of poverty entry by sex, race, and ethnicity are similar across the four models and specifications, with odds ratios of similar size and statistical significance. Men were 20 percent less likely than women to enter poverty, controlling for time-varying factors, whereas Black individuals were 2.5 times as likely as White individuals and Hispanic individuals were about 2.4 times as likely as Non-Hispanic individuals to enter poverty. The likelihood of poverty entrance increased with educational attainment, and again the odds ratios for each education level were similar in size and significance across the four models and specifications. Controlling for time-varying characteristics, married persons were 51–56 percent less likely to enter poverty than nonmarried individuals were. The presence of each additional dependent child was associated with a 14–16 percent higher risk of entering poverty across the models and specifications. Working for pay reduced peoples' poverty entry risk, with the estimated risks being slightly greater in the competing risks model specifications. Persons who reported having a disability were more than twice as likely as respondents who were unemployed, retired, or otherwise not in the labor force to enter poverty, with robust estimates in all four models and specifications. Residence in the South was consistently positively associated with poverty entry, with the risk estimated as 17–26 percent greater than that for residents of the West. Finally, there were few significant differences between HRS cohorts in the probability of entering poverty in later life, and no coefficient was significant at the 5 percent level in the competing risks framework.

In general, the hazard rate estimates prove to be comparable with those from the competing risks models. The key time-varying characteristics adding to the models' explanatory power include a change in the household head, divorce, worsening health of either the respondent or his or her spouse, a change in the respondent's employment status from unemployed to employed, and having children leave home. All of these factors are substantially and significantly correlated with a higher likelihood of poverty entry.

Table 5 shows poverty exit patterns. For all age groups older than 59, the coefficient estimates are statistically significant when time-varying characteristics are included in both the hazard and competing risks models. One key difference, however, is that the estimated magnitudes are often larger when attrition

Table 4.
Proportional hazards and competing risks regression results for poverty entry, 2002–2018: Without and with time-varying characteristics

Variable	Proportional hazards model						Competing risks model					
	Without time-varying characteristics			With time-varying characteristics			Without time-varying characteristics			With time-varying characteristics		
	Adjusted hazard odds ratio	95% confidence interval		Adjusted hazard odds ratio	95% confidence interval		Adjusted subhazard odds ratio	95% confidence interval		Adjusted subhazard odds ratio	95% confidence interval	
		Minimum	Maximum		Minimum	Maximum		Minimum	Maximum		Minimum	Maximum
	Baseline characteristics											
Age												
50–54 (reference category)	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
55–59	0.97	0.72	1.30	0.91	0.67	1.22	1.01	0.75	1.35	0.93	0.69	1.25
60–64	0.77*	0.56	1.05	0.73**	0.53	1.00	0.86	0.63	1.16	0.76*	0.55	1.03
65–69	0.76*	0.55	1.04	0.75*	0.55	1.04	0.82	0.60	1.12	0.77	0.56	1.06
70–74	0.75	0.54	1.06	0.77	0.55	1.08	0.78	0.56	1.09	0.76	0.54	1.08
75–79	0.71*	0.49	1.04	0.75	0.51	1.09	0.68**	0.46	0.99	0.72*	0.49	1.05
80–84	0.76	0.50	1.15	0.95	0.63	1.44	0.61**	0.40	0.92	0.81	0.53	1.23
85–89	0.75	0.47	1.18	1.14	0.72	1.80	0.42***	0.27	0.67	0.73	0.46	1.15
90 or older	1.02	0.60	1.74	2.00**	1.17	3.43	0.37***	0.21	0.63	0.83	0.48	1.43
Sex												
Women (reference category)	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
Men	0.85***	0.77	0.95	0.80***	0.72	0.89	0.83***	0.75	0.92	0.80***	0.72	0.89
Race												
White (reference category)	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
Black	2.41***	2.16	2.69	2.50***	2.24	2.79	2.36***	2.11	2.63	2.52***	2.26	2.82
Other [a]	1.28**	1.02	1.60	1.30**	1.03	1.62	1.32**	1.06	1.64	1.29**	1.03	1.63
Ethnicity												
Hispanic	2.34***	2.01	2.72	2.37***	2.03	2.76	2.34***	2.01	2.71	2.44***	2.08	2.85
Non-Hispanic (reference category)	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
Education level												
Did not finish high school	0.38***	0.34	0.43	0.35***	0.31	0.40	0.41***	0.36	0.46	0.36***	0.32	0.41
High school graduate, no college	0.56***	0.50	0.63	0.55***	0.49	0.61	0.58***	0.52	0.65	0.55***	0.50	0.62
Some college or higher (reference category)	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .

