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Perspectives

Mixed-Methods Study to Understand Public Use of Social Security's Online Platform

by Lila Rabinovich and Francisco Perez-Arce*

Since 2012, the Social Security Administration has offered online my Social Security accounts to provide a key informational resource to the public. Yet the number of my Social Security accountholders remains lower than the agency had hoped for. We conducted a mixed-methods study involving quantitative analysis of survey data and qualitative analysis of personal interviews to examine potential barriers to my Social Security access and to evaluate account users' experiences. The quantitative analysis shows that lower levels of internet literacy and educational attainment are barriers to accountholding and use. Our qualitative findings suggest that my Social Security can be useful in retirement planning, especially for younger adults, by filling knowledge gaps and correcting mistaken expectations. Further research can address ways to minimize or eliminate barriers to my Social Security access and use, and explore how to maximize its effectiveness in supporting retirement readiness and Social Security literacy.

Introduction

Knowledge about Social Security is critical to workers and their families. Well-informed individuals tend to make better financial decisions and prepare more effectively for retirement (Chan and Stevens 2008; Mastrobuoni 2011; Bhargava and Manoli 2015). Incomplete information about Social Security benefits and program rules may result in suboptimal decisions, such as claiming retirement benefits too early or too late to maximize likely lifetime benefit amounts.

The Social Security Administration (SSA) operates an extensive information outreach program. The *Social Security Statement,* containing general facts about the program along with individualized earnings histories and future benefit projections, has been the agency's primary channel for providing information to the public since its introduction in 1995 (Smith 2020). Research has shown that the *Statement* increases workers' knowledge about their Social Security benefits (Mastrobuoni 2011; Smith and Couch 2014; Sass 2015) and informs their planned claiming ages (Armour 2020) and Disability Insurance application decisions (Armour 2018).

In the late 1990s and the 2000s, SSA sent the *Statement* to all covered workers via annual mailings. Although budget constraints led the agency to scale back annual mailings beginning in 2012, SSA established *my* Social Security, an online portal for the public providing access to general and individualized program information. By signing up for a *my* Social Security account on the agency's website, users have a single point of access to many SSA electronic services and can obtain information about their own benefit entitlements—including their latest *Social Security Statement*, with their earnings history and personalized estimates of future benefits. Users are also able to conduct transactions online, such as requesting a replacement Social Security card, changing personal information, or applying for benefits (via a link) without calling or visiting a Social Security office.

Selected Abbreviations

SSA	Social Security Administration
UAS	Understanding America Study

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This multipurpose platform therefore has two main advantages. First, it offers users significant time savings compared with seeking information or conducting transactions in person or by phone. Individuals can access *my* Social Security from anywhere that provides internet service. Second, *my* Social Security provides personalized information about key aspects of financial and retirement planning. This may be especially critical in the context of low Social Security and retirement-planning literacy among Americans. For instance, 63 percent of adult survey respondents feel that they are not knowledgeable about what their retirement benefits will be (Yoong, Rabinovich, and Wah 2015). Carman and Hung (2018) also document low Social Security literacy.

The increasing availability of personal devices with internet access expands the potential reach of online financial education resources that can quickly provide useful information. Lusardi and others (2017) examine innovative online financial education tools and observe that their potential effectiveness depend on ease of access and efficiency while requiring a low time commitment of their users. The *my* Social Security portal is a key source of information that is critical to financial well-being, and it meets those criteria. Yet the number of people who have opened a *my* Social Security account is lower than SSA had hoped for.

To our knowledge, no research has studied the low level of public engagement with *my* Social Security. To address this gap, we conducted a mixed-methods study, combining qualitative and quantitative data collection and analysis, to examine the perceived and actual barriers to use of *my* Social Security, along with the experiences reported by *my* Social Security accountholders. We hope the findings suggest ways to increase participation, enhance Social Security literacy, and enable the public to optimize their retirement planning and decisions.

General Approach

In phase 1 of our study (quantitative data collection), we used existing data from surveys administered through the University of Southern California's Understanding America Study (UAS), a probability panel of more than 8,000 respondents recruited using address-based sampling (Alattar, Messel, and Rogofsky 2018).[1] The UAS panel is representative of the U.S. population aged 18 or older. After joining the panel, individuals are invited to take, on average, two surveys each month. Surveys are administered online (a tablet, broadband internet access, and training are provided for individuals who need them).[2] Respondents are compensated $20 for a 30-minute survey (proportionally less for shorter surveys).

Two recurring surveys fielded to all UAS panelists every 2 years respectively measure respondents' Social Security literacy and their preferred sources of information about Social Security and retirement. These surveys include questions on awareness and use of *my* Social Security. Wave 3 of the Social Security program knowledge survey also measured respondents' internet literacy and the types and frequencies of their online activities. We used the quantitative data from these surveys for two distinct purposes: to analyze the determinants of *my* Social Security account usage and to recruit follow-up interviewees in a procedure described below.

For phase 2 (qualitative assessment of users' experience with the platform), we aimed to ensure that our interview subjects were diverse in terms of internet literacy, current usage of *my* Social Security, and Social Security beneficiary status. These variables were chosen because we anticipated that they would significantly affect individuals' perceptions of, awareness of, and experiences with *my* Social Security. Beneficiaries and nonbeneficiaries are likely to be interested in different aspects of *my* Social Security. For instance, nonbeneficiaries may profit from learning about their expected benefits, whereas beneficiaries may want to use the account to set up direct deposits or obtain a benefit verification letter, among other purposes.

We recruited 24 participants for phase 2 of our study. We chose 24 as our sample size because qualitative research literature suggests that data saturation—the point at which no new themes emerge from the data—is often achieved after as few as 10 to 20 interviews, depending on the type of population under investigation (Hennink, Kaiser, and Marconi 2017; Morgan and others 2002; Francis and others 2010; Guest, Bunce, and Johnson 2006; Namey and others 2016). We did not set out to understand how *often* these issues are found in the population, but rather the *range* and *type* of issues that may emerge in individuals' interactions with *my* Social Security. We sought adequate sample sizes both of platform users, whom we could ask about their experiences, and nonusers, whose reactions to first platform contact we could observe. Hence, we stratified respondents by accountholder status. To analyze whether internet literacy is an important determinant of *my* Social Security experiences, we also sought sufficient numbers of interviewees with levels of internet literacy both above and below the median.

To that end, we created an internet literacy index. The 2020 wave of the UAS Social Security program knowledge survey included a set of 35 questions designed to build a measure of internet literacy, which we adapted from the Internet Skills Scale developed by Van Deursen, Helsper, and Eynon (2016). For these questions, respondents reported their ability in a number of online tasks, such as downloading files, filling online forms, changing privacy settings, bookmarking a website, and downloading applications ("apps") to a mobile device. Using a technique called principal component analysis (PCA), we created an internet literacy index comprising 35 weighted variables.[3]

To ensure adequate variation in the characteristics of interest in our sample, we used a stratified selection process. First, we divided the entire sample from the UAS Social Security literacy survey into eight groups, determined by the intersection of three binary variables: above or below the median level of internet literacy; *my* Social Security accountholder status; and Social Security beneficiary status. Then, we randomly chose three people from each group for interviews. The invitation to participate included a screening question eliciting participants' willingness to log into or open their *my* Social Security account online during the interview, a requirement for the qualitative assessment of users' experiences with the platform.