(Continued)

Table 4.
Proportional hazards and competing risks regression results for poverty entry, 2002–2018: Without and with time-varying characteristics—*Continued*

Variable	Proportional hazards model						Competing risks model					
	Without time-varying characteristics			With time-varying characteristics			Without time-varying characteristics			With time-varying characteristics		
	Adjusted hazard odds ratio	95% confidence interval: Minimum	95% confidence interval: Maximum	Adjusted hazard odds ratio	95% confidence interval: Minimum	95% confidence interval: Maximum	Adjusted subhazard odds ratio	95% confidence interval: Minimum	95% confidence interval: Maximum	Adjusted subhazard odds ratio	95% confidence interval: Minimum	95% confidence interval: Maximum
	Baseline characteristics (cont.)											
Marital status												
Married	0.57***	0.51	0.64	0.44***	0.39	0.49	0.76***	0.68	0.84	0.49***	0.44	0.55
Other (reference category)	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
Employment status												
Working for pay	0.78***	0.70	0.87	0.77***	0.68	0.86	0.86***	0.76	0.96	0.80***	0.71	0.89
Not working and reporting a disability	2.22***	1.79	2.74	2.35***	1.90	2.92	2.01***	1.61	2.50	2.28***	1.82	2.85
Unemployed, retired, or not in labor force (reference category)	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
Region of residence												
West (reference category)	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
Northeast	0.97	0.82	1.15	0.97	0.82	1.14	0.94	0.79	1.11	0.96	0.81	1.14
Midwest	0.96	0.82	1.13	0.97	0.83	1.14	0.95	0.81	1.11	0.96	0.82	1.12
South	1.21***	1.06	1.39	1.26***	1.09	1.44	1.17**	1.02	1.34	1.23***	1.07	1.41
HRS cohort												
AHEAD (born 1923 or earlier)	1.30	0.94	1.81	1.49**	1.07	2.07	1.04	0.75	1.44	1.36*	0.98	1.89
CODA (born 1924–1930)	1.19	0.88	1.61	1.26	0.93	1.70	1.01	0.76	1.35	1.20	0.89	1.61
HRS original (born 1931–1941)	1.10	0.88	1.36	1.07	0.86	1.34	1.05	0.86	1.28	1.06	0.87	1.30
War Baby (reference category, born 1942–1947)	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
Effect of each additional—												
Marriage	1.05	0.98	1.12	1.02	0.96	1.09	1.05	0.99	1.12	1.03	0.96	1.10
Child younger than 18	1.14*	0.99	1.30	1.16**	1.02	1.33	1.16**	1.02	1.31	1.16**	1.02	1.33

(Continued)

Table 4.
Proportional hazards and competing risks regression results for poverty entry, 2002–2018: Without and with time-varying characteristics—*Continued*

Variable	Proportional hazards model						Competing risks model					
	Without time-varying characteristics			With time-varying characteristics			Without time-varying characteristics			With time-varying characteristics		
	Adjusted hazard odds ratio	95% confidence interval		Adjusted hazard odds ratio	95% confidence interval		Adjusted subhazard odds ratio	95% confidence interval		Adjusted subhazard odds ratio	95% confidence interval	
		Minimum	Maximum		Minimum	Maximum		Minimum	Maximum		Minimum	Maximum
	Time-varying characteristics											
Between survey waves, respondent experienced—												
Change in head of household	. . .	. . .	. . .	2.98***	2.49	3.57	. . .	. . .	. . .	3.05***	2.56	3.64
Poor health (self)	. . .	. . .	. . .	1.50***	1.36	1.65	. . .	. . .	. . .	1.41***	1.28	1.55
Poor health (spouse)	. . .	. . .	. . .	1.16*	0.99	1.35	. . .	. . .	. . .	1.15*	0.99	1.34
Divorce	. . .	. . .	. . .	2.03***	1.32	3.11	. . .	. . .	. . .	2.07***	1.33	3.23
Marriage	. . .	. . .	. . .	0.74	0.43	1.28	. . .	. . .	. . .	0.73	0.43	1.25
Children leaving home	. . .	. . .	. . .	1.99***	1.52	2.62	. . .	. . .	. . .	1.80***	1.37	2.38
Employment change from—												
Unemployed to employed (self)	. . .	. . .	. . .	4.01***	1.98	8.12	. . .	. . .	. . .	3.59***	1.72	7.48
Inactive to employed (self)	. . .	. . .	. . .	0.54**	0.32	0.90	. . .	. . .	. . .	0.53**	0.31	0.89
Unemployed to employed (spouse)	. . .	. . .	. . .	2.44	0.61	9.81	. . .	. . .	. . .	2.28	0.60	8.57
Inactive to employed (spouse)	. . .	. . .	. . .	0.40	0.13	1.25	. . .	. . .	. . .	0.38*	0.12	1.17
Number of respondents	10,293			57,083			10,293			57,083		
Log pseudolikelihood	-15,839.0			-17,875.4			-16,666.0			-18,168.0		
Wald/LR chi^2	1,267.5***			2,057.8***			1,141.6***			2,104.8***		

SOURCE: Authors' calculations based on HRS data.

NOTES: The competing risks model incorporates nonrandom sample attrition because of death or LTF.

. . . = not applicable.

* = statistically significant at the 0.10 level; ** = statistically significant at the 0.05 level; *** = statistically significant at the 0.01 level.

a. Consists primarily of respondents identifying as American Indian, Alaskan Native, Asian, or Pacific Islander.

Table 5.
Proportional hazards and competing risks regression results for poverty exit, 2002–2018: Without and with time-varying characteristics

Variable	Proportional hazards model						Competing risks model					
	Without time-varying characteristics			With time-varying characteristics			Without time-varying characteristics			With time-varying characteristics		
	Adjusted hazard odds ratio	95% confidence interval		Adjusted hazard odds ratio	95% confidence interval		Adjusted subhazard odds ratio	95% confidence interval		Adjusted subhazard odds ratio	95% confidence interval	
		Minimum	Maximum		Minimum	Maximum		Minimum	Maximum		Minimum	Maximum
	Baseline characteristics											
Age												
50–54 (reference category)	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
55–59	0.96	0.62	1.49	1.07	0.69	1.68	0.93	0.68	1.25	1.02	0.70	1.50
60–64	1.23	0.80	1.90	1.79**	1.15	2.80	1.14	0.86	1.52	1.72***	1.16	2.55
65–69	1.16	0.73	1.82	1.57*	0.98	2.50	1.10	0.81	1.49	1.55**	1.02	2.35
70–74	1.20	0.73	1.96	1.86**	1.12	3.07	0.94	0.67	1.33	1.67**	1.07	2.60
75–79	1.58	0.88	2.84	3.42***	1.86	6.28	1.09	0.70	1.69	2.78***	1.62	4.77
80–84	1.21	0.61	2.39	2.31**	1.15	4.64	0.66	0.38	1.15	1.76*	0.94	3.32
85–89	1.21	0.59	2.47	2.63***	1.28	5.39	0.58*	0.32	1.05	1.83*	0.96	3.48
90 or older	1.40	0.64	3.07	3.52***	1.58	7.84	0.43**	0.22	0.85	1.80	0.87	3.73
Sex												
Women (reference category)	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
Men	1.09	0.92	1.29	1.14	0.95	1.36	1.06	0.93	1.21	1.12	0.95	1.31
Race												
White (reference category)	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
Black	0.81**	0.68	0.96	0.67***	0.56	0.80	0.93	0.81	1.07	0.72***	0.62	0.85
Other [a]	0.76*	0.57	1.01	0.72**	0.53	0.96	0.81*	0.65	1.02	0.74**	0.56	0.96
Ethnicity												
Hispanic	0.81**	0.66	1.00	0.67***	0.54	0.83	0.96	0.82	1.13	0.73***	0.61	0.89
Non-Hispanic (reference category)	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
Education level												
Did not finish high school	1.38***	1.13	1.70	1.63***	1.33	2.01	1.33***	1.14	1.55	1.59***	1.33	1.89
High school graduate, no college	1.22**	1.01	1.47	1.23**	1.02	1.50	1.25***	1.08	1.44	1.26***	1.06	1.50
Some college or higher (reference category)	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .

(Continued)

Table 5.
Proportional hazards and competing risks regression results for poverty exit, 2002–2018: Without and with time-varying characteristics—*Continued*

Variable	Proportional hazards model						Competing risks model					
	Without time-varying characteristics			With time-varying characteristics			Without time-varying characteristics			With time-varying characteristics		
	Adjusted hazard odds ratio	95% confidence interval: Minimum	95% confidence interval: Maximum	Adjusted hazard odds ratio	95% confidence interval: Minimum	95% confidence interval: Maximum	Adjusted subhazard odds ratio	95% confidence interval: Minimum	95% confidence interval: Maximum	Adjusted subhazard odds ratio	95% confidence interval: Minimum	95% confidence interval: Maximum
	Baseline characteristics (cont.)											
Marital status												
Married	1.31***	1.10	1.56	1.30**	1.05	1.60	1.49***	1.31	1.69	1.38***	1.16	1.65
Other (reference category)	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
Employment status												
Working for pay	1.49***	1.21	1.84	1.92***	1.54	2.38	1.42***	1.24	1.64	1.89***	1.59	2.26
Not working and reporting a disability	0.84	0.66	1.06	0.81*	0.64	1.04	0.83*	0.68	1.00	0.82*	0.66	1.03
Unemployed, retired, or not in labor force (reference category)	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
Region of residence												
West (reference category)	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
Northeast	1.04	0.79	1.37	1.05	0.79	1.39	1.02	0.82	1.26	1.06	0.82	1.36
Midwest	0.92	0.70	1.21	0.88	0.67	1.16	0.95	0.77	1.18	0.91	0.71	1.17
South	0.94	0.76	1.18	0.94	0.75	1.18	0.95	0.80	1.12	0.95	0.78	1.17
HRS cohort												
AHEAD (born 1923 or earlier)	0.69	0.39	1.23	0.45***	0.25	0.82	0.76	0.48	1.22	0.48***	0.29	0.81
CODA (born 1924–1930)	0.66	0.40	1.09	0.44***	0.26	0.74	0.66**	0.44	0.97	0.45***	0.28	0.71
HRS original (born 1931–1941)	0.85	0.61	1.19	0.69**	0.48	0.98	0.79**	0.63	0.99	0.67***	0.50	0.91
War Baby (reference category, born 1942–1947)	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
Effect of each additional—												
Marriage	0.94	0.85	1.03	0.95	0.86	1.05	0.95	0.88	1.02	0.95	0.88	1.04
Child younger than 18	1.05	0.88	1.24	1.00	0.83	1.20	1.13**	1.02	1.24	1.03	0.87	1.22

(Continued)

Table 5.
Proportional hazards and competing risks regression results for poverty exit, 2002–2018: Without and with time-varying characteristics—*Continued*