All interviews were conducted by phone during May and June 2021, with participants required to have their laptops or tablets and internet access ready. The interview consisted of two segments. First, participants were asked about their prior interactions with SSA, their online habits, and, for *my* Social Security accountholders, their experience opening the account. In the second segment, accountholders were asked to log into their account and answer a series of questions about their experience as they navigated various elements within the platform. By contrast, respondents without an account were asked to create one during the interview, then asked to answer a similar series of questions about their impressions of the platform.

All interviews were recorded and transcribed verbatim. We employed thematic analysis of the transcripts, a technique that focuses on description and interpretation of narrative materials (Braun and Clarke 2006; Thomas 2006). That process began with the development of a preliminary codebook, based on the research questions with which we coded the raw interview data. New codes were developed inductively; that is, as themes emerged through review of the data. Ultimately, we generated 41 individual codes, which allowed us to identify major manifest and latent themes, key concepts, areas of divergence, and connections between messages inherent in the raw data.

The study approach received ethics approval by the University of Southern California's Institutional Review Board. Participants in the qualitative interviews, who provided informed consent both at the time of recruitment and at the start of the interview, were compensated $40 for participating.

Quantitative Study

We had two main goals for the quantitative part of the study. The first goal was to identify and measure the factors affecting *my* Social Security use and the usage patterns in the most recent years. Analyzing the correlates of *my* Social Security usage could shed light on barriers to expansion of the platform's reach. The second goal was to gather information on current Social Security beneficiary status, internet literacy, and *my* Social Security use, which we could use to ensure sufficient diversity among participants selected for our qualitative study.

Data

From the UAS, we used data mainly from the first three rounds of two longitudinal surveys, formally titled *What do People Know about Social Security*[4] and *Retirement Planning,*[5] with the latter survey focusing on how respondents "get and/or would prefer to receive information on retirement planning from [SSA] and other sources" (Rabinovich, Perez-Arce, and Yoong 2022). Hereafter, we refer to these as the *What People Know* and *Information Channels* surveys, respectively. Because UAS panel membership increased during the study period, every follow-up wave included both respondents who had answered prior survey rounds and new panelists who were participating for the first time.

The first three rounds of the *What People Know* survey were conducted during the period 2015–2021. This survey, covering respondent knowledge of Social Security programs and about retirement in general, includes questions about intended retirement and benefit-claiming ages. The third round also included a battery of questions intended to measure internet literacy and use.

The first three rounds of the *Information Channels* survey were also conducted during 2015–2021. It covers preferred means of receiving information and contacting SSA field offices (internet, regular mail, phone, or in-person visits); receipt of the *Social Security Statement;* and *my* Social Security accountholder status.

Other UAS surveys (including modules containing questions from the University of Michigan's Health and Retirement Study) collect information on a broad range of related topics such as retirement income from Social Security benefits and other sources. The UAS Comprehensive File compiles the data from the Social Security and related surveys. We used data from the June 2021 update of the Comprehensive File.[6]

Outcome Variables

To gauge the extent of *my* Social Security awareness, accountholding, and use, we looked at responses to three specific questions in the *Information Channels* survey:

1. Have you previously heard about *my* Social Security?
2. Have you set up a *my* Social Security account?
3. Have you ever used *my* Social Security to do any of the following? Please select all that apply:
   - Track and verify your earnings;
   - Get a replacement Social Security card;
   - Get an estimate of future benefits;
   - Get a letter with proof of benefits;
   - Change your personal information such as address;
   - Start or change your direct deposit;
   - Get a replacement Medicare card;
   - Get a replacement SSA-1099 or SSA-1042S;
   - None of the above.

We constructed *awareness* and *accountholding* variables, respectively, as indicators of affirmative responses to the first and second questions above. To proxy for the extent of account use, we constructed the *frequency of use* variable by counting how many of the activities were selected in the response to the third question. *Frequency of use* is coded zero if the respondent does not have an account. To construct these variables, we restricted our analysis to results of the third wave of the *Information Channels* survey.

Predictor Variables

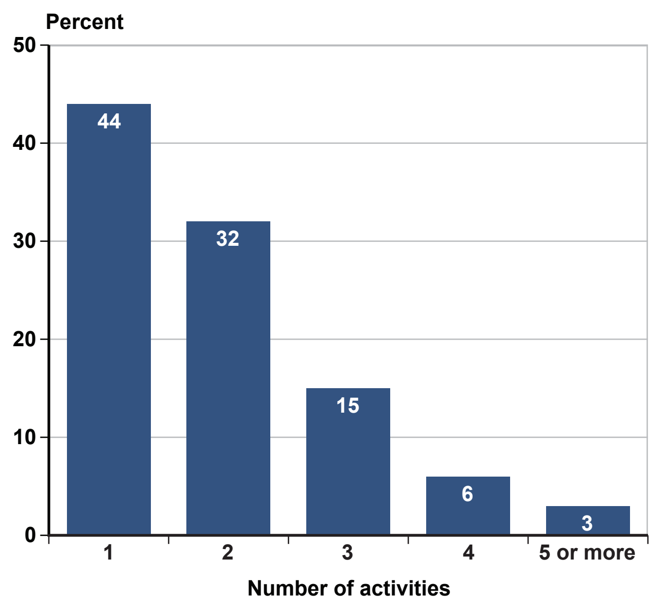
We explored the extent to which demographic variables such as age, sex, race, ethnicity, and education may determine *my* Social Security awareness, accountholding, and use. To measure education, we used either a dummy variable indicating that the respondent attended college, or a variable measuring number of years of education. We also used a *beneficiary* variable to indicate whether the respondent currently receives or recently received Social Security benefits. To identify the extent to which limited internet literacy inhibits *my* Social Security access and use, we used the internet literacy index described in the preceding section.

Quantitative Results

Using wave 3 of the *Information Channels* survey (UAS 238, fielded in April 2020), we found that 81 percent of U.S. adults do not have an account and have never used *my* Social Security, while 19 percent have used it at least once (not shown). Among account users, 44 percent have conducted only one activity on the platform, 32 percent have conducted two activities, and 24 percent have conducted three or more activities (Chart 1).

Table 1 shows the unweighted distributions of our sample respondents by age group, sex, race and ethnicity, Social Security beneficiary status, educational attainment, and *my* Social Security accountholder

Chart 1.
Percentage distribution of *my* Social Security accountholders, by number of account activities initiated in most recent year, 2020–2021



SOURCE: Authors' calculations based on UAS238.

NOTE: Sample size = 743.

status. The age groups are fairly evenly represented, as are individuals with and without a college degree; women are overrepresented in this sample.