Variable	Proportional hazards model						Competing risks model					
	Without time-varying characteristics			With time-varying characteristics			Without time-varying characteristics			With time-varying characteristics		
	Adjusted hazard odds ratio	95% confidence interval		Adjusted hazard odds ratio	95% confidence interval		Adjusted subhazard odds ratio	95% confidence interval		Adjusted subhazard odds ratio	95% confidence interval	
		Minimum	Maximum		Minimum	Maximum		Minimum	Maximum		Minimum	Maximum
	Time-varying characteristics											
Between survey waves, respondent experienced—												
Change in head of household	. . .	. . .	. . .	0.83	0.48	1.44	. . .	. . .	. . .	0.85	0.54	1.34
Poor health (self)	. . .	. . .	. . .	0.76***	0.66	0.89	. . .	. . .	. . .	0.75***	0.65	0.85
Poor health (spouse)	. . .	. . .	. . .	1.31**	1.00	1.70	. . .	. . .	. . .	1.30**	1.05	1.61
Divorce	. . .	. . .	. . .	1.83	0.74	4.57	. . .	. . .	. . .	1.72*	0.99	2.98
Marriage	. . .	. . .	. . .	1.63	0.89	3.01	. . .	. . .	. . .	1.62*	0.98	2.68
Children leaving home	. . .	. . .	. . .	1.05	0.57	1.93	. . .	. . .	. . .	1.00	0.58	1.74
Employment change from—												
Unemployed to employed (self)	. . .	. . .	. . .	2.64**	1.14	6.08	. . .	. . .	. . .	2.63***	1.36	5.11
Inactive to employed (self)	. . .	. . .	. . .	1.78***	1.17	2.70	. . .	. . .	. . .	1.88***	1.37	2.59
Unemployed to employed (spouse)	. . .	. . .	. . .	1.72	0.39	7.61	. . .	. . .	. . .	1.62	0.44	5.93
Inactive to employed (spouse)	. . .	. . .	. . .	1.46	0.77	2.74	. . .	. . .	. . .	1.51*	0.96	2.38
Number of respondents	1,256			3,615			1,256			3,615		
Log pseudolikelihood	-5,035.8			-5,619.2			-5,322.5			-5,714.9		
Wald/LR chi^2	95.7***			251.4***			319.3***			475.8***		

SOURCE: Authors' calculations based on HRS data.

NOTES: The competing risks model incorporates nonrandom sample attrition because of death or LTF.

. . . = not applicable.

* = statistically significant at the 0.10 level; ** = statistically significant at the 0.05 level; *** = statistically significant at the 0.01 level.

a. Consists primarily of respondents identifying as American Indian, Alaskan Native, Asian, or Pacific Islander.

is not considered. For example, the risk of exiting poverty for an individual aged 85–89 was 2.63 times higher than that of an individual aged 50–54 in the hazards model, versus 1.83 times higher in the competing risks model. A person aged 90 or older would be 3.52 times more likely than someone aged 50–54 to exit poverty in the hazards model but only 1.80 times more likely in the competing risks framework. Therefore, the protective effect of older age is likely to be overstated in models that ignore endogenous attrition. Men were not differentially likely to exit poverty in later life, compared with women across both models.

Although the likelihood of poverty exit was similar by sex, other variables affected poverty exit patterns. For instance, the poverty exit odds ratios for Black and Hispanic individuals were about 27–33 percent lower than those of their respective reference groups (White and Non-Hispanic), and statistically significant, when controlling for time-varying characteristics. The likelihood of poverty exit declines as education level increases, with odds ratios of similar size and significance for each level across the four models and specifications. Among employment statuses, not working and reporting a disability was not a significant differentiator for exiting poverty at the 5 percent level or better. With time-varying characteristics controlled, people who worked for pay were about 1.9 times more likely to exit poverty than those who were unemployed, retired, or not in the labor force. In contrast with the poverty entry results, region of residence was not a statistically significant differentiator of poverty exit, and the results were similar across models and specifications. Finally, although Table 4 showed no significant difference between HRS cohorts, Table 5 shows that respondents from the three older cohorts (AHEAD, CODA, and HRS original) were less likely to exit poverty than the members of the War Baby cohort. The estimates with time-varying factor controls were similar in both models, as were those without the controls; but estimates under the two specifications differed from each other.