Determinants of Awareness and Usage

To identify factors that may explain *my* Social Security awareness and usage, we used regression models that account for general demographic characteristics and include variables that may indicate barriers to platform use such as limited internet literacy. We began by using probit models and results from the most recent wave of the two surveys to calculate equation 1, where Y_i represents the dependent variable (*my* Social Security awareness or accountholding) and X_i represents the vector of dependent variables for individual *i* (which include age, sex, education, internet literacy and usage, and beneficiary status), and ε_i is the error term:

$$\Pr(Y_i = 1) = \Phi(\alpha + X_i\beta + \varepsilon_i) \qquad (1)$$

Table 1.
Survey sample demographic characteristics, 2020–2021 (unweighted)

Characteristic	Percent
Age	
18–29	19
30–39	13
40–49	20
50–59	18
60–69	17
70 or older	12
Sex	
Women	59
Men	41
Race and ethnicity	
Hispanic (any race)	18
Non-Hispanic—	
White	63
Black	8
Other race [a]	11
Social Security beneficiary	
Yes	26
No	74
Education	
Has bachelor's degree	40
No bachelor's degree	60
my Social Security accountholder	
Yes	19
No	81
Sample size	3,913

SOURCE: Authors' calculations based on UAS238.

NOTE: Rounded components of percentage distributions do not necessarily sum to 100.

a. Includes Asian, Native American, Pacific Islander, and multiracial.

Table 2 shows the regression estimates from two probit models for determinants of *my* Social Security awareness. People with higher levels of internet literacy are 2.8 percentage points more likely than others to be aware of the platform's existence, and beneficiaries are 6.6–7.5 percentage points more likely to be aware of *my* Social Security than nonbeneficiaries. Even though the regression models account for beneficiary status, age is still a significant determinant of awareness: From the sample mean, an additional year of age would be associated with a 0.8 or 0.9 percentage-point increase in awareness. Neither sex nor household earnings is a significant predictor of awareness, but personal earnings level is, suggesting that higher earners are also more likely to be aware of *my* Social Security.

Table 3 repeats Table 2 for *my* Social Security accountholding. It shows that internet literacy and beneficiary status are statistically significant predictors of having an account. The coefficient for internet literacy implies that a respondent whose proficiency is one standard deviation above the mean is 2.7 percentage points more likely to have an account. Likewise, the probability of a Social Security beneficiary having an account is 4.5 percentage points higher than that of a nonbeneficiary. Age and education are also significant predictors, with an additional year of age and an additional year of education each predicting an increase of about 0.1 percentage point in the probability of having an account.

In Table 4, we present results of similar probit models analyzing the determinants of *my* Social Security awareness and accountholding, but with the age variable expanded to comprise a series of age-group dummies. The coefficients suggest a roughly linear increase in both awareness and accountholding as age increases. In addition to the probit models, we used linear probability models to generate estimates (not shown) that are qualitatively similar to those shown in Tables 2–4.

One potential concern of using data from panel surveys is that respondents' knowledge and behavior may be affected by their participation in earlier similar surveys—a phenomenon called *panel conditioning*. Having answered a given question in one or two prior survey rounds could, in principle, affect the response in a current round (although to affect the results of Tables 2 and 3, panel conditioning would have to affect

Table 2.
Determinants of *my* Social Security awareness: Probit model estimates, 2020–2021

Independent variable	Model 1 (incorporating five independent variables) Coefficient	Model 1 Standard error	Model 2 (incorporating ten independent variables) Coefficient	Model 2 Standard error
Binary variables				
Internet literacy	0.028***	0.003	0.028***	0.003
Social Security beneficiary	0.066***	0.023	0.075***	0.024
Women	-0.010	0.016	-0.006	0.017
Race and ethnicity				
Hispanic (any race)	. . .	. . .	0.045	0.028
Non-Hispanic Black	. . .	. . .	0.066**	0.033
Other race (non-Hispanic) [a]	. . .	. . .	0.033	0.030
Incremental variables				
Age	0.008***	0.001	0.009***	0.001
Years of education	0.000	0.004	0.000	0.004
Earnings	. . .	. . .	0.031*	0.016
Household income	. . .	. . .	0.000	0.005
Observations	3,915		3,901	
Pseudo R^2	0.055		0.057	

SOURCE: Authors' calculations based on UAS238.

NOTES: Omitted reference categories for binary variables are low internet literacy, Social Security nonbeneficiary, men, and non-Hispanic White, as applicable.

Intervals for incremental variables are 1 year for age and years of education and $10,000 for earnings and household income.

. . . = not applicable.

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

a. Includes Asian, Native American, Pacific Islander, and multiracial.

responses differently across the characteristics of interest in our analysis). To assess the extent to which this may have occurred, we reused the probit models of Tables 2 and 3 and calculated separate estimates for wave 3's new and repeat respondents. We found that the results are qualitatively similar, with age, education, internet literacy, and beneficiary status being important predictors of the outcome variables in both subsamples. Table 5 shows the results.

To measure the frequency of account activity, we used linear models having the same independent variables as the probit models, with the dependent variable being the number of activities conducted.[7] The results (Table 6) are shown separately for all respondents—including those without a *my* Social Security account—and for accountholders only. The latter estimates are useful not only for understanding the factors that affect frequency of use, but also whether they differ from those that affect opening an account.

Overall, we found that the strongest predictor of more frequent account activity is being a Social Security beneficiary, as it was for platform awareness and accountholding. On average, beneficiaries conduct 0.24 more activities than nonbeneficiaries overall (and, conditional on having an account, they conduct 0.33–0.35 additional activities). Higher internet literacy and educational levels are also important determinants of increased account use. Younger individuals are likely to use *my* Social Security less frequently than older ones, even when controlling for beneficiary status (not shown).

Trajectories of Platform Awareness and Account Usage

Our use of longitudinal data allows us to study trends in *my* Social Security awareness, accountholding, and frequency of use. Awareness has increased substantially: From 2015 to 2018, the proportion of respondents who had heard about the platform rose steadily from 21 percent to 34 percent; since then, the proportion has hovered between 29 percent and 37 percent (Chart 2, Panel A).

Table 3.
Determinants of *my* Social Security accountholding: Probit model estimates, 2020–2021

Independent variable	Model 1 (incorporating five independent variables)		Model 2 (incorporating ten independent variables)	
	Coefficient	Standard error	Coefficient	Standard error
Binary variables				
Internet literacy	0.027***	0.000	0.027***	0.000
Social Security beneficiary	0.045**	0.020	0.047**	0.020
Women	0.003	0.010	0.004	0.020
Race and ethnicity				
Hispanic (any race)	. . .	. . .	0.013	0.030
Non-Hispanic Black	. . .	. . .	0.014	0.030
Other race (non-Hispanic) [a]	. . .	. . .	0.054*	0.030
Incremental variables				
Age	0.009***	0.000	0.009***	0.000
Years of education	0.010***	0.000	0.010***	0.000
Earnings	. . .	. . .	0.009	0.010
Household income	. . .	. . .	-0.001	0.000
Observations	3,913		3,899	
Pseudo R^2	0.087		0.088	

SOURCE: Authors' calculations based on UAS238.

NOTES: Omitted reference categories for binary variables are low internet literacy, Social Security nonbeneficiary, men, and non-Hispanic White, as applicable.

Intervals for incremental variables are 1 year for age and years of education and $10,000 for earnings and household income.

. . . = not applicable.

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

a. Includes Asian, Native American, Pacific Islander, and multiracial.

It is important to reiterate that the samples for later years include new respondents, as the panel grows. Hence the respondent population is not identical across years (although UAS uses weights to maintain the sample's representativeness of the adult U.S. population each year). Although panel conditioning could have been a factor in rising awareness over time, Table 5 showed no significant differences between the new and repeat respondents.

Because the first round of the survey did not include the questions we used to code accountholding and usage, we can track those variables only since 2017. Nevertheless, a slightly upward trend emerges. In the first two years the survey included the questions on accountholding and use (2017 and 2018), about 21 percent of respondents had an account (Chart 2, Panel B). In 2020 and 2021, about 24 percent of respondents had an account. For all respondents, including those without an account, the average number of activities initiated on the platform increased from 0.39 in 2017 and 0.38 in 2018 to 0.46 in 2020 and 0.42 in 2021.

Determinants of Changes in Account Usage

We studied the determinants of change in *my* Social Security awareness, accountholding, and use by comparing the UAS results from the earliest available and most recent survey waves. Hence, for the awareness variable, we examined changes between the first wave (2015–2016) and third wave (2020–2021) of the surveys, while for the accountholding and frequency of use variables, we examined changes between the second (2017–2019) and third waves.

We used regression models in which the dependent variable is the change in each outcome variable over the study period. In equation 2, Y_i^{POST} and Y_i^{PRE} denote the values of the outcome variable in the final and initial period, respectively, X_i^{PRE} includes the independent variables (age, race, ethnicity, education, internet literacy, internet use, and beneficiary status) measured in the baseline wave, and ε_i represents random error:

$$Y_i^{POST} - Y_i^{PRE} = \alpha + X_i^{PRE}\beta + \varepsilon_i \qquad (2)$$

Table 4.
Expanded analysis of determinants of *my* Social Security awareness and accountholding: Probit model estimates, 2020–2021

	Awareness				Accountholding			
	Model 1 (incorporating eight independent variables)		Model 2 (incorporating 13 independent variables)		Model 3 (incorporating eight independent variables)		Model 4 (incorporating 13 independent variables)	
Independent variable	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error
Binary variables								
Age								
30–39	0.125***	0.043	0.127***	0.043	0.181***	0.054	0.185***	0.055
40–49	0.209***	0.041	0.212***	0.042	0.280***	0.054	0.289***	0.055
50–59	0.321***	0.039	0.325***	0.040	0.415***	0.051	0.422***	0.052
60 or older	0.441***	0.037	0.454***	0.038	0.537***	0.044	0.548***	0.044
Internet literacy	0.029***	0.003	0.029***	0.003	0.027***	0.002	0.027***	0.002
Social Security beneficiary	0.072***	0.023	0.082***	0.024	0.057***	0.020	0.059***	0.021
Women	-0.009	0.016	-0.006	0.017	0.002	0.014	0.003	0.014
Race and ethnicity								
Hispanic (any race)	. . .	. . .	0.055**	0.028	. . .	. . .	0.024	0.026
Non-Hispanic Black	. . .	. . .	0.069**	0.033	. . .	. . .	0.014	0.030
Other race (non-Hispanic) [a]	. . .	. . .	0.038	0.030	. . .	. . .	0.060**	0.028
Incremental variables								
Years of education	0.001	0.004	0.001	0.004	0.011***	0.003	0.011***	0.004
Earnings	. . .	. . .	0.029*	0.017	. . .	. . .	0.006	0.010
Household income	. . .	. . .	-0.001	0.005	. . .	. . .	-0.002	0.004
Observations	3,915		3,901		3,913		3,899	
Pseudo R^2	0.068		0.071		0.107		0.109	

SOURCE: Authors' calculations based on UAS238.

NOTES: Omitted reference categories for binary variables are ages 18–29, low internet literacy, Social Security nonbeneficiary, men, and non-Hispanic White, as applicable.

Intervals for incremental variables are 1 year for years of education and one standard deviation for earnings and household income.

. . . = not applicable.

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

a. Includes Asian, Native American, Pacific Islander, and multiracial.

Table 5.
Expanded analysis of determinants of *my* Social Security awareness and accountholding: Linear regression model estimates, comparing new and repeating respondents, 2020–2021

Independent variable	Awareness				Accountholding			
	Model 1 (repeat respondents)		Model 2 (first-time respondents)		Model 3 (repeat respondents)		Model 4 (first-time respondents)	
	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error
Binary variables								
Internet literacy	0.025***	0.003	0.015***	0.005	0.022***	0.002	0.026***	0.006
Social Security beneficiary	0.071***	0.027	0.040	0.045	0.054**	0.022	0.029	0.048
Women	-0.006	0.018	0.016	0.033	0.008	0.015	0.013	0.036
Race and ethnicity								
Hispanic (any race)	0.027	0.030	0.022	0.053	-0.008	0.026	0.033	0.061
Non-Hispanic Black	0.086**	0.036	-0.044	0.069	0.023	0.030	-0.044	0.074
Other race (non-Hispanic) [a]	0.016	0.032	0.035	0.055	0.026	0.028	0.099	0.062
Incremental variables								
Age	0.008***	0.001	0.005***	0.002	0.008***	0.001	0.009***	0.002
Years of education	0.001	0.004	0.000	0.009	0.005	0.004	0.024**	0.009
Earnings	0.014	0.018	0.086**	0.037	0.022	0.015	0.004	0.021
Household income	0.004	0.005	-0.026**	0.013	0.001	0.004	-0.009	0.014
Observations	3,077		824		3,077		822	
Pseudo R^2	0.0598		0.0262		0.0956		0.0517	

SOURCE: Authors' calculations based on UAS238.

NOTES: Omitted reference categories for binary variables are low internet literacy, Social Security nonbeneficiary, men, and non-Hispanic White, as applicable.

Intervals for incremental variables are 1 year for age and years of education and $10,000 for earnings and household income.

. . . = not applicable.

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

a. Includes Asian, Native American, Pacific Islander, and multiracial.

Table 6.
Determinants of frequency of *my* Social Security account use: Linear regression model estimates, 2020–2021

Independent variable	All respondents: Model 1 (incorporating five independent variables) Coefficient	Standard error	All respondents: Model 2 (incorporating ten independent variables) Coefficient	Standard error	Accountholders only: Model 3 (incorporating five independent variables) Coefficient	Standard error	Accountholders only: Model 4 (incorporating ten independent variables) Coefficient	Standard error
Binary variables								
Internet literacy	0.057***	0.005	0.058***	0.005	0.036***	0.011	0.036***	0.011
Social Security beneficiary	0.244***	0.044	0.243***	0.045	0.352***	0.078	0.329***	0.082
Women	-0.025	0.031	-0.025	0.032	-0.099	0.065	-0.112*	0.066
Race and ethnicity								
Hispanic (any race)	. . .	. . .	0.047	0.052	. . .	. . .	0.080	0.122
Non-Hispanic Black	. . .	. . .	0.133**	0.061	. . .	. . .	0.347***	0.131
Other race (non-Hispanic) [a]	. . .	. . .	0.189***	0.056	. . .	. . .	0.321***	0.112
Incremental variables								
Age	0.016***	0.001	0.017***	0.001	0.005*	0.003	0.007**	0.003
Years of education	0.018**	0.007	0.019**	0.008	0.005	0.016	0.006	0.017
Earnings	. . .	. . .	0.008	0.024	. . .	. . .	-0.041	0.066
Household income	. . .	. . .	-0.002	0.010	. . .	. . .	0.005	0.018
Constant	-0.563***	0.117	-0.632***	0.121	1.548***	0.274	1.433***	0.282
Observations	3,913		3,899		1,051		1,047	
Pseudo R^2	0.092		0.096		0.041		0.055	

SOURCE: Authors' calculations based on UAS238.