The estimated effects of the time-varying characteristics were not consistently and significantly different between the two models, including those of head of household changes, a marriage or divorce, children leaving home, or a spouse's employment transitions. When one's own health deteriorated, the likelihood of poverty exit declined; but somewhat surprisingly, the chances of poverty exit increased when a spouse's health deteriorated.

Discussion

Poverty rates among older Americans have declined by more than two-thirds in the last five decades (Li and Dalaker 2021), and the household poverty rate is lower among those headed by an individual aged 65 or older (9.0 percent) than among those with a head aged 18–64 (10.4 percent, Shrider and others 2021). Nevertheless, such static poverty measures reveal little about older persons' poverty exposure over time, and because most older Americans have stopped working, they may be increasingly vulnerable to poverty as they age.

This article evaluates older households' poverty entry and exit patterns using data from the HRS, a longitudinal survey of older Americans. Few researchers to date have explored poverty entry and exit patterns among the older population and the sociodemographic variables associated with those patterns,[11] although Larrimore, Mortensen, and Splinter (2020) used tax data to estimate household poverty transitions during a shorter period (2007–2018) than we examined. That analysis had the advantage of relying on administrative data to trace income changes, but the rich sociodemographic information available in the HRS permits us to examine additional variables, unavailable in tax records, that can illuminate movements into and out of poverty.

We have focused on whether and how variables associated with poverty entry and exit are influenced by nonrandom attrition over time, and whether modeling nonrandom attrition alters our interpretation of the factors associated with poverty transitions. We show that poverty entry models exhibit relatively less sample-attrition bias than poverty exit models do, and in many cases, the variables associated with poverty entry among older Americans are similar in proportional hazards and competing risks models. For example, differences in race and ethnicity effects are not statistically significant across models. Nevertheless, competing risks models indicate smaller effects of aging on poverty entry risk. After handling nonrandom attrition because of death and LTF and controlling for the time-varying characteristics, there are only moderate differential age effects on the risk of poverty entry, whereas the simpler hazards model estimates more significant age effects. Overall, though, we conclude that attrition bias is not highly problematic for analysts focusing on poverty entry.

There are a few more differences across models for the poverty exit data, particularly regarding the age effects. Specifically, older persons' chances of leaving poverty appear to be overstated in models that ignore endogenous attrition. When looking at race and ethnicity differences, Black people are 5 percentage points more likely than White individuals and Hispanic people are 6 percentage points more likely than non-Hispanic individuals to exit poverty in the competing risks model, compared with the simpler hazards model's estimates. Additionally, poverty exit was more likely for respondents who remained longer in the HRS panel than were those who attrited from the sample because of LTF or death. Such a finding implies a change in the representativeness of the sample over time.

Analysis of poverty transitions in the older population is becoming increasingly important because several government programs look at peoples' past resources when determining their eligibility for benefits. For instance, applicants for Medicaid nursing home and home care benefits must not only have little current income and assets; they also must have had limited financial resources over a recent period (usually the last 5 years). Medicare premiums for prescription drug and outpatient services coverage are likewise conditioned on participants' income in the last 2 years. The Temporary Assistance for Needy Families (TANF) program can provide food assistance to low-income grandparents who care for young children. However, TANF benefits are time-limited, and eligibility requirements do not account for the possibility that the aged may move in and out of poverty. For these reasons, our research confirms the importance of understanding attrition biases when examining which older Americans are particularly vulnerable to poverty transitions.

We also acknowledge caveats regarding our findings. The HRS income, wealth, and independent variables are self-reported and are subject to reporting error, potentially biasing estimates of the variables associated with poverty transitions (Bound, Brown, and Mathiowetz 2001).[12] We leave to future study an examination of that possibility. Several prior analyses (Meijer and Karoly 2017; Meijer, Karoly, and Michaud 2010; Sierminska, Michaud, and Rohwedder 2008) have compared income and wealth self-reports for HRS subsamples with other nationally representative surveys or administrative data from SSA, and they have generally concluded that HRS income and wealth measures suffer less from measurement error than measures from the other sources.[13] Finally, we have focused on money income to define poverty, consistent with the Census Bureau's official poverty measure and a wide range of other poverty analyses. For this reason, future analysts could include in-kind benefits, such as health care, rent subsidies, and food stamps, in a broader analysis of financial vulnerability.[14] Nevertheless, the official Census Bureau measure remains the most consistent measure of poverty used in the United States for the last half-century.