NOTES: Omitted reference categories for binary variables are low internet literacy, Social Security nonbeneficiary, men, and non-Hispanic White, as applicable.

Intervals for incremental variables are 1 year for age and years of education and $10,000 for earnings and household income.

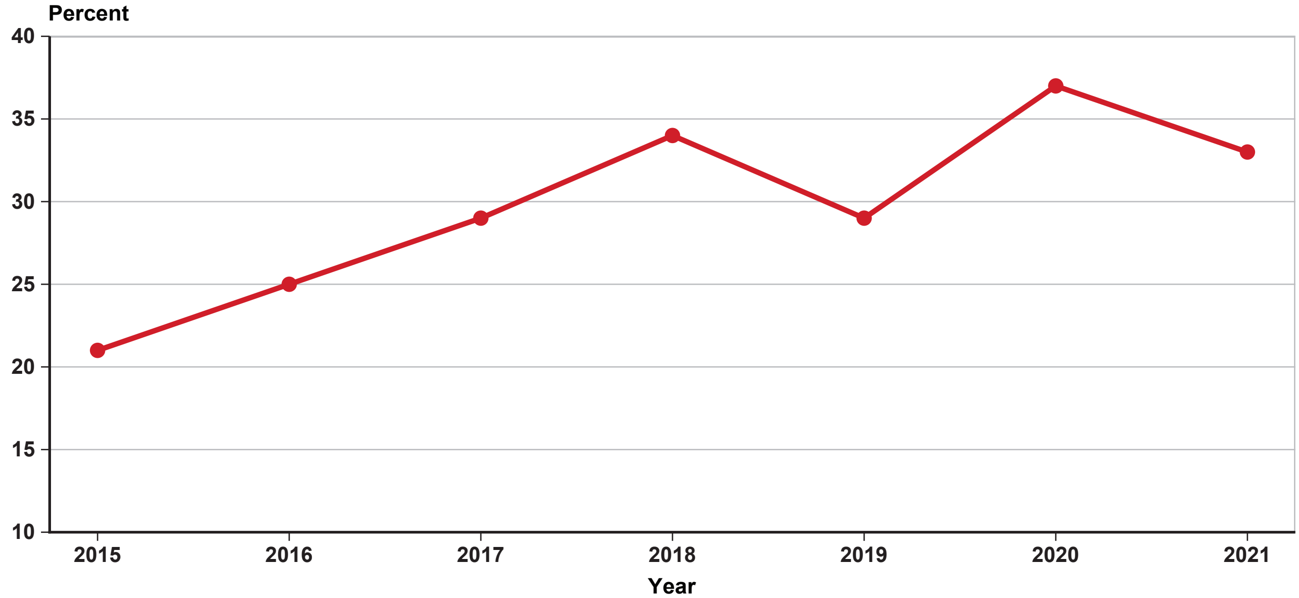
. . . = not applicable.

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

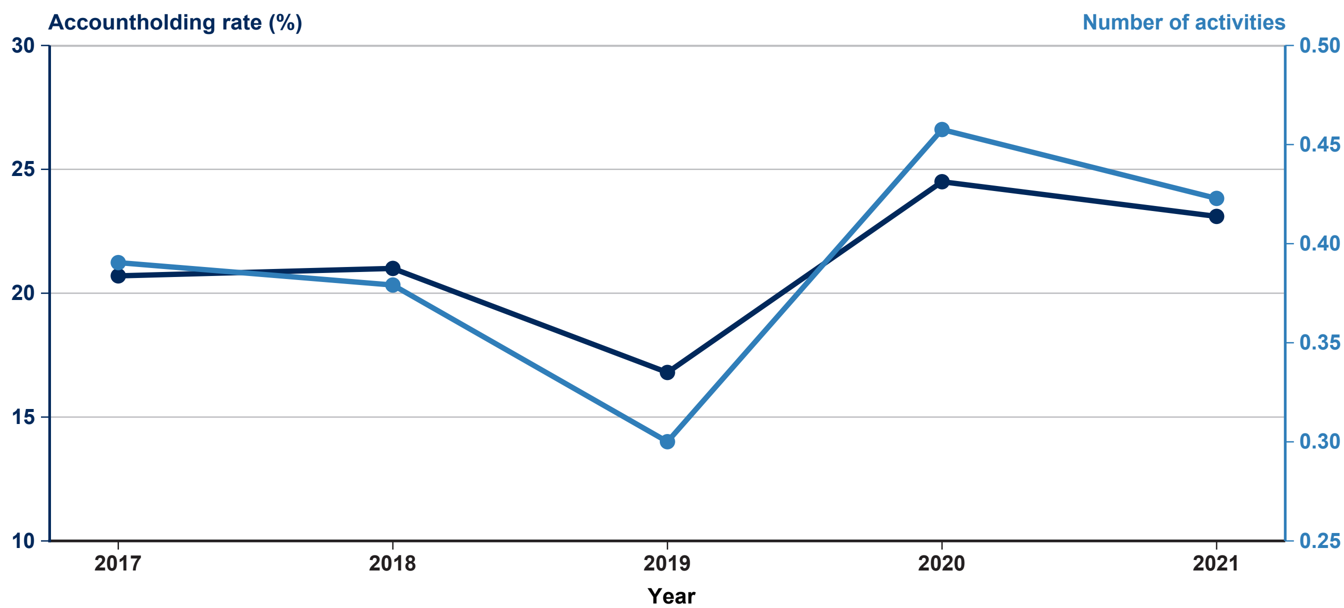
a. Includes Asian, Native American, Pacific Islander, and multiracial.

Chart 2.
Trends in *my* Social Security awareness, accountholding, and frequency of use, selected years 2015–2021

Panel A: Have heard of my Social Security (%)



Panel B: Have an account (%) and frequency of use (average number of activities initiated)



SOURCE: Authors' calculations based on UAS238.

We used ordered probit models. For *awareness* and *accountholding,* the dependent variable ($Y_i^{POST} - Y_i^{PRE}$) can take on three values: −1, if the respondent was aware of or had an account in the earlier survey wave and was not aware of or did not have an account in the third wave; 0, if there was no change in status during the period; and 1, if the respondent was newly aware of or had first opened an account as of the third survey wave.

Table 7 shows the determinants of transitions in awareness, opening an account, and frequency of account use. For all outcomes, the coefficients for internet literacy are indistinguishable from zero. By contrast, the coefficient for beneficiary status is significantly below zero for all three outcome variables, showing that the increases have been greater among nonbeneficiaries than among beneficiaries. This may be seen as a positive sign that reach is increasing among the nonbeneficiary population.

Accountholding and frequency of use have increased among women. Age is likewise positively related to increases in both awareness and use, suggesting that the growth has been greater among older respondents. These results are based on only a few years, and clearer patterns may emerge over a longer observation period.

Qualitative Study

Table 8 presents summary characteristics of our qualitative study sample. As intended, our sample was evenly split between individuals with and without a preexisting *my* Social Security account, and between those with internet literacy below and above the median. Although a majority (15) of sample members were Social Security beneficiaries, seven of them were not accountholders prior to the interview (not shown).

Table 7.
Determinants of change in *my* Social Security awareness, accountholding, and frequency of use: Ordered probit model estimates, various periods 2015–2021

Independent variable	Awareness [a] Coefficient	Awareness [a] Standard error	Accountholding [b] Coefficient	Accountholding [b] Standard error	Frequency of use [b] Coefficient	Frequency of use [b] Standard error
Binary variables						
Internet literacy	0.004	0.006	0.006	0.007	0.009	0.006
Social Security beneficiary	-0.261***	0.059	-0.295***	0.065	-0.289***	0.056
Women	0.015	0.041	0.108**	0.046	0.077*	0.040
Race and ethnicity						
Hispanic (any race)	0.065	0.068	0.049	0.076	0.001	0.066
Non-Hispanic Black	0.012	0.080	-0.009	0.089	0.142*	0.077
Other race (non-Hispanic) [c]	0.034	0.074	0.257***	0.081	0.223***	0.071
Incremental variables						
Age	0.004**	0.002	0.008***	0.002	0.009***	0.002
Years of education	0.008	0.010	0.000	0.011	0.002	0.010
Earnings	0.008	0.031	0.008	0.034	-0.016	0.030
Household income	0.005	0.012	0.000	0.014	0.008	0.012
Observations	3,846		3,842		3,842	
Pseudo R^2	0.005		0.010		0.007	

SOURCE: Authors' calculations based on various UAS surveys.

NOTES: Omitted reference categories for binary variables are low internet literacy, Social Security nonbeneficiary, men, and non-Hispanic White, as applicable.

Intervals for incremental variables are 1 year for age and years of education and $10,000 for earnings and household income.

. . . = not applicable.

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

a. Differences between survey wave 1 (2015–2016) and wave 3 (2020–2021).

b. Differences between survey wave 2 (2017–2019) and wave 3 (2020–2021).

c. Includes Asian, Native American, Pacific Islander, and multiracial.

Table 8.
Summary characteristics of the qualitative study sample, 2022

Characteristic	Number
Total	24
Sex	
Women	11
Men	13
Preinterview accountholder	
Yes	12
No	12
Internet literacy	
High	12
Low	12
Social Security beneficiary status	
Retirement benefits	9
Disability program benefits [a]	5
Other benefits	1
Nonbeneficiary	9
Educational attainment	
High school diploma or equivalent	5
Some college	10
Bachelor's degree or higher	9
Age (years)	
Average	59
Youngest	27
Oldest	81

SOURCE: Authors' calculations using UAS231.

a. Disability Insurance or Supplemental Security Income.

Results

Our interviews sought participants' views and experiences with online transactions generally and with *my* Social Security specifically, and participants' perceptions of the *my* Social Security platform as they navigated it in real time during the interview. We provide selected direct quotations to convey participants' views and reactions in their own words.

Overall Attitudes Toward Online Transactions

At the start of the interview, we asked participants to tell us about their typical online habits, to help us frame their views of *my* Social Security in the context of their overall internet activities. Note that all interviewees use the internet to participate in the UAS panel from which they were recruited. This likely introduces some selection bias to our sample, as we had no participants with little or no exposure to and use of the internet. However, even among UAS panel members, we found diverse views on internet usage, including a refusal by some individuals to use the internet for potentially sensitive transactions such as shopping or banking.

Most of our participants reported at least some internet usage beyond UAS participation. Both users and nonusers of online services expressed the importance of privacy and security and acknowledged that conducting online transactions requiring personal information such as bank account or Social Security numbers comes with risks. Nevertheless, more active users of online services accept those risks as inevitable:

> *[Security and privacy] concern me, but I think it's also in our current environment of working and trying to do some of these things that we have to do. So, I think there's a compromise. Yes, I'm concerned about the level of security, but at the same time I think it's a necessary thing.*
>
> Interviewee 18; Male, Age 67

Those who did not use the internet for shopping and banking cited two main reasons: first, security and privacy concerns; and second, low internet or computer literacy. One interviewee reported:

> *I'm old-fashioned. I still believe in keeping cash in my pocket. I don't trust the credit cards. [I only use computers to] look at Facebook. Communicate with my family... That's about it really. I'm really not too good on them.*
>
> Interviewee 13; Female, Age 71

In addition to privacy concerns and low internet or computer literacy, participants without a *my* Social Security account prior to the interview cited two additional reasons for not having engaged with the platform before. First, some participants hadn't known it existed:

> *When I got married, I had to change my name legally on my [Social Security] card—but I physically went to the office. I did not know that online was an option. If I knew, I would have done it.*
>
> Interviewee 19; Female, Age 43

Second, some individuals did not consider it necessary to create an account because they had no need for the information and services available on the platform—although some recognized that they might in the future:

> *I'm getting closer to the age, so I kind of want to see where my benefits are as it gets*

closer. I want to see…how much longer I have to work. Knowing myself, I won't do it until I'm like 55 and 10 years from retirement and see what I need to do to make things better.

Interviewee 27; Male, Age 31

Prior Interactions with SSA

Participants who had a *my* Social Security account prior to the interview reported creating the account under three broad circumstances: (1) when filing for disability, retirement, or survivor benefits; (2) when seeking information to prepare to file for benefits; and (3) when requesting new or replacement documents. Some interviewees created the account for a specific purpose (for example, to obtain a replacement card) and have used the account infrequently or not at all since then. Others reported using it more regularly (for example, every year), to check benefit amounts, payment dates, or the accuracy of their recorded earnings history:

We used to get paperwork where Social Security would send you letters about how much money you could expect and how much money you had made before we retired. So that's when I had called and made an [online] account and left it at that. [Since then] I haven't used my account online, for probably nothing really.

Interviewee 14; Female, Age 71

Participants who did not have an account before the interview tended to have relatively few prior interactions with SSA, even though some of them were beneficiaries. These participants either had not yet needed to interact with SSA or had done so only once or twice, in person or by phone. Some of these participants said that they had never heard of *my* Social Security and did not consider it to be relevant or useful to them yet.

Logging Into or Creating a *my* Social Security Account

Following the broader discussion about online habits and prior interactions with SSA, we asked participants to log into their *my* Social Security account or create one if they did not already have one.

For some participants, creating the account or logging into an existing account was straightforward and quick, while for others (including some accountholders), the process was more fraught. Some found the validation process (receiving a security code by text message or email) confusing; some no longer had access to registered email accounts; others were confused by complex identification requirements or other issues. Three participants were unable to log into their accounts, and another decided not to proceed with creating an account during the interview.

Those who created or logged into *my* Social Security noted that even if the process was easy for them, it may be too complex for others. They commented that some degree of comfort with computers may be a prerequisite for successful signups, especially among people who may have trouble with obtaining the security code for access to the platform, which involves checking email or receiving a code by phone, and thus may require using two devices.

Platform Layout

Among the 20 participants who were able to access their accounts, the majority reported satisfaction with the layout and visual aspects of the site. Overall, participants expressed a preference for the platform's lean and simple style over more "bells and whistles" like those they might find on commercial websites. Nevertheless, participants noted that the platform would benefit from better signposting for certain important features, such as Medicare-related information and the sliding scale for the retirement estimator, which went unnoticed by several participants until they were prompted.

During the interview, participants were also asked to find specific items of information on the site, such as benefit eligibility information or how to request a verification letter or replacement documents. When asked to rate the ease of finding the information, most rated it 1 or 2 on a scale of 1 to 5, with 1 being very easy and 5 being not at all easy. Participants typically needed well under a minute to find the various items of information on the platform.

One notable exception, however, was Medicare information, which several people had trouble finding on the platform. In fact, when prompted, a number of participants said that *my* Social Security (or SSA more generally) would not be where they would have thought they could find Medicare information or conduct Medicare-related transactions in the first place.

This just says Social Security. I've never seen anything in here that talks about Medicare. That's a different department.

Interviewee 12; Male, Age 60

I most likely would not go to a Social Security site to look for a Medicare card replacement. That wouldn't be the first—I wouldn't even go to that site. I'd probably Google it first.

Interviewee 8; Male, Age 72

Clarity of the Information

Participants said that most of the functions they sought on the platform, such as finding basic benefit eligibility information, application links, and how to replace documents, were straightforward and clear. Nevertheless, some of our preretirement participants were dissatisfied with the information available on two particular topics: (1) the interaction between benefits and pensions, and (2) the interaction between retirement benefits and spousal/survivor benefits. For this type of information, participants wanted a clear way to estimate optimal claiming behavior, which they did not feel the platform afforded them:

I'm going to have to look around here. They explained to me that it might not even benefit me [to claim retirement benefits] when I am 62, that if I'm going to get more money from myself or it's just going to be about the same as me getting it from survivor benefits. So that's exactly what I'm interested in now…I actually don't see where it just says that here.

Interviewee 20; Female, Age 62

Usefulness/Relevance of the Information

Finally, participants found the information on the platform to be relevant to their circumstances. This was true for current beneficiaries and nonbeneficiaries alike, as well as for those with and without an account before the interview. Nonretirees particularly appreciated the retirement benefit information, some of which was a surprise to them. One participant, for instance, did not realize that his full retirement age was 67 (he had assumed it was 65). Another realized he qualified for Social Security benefits only while checking his account during the interview:

It's pretty cool, because I remember the last time I checked, I didn't have enough quarters [of coverage]. Nothing has changed that I've been aware of, because it wasn't like I worked a year and forgot about it, and then they added that information in. And, I mean, it's right there. There's no hard search, and it's written in a simple way that I think most people will be able to understand if they're trying to. Now that I have this, I will look into it further to find out exactly what's going on.

Interviewee 6; Male, Age 60

A few said that the amounts indicated in the platform's benefits estimator were lower than they had expected:

You can see the difference in the benefit amount, as you start thinking about if you want to retire earlier in life or later in life. It'll definitely make me think about my financial situation…. Putting some money aside in some sort of a retirement account… If I were to retire at full retirement age at 67, it gives me my benefit amount, and that is not quite nearly enough to survive on. It's significantly less than the rent or mortgage. So yeah, you can't really count on that.

Interviewee 24; Male, Age 31

When I see the verbiage right away, "Your spouse's decision on when to begin this benefit can impact the amount of their spousal benefit." So, then I'm thinking "oh my gosh, she's five years older. What is that going to do to me if she is going to retire earlier?" It kind of makes me go "oh, you know, I need to really look into that." It makes me right away think "oh gosh, I had no idea. I did not think that"… [It's] just a little bit of a reality check.

Interviewee 21; Female, Age 43

Retirees felt that access to *my* Social Security was good to have, although the platform was not as needed once they started receiving their benefit payments. Some participants, especially older ones, said they would like to see more information resources for financial well-being, such as articles or links to other resources. A few of the retirees who did not have an account prior to the interview said it would have been helpful when they started getting ready to retire.

Conclusions

Our mixed-methods exploration of *my* Social Security awareness and user experiences yields revealing results. The quantitative analysis suggests that lower internet literacy, and lower educational levels in general, are barriers to *my* Social Security use. This is important because groups with lower educational attainment may benefit most from the types of information available through the platform. This analysis also suggests that people learn about *my* Social Security primarily when they become beneficiaries, and as a result, users tend to be older. However, younger groups are typically more internet-literate, and thus possibly better able to take advantage of the platform's features. Moreover, as our qualitative results suggest, younger participants are likely to view *my* Social Security as a useful financial planning resource.

In our qualitative study, interviewees reported four key reasons for not creating a *my* Social Security account: (1) lack of awareness of the platform; (2) no perceived relevance/need; (3) security and privacy concerns; and (4) low internet/computer literacy. The latter factor in particular echoes the quantitative finding that low internet literacy inhibits access to and use of the platform. We also observe that, overall, the *my* Social Security platform is perceived to be clear, navigable, and relevant. Nonretired, nonbeneficiary participants view the information on the platform as instructive and useful. Retirees appreciate but do not have as much use for the platform, although some note that it would have been a useful resource when they were preparing to retire and file for benefits.

Both our quantitative and qualitative evidence show that many individuals start using the platform during or after the benefit-claiming process. Yet our findings imply that *my* Social Security could be better targeted to, and its retirement preparedness features enhanced for, younger adults (who, our quantitative analysis shows, are less likely to have an account). Our interview sample included 15 nonretirees (some of whom were receiving Social Security benefits other than retirement). The interviews provide evidence suggesting that, in addition to bridging knowledge gaps, *my* Social Security could help address some behavioral barriers to retirement preparedness or financial planning, such as procrastination, overconfidence, and wariness of the complexity of program rules and information (Kopanidis, Robinson, and Shaw 2016; Blanco, Duru, and Mangione 2020; Choi and others 2006; Benartzi and Thaler 2007; Beshears and others 2013).

The interviews clearly show that the information available at *my* Social Security can provide a needed jolt of knowledge and correct mistaken expectations (as seen in the reactions of those who had assumed an earlier full retirement age or higher benefit amounts for themselves). It can also serve a critical educational purpose (as seen for those who learned that benefit claiming ages affect survivor and spousal benefit amounts). At the very least, the fact that most Americans claim Social Security retirement benefits at or before their full retirement age (Shoven, Slavov, and Wise 2018) highlights the need for increased awareness of the implications of early claiming.

In a context of low financial literacy and Social Security program knowledge, especially among younger adults, a widely accessible, clear, and personalized information resource could play an important role in both improving financial literacy and supporting financial planning and decision-making. In fact, based on the literature, the platform already meets several of the criteria for effective financial literacy interventions, including clarity and conciseness (Gruber and Orszag 2003; Rabinovich and Perez-Arce 2019), consequence messaging (which is in essence provided by the retirement-benefit estimator) (Samek, Kapteyn, and Gray 2022; Samek and Sydnor 2020), and accessibility and scope (Lusardi and others 2017).

We also find that a key challenge to expanding *my* Social Security accountholding and use involves the initial capture of users; that is, getting people to create an account. Once they create an account, participants seem broadly happy about how the platform works and what it does. Yet both our quantitative and qualitative findings show that some participants face important barriers to *my* Social Security account creation, notably low internet literacy. How to address these barriers remains an important question. Nevertheless, over time, internet literacy will improve among older adults (who today are the younger groups with higher levels of internet capability), and this particular barrier should diminish automatically.

This study strongly indicates that further research should address ways to reduce the barriers to using *my* Social Security, increase public engagement with the platform, and realize its potential as a key resource to support retirement readiness and general financial literacy in nonbeneficiary populations.

Notes

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[1] Address-based sampling mitigates selection problems facing convenience or "opt-in" panels, whose respondents are recruited from among current internet users only. Chang and Krosnick (2009) and Yeager and others (2011) find evidence that address-based samples are better able to match a population's demographics than nonprobability or random digit-dialing telephone surveys. Prior research has

shown that UAS results are close to nationally representative, as benchmarked against well-established surveys (Angrisani, Finley, and Kapteyn 2019).

[2] Although respondents to whom UAS provides devices and internet access may increase their internet use and proficiency over time, studies have found that about half of those households continue to be internet nonusers. Even the UAS households that begin to be internet users still make less use of it than those who had prior internet access, and they tend to restrict their use to simple applications (Leenheer and Scherpenzeel 2013). Hence, in providing a tablet and internet access to households with no prior access, the UAS and similarly designed probability panels are likely to be substantially more representative than typical nonprobability panels, which do not.

[3] We also conducted a separate analysis in which we calculated an alternative internet literacy variable: the simple mean of the variables in the modules (after changing the sign of the values so that in all cases a higher number represents more knowledge). The correlation between this index and the PCA-based index was 0.994. Given the strong similarities, we used only the PCA-based index.

[4] Specifically, UAS 16 (https://uasdata.usc.edu/survey/UAS+16), UAS 94 (https://uasdata.usc.edu/survey/UAS+94), and UAS 231 (https://uasdata.usc.edu/survey/UAS+231).

[5] Specifically, UAS 26 (https://uasdata.usc.edu/survey/UAS+26), UAS 113 (https://uasdata.usc.edu/survey/UAS+113), and UAS 238 (https://uasdata.usc.edu/survey/UAS+238).

[6] The UAS Comprehensive File is produced by the University of Southern California Dornsife Center for Economic and Social Research, with funding from SSA and the National Institute on Aging. The Comprehensive File is continually updated. The version we used was downloaded on July 1, 2022. For more information, see https://uasdata.usc.edu/page/UAS+Comprehensive+File.

[7] The most reported activities were "getting an estimate of future benefits," "tracking and verifying earnings," and "changing personal information."

References

Alattar, Laith, Matt Messel, and David Rogofsky. 2018. "An Introduction to the Understanding America Study Internet Panel." *Social Security Bulletin* 78(2): 13–28.

Angrisani, Marco, Brian Finley, and Arie Kapteyn. 2019. "Can Internet Match High-Quality Traditional Surveys? Comparing the Health and Retirement Study and Its Online Version." In *The Econometrics of Complex Survey Data: Theory and Applications,* edited by Kim P. Huynh, David T. Jacho-Chávez, and Gautam Tripathi (3–33). Bingley (UK): Emerald Publishing Limited.

Armour, Philip. 2018. "The Role of Information in Disability Insurance Application: An Analysis of the Social Security Statement Phase-In." *American Economic Journal: Economic Policy* 10(3): 1–41.

———. 2020. "How Did the Reintroduction of the *Social Security Statement* Change Workers' Expectations and Plans?" *Social Security Bulletin* 80(4): 23–38.

Benartzi, Shlomo, and Richard Thaler. 2007. "Heuristics and Biases in Retirement Savings Behavior." *Journal of Economic Perspectives* 21(3): 81–104.

Beshears, John, James J. Choi, David Laibson, Brigitte C. Madrian. 2013. "Simplification and Saving." *Journal of Economic Behavior & Organization* 95: 130–145.

Bhargava, Saurabh, and Dayanand Manoli. 2015. "Psychological Frictions and the Incomplete Take-Up of Social Benefits: Evidence from an IRS Field Experiment." *American Economic Review* 105(11): 3489–3529.

Blanco, Luisa R., O. Kenrik Duru, and Carol M. Mangione. 2020. "A Community-Based Randomized Controlled Trial of an Educational Intervention to Promote Retirement Saving Among Hispanics." *Journal of Family and Economic Issues* 41(2): 300–315.

Braun, Virginia, and Victoria Clarke. 2006. "Using Thematic Analysis in Psychology." *Qualitative Research in Psychology* 3(2): 77–101. https://doi.org/10.1191/1478088706qp063oa.

Carman, Katherine Grace, and Angela A. Hung. 2018. "Social Security Household Benefits: Measuring Program Knowledge." MRRC Working Paper No. 2018-384. Ann Arbor, MI: University of Michigan Retirement Research Center.

Chan, Sewin, and Ann Huff Stevens. 2008. "What You Don't Know Can't Help You: Pension Knowledge and Retirement Decision-Making." *The Review of Economics and Statistics* 90(2): 253–266.

Chang, Linchiat, and Jon A. Krosnick. 2009. "National Surveys Via RDD Telephone Interviewing Versus the Internet: Comparing Sample Representativeness and Response Quality." *Public Opinion Quarterly* 73(4): 641–678.

Choi, James J., David Laibson, Brigitte C. Madrian, and Andrew Metrick. 2006. "Saving for Retirement on the Path of Least Resistance." In *Behavioral Public Finance: Toward a New Agenda,* edited by Edward J. McCaffrey and Joel Slemrod (304–351). New York, NY: Russell Sage Foundation.

Francis, Jill J., Marie Johnston, Clare Robertson, Liz Glidewell, Vikki Entwistle, Martin P. Eccles, and Jeremy M. Grimshaw. 2010. "What Is an Adequate Sample Size? Operationalising Data Saturation for Theory-Based Interview Studies." *Psychology and Health* 25(10): 1229–1245.

Gruber, Jonathan, and Peter Orszag. 2003. "Does the Social Security Earnings Test Affect Labor Supply and Benefits Receipt?" *National Tax Journal* 56(4): 755–773.

Guest, Greg, Arwen Bunce, and Laura Johnson. 2006. "How Many Interviews Are Enough? An Experiment with Data Saturation and Variability." *Field Methods* 18(1): 59–82.

Hennink, Monique M., Bonnie N. Kaiser, and Vincent C. Marconi. 2017. "Code Saturation Versus Meaning Saturation: How Many Interviews Are Enough?" *Qualitative Health Research* 27(4): 