Our work has relied on data from the longest available survey panel to provide insights into the older population's poverty entry and exit patterns, and we have documented substantial heterogeneity, particularly in models allowing for competing risks of sample attrition. Policymakers concerned with programs designed to alleviate retirement insecurity may wish to consider a more dynamic perspective on financial insecurity at older ages and to take one that acknowledges the importance of attrition bias in the older population.

Notes

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[1] Much of that research focused on nonelderly Americans using the Panel Study of Income Dynamics (for example, Morgan and Smith 1968) or the Survey of Income and Program Participation (for example, Card and Blank 2008) to track poverty spells.

[2] Longitudinal data collection continues in the HRS, but at the time this article was written, some of the key variables required for our analysis were available only through the 2018 wave.

[3] Such models are widely used in medical research to account for attrition bias in longitudinal data because of multiple endogenous causes (for example, Graham and others 2013).

[4] No restricted data were used in this evaluation, and both the University of Pennsylvania and the University of Michigan's Survey Research Center have approved the study as exempt under institutional review board rules (Weir 2017).

[5] Efforts include following up, when possible, with respondents who moved to nursing homes during the survey period. Because of these and other efforts, HRS response rates regularly exceed 80 percent (HRS 2023a).

[6] Although the NDI will eventually generate an "essentially complete" tally of deaths among all prior HRS respondents, the NDI follow-up may lag current status (Weir 2016).

[7] Similar sociodemographic variables are used in many other poverty studies including Dushi and Trenkamp (2021); Larrimore, Mortensen, and Splinter (2020); and Li and Dalaker (2021).

[8] The Kaplan-Meier curve makes no assumptions about the underlying distribution of the data (Schober and Vetter 2024).

[9] The cumulative probability refers to the proportion of a population at risk that develops the outcome of interest over a specific time period. Specifically,

$$S(t) = S(t-1) \times [1-(d_t/n_t)],$$

where $S(t)$ is the probability of being in the survey in wave t, given that the person was observed in wave $t-1$; n_t is the number of respondents observed in wave $t-1$ (those still in the survey in wave t plus those who attrited from wave $t-1$); and d_t is the number of people entering or exiting poverty in wave t.

[10] There is a difference between the adjusted hazard odds ratio and the adjusted subhazard odds ratio. In the proportional hazards model, there is only one type of event that respondents can experience. By contrast, the competing risks model allows subjects to potentially experience more than one type of event. It models the subdistribution hazard function of each type of event.

[11] Some studies have explored the extent of income underreporting in survey data, and the possible implications for estimated poverty rates (Sierminska, Michaud, and Rohwedder 2008; Bee and Mitchell 2017; Dushi, Iams, and Trenkamp 2017; Dushi and Trenkamp 2021).

[12] Dushi and Trenkamp (2021) report that the HRS "provides better estimates of the income of the aged population than the public-use CPS data."

[13] Further, Mazzonna and Peracchi (2021) found that older HRS respondents suffering cognitive declines were also more likely to experience drops in wealth, suggesting that measurement error would be heterogeneous across the HRS sample.

[14] Citro and Michaels (1995) proposed a comprehensive new poverty measure that would account for in-kind benefits. Chavez and others (2018) estimated poverty rates that accounted for potential annuitized asset income for HRS respondents aged 65 or older in 2009. They concluded that poverty rates among older households would range from 9.2 percent to 11.4 percent overall, depending on the annuitization strategy, versus 14.6 percent if annuitized assets are excluded. Mitchell, Clark, and Lusardi (2022) explored income dynamics and labor force participation using longitudinal HRS data. Unfortunately, the HRS does not consider respondents' nonmonetary benefits.

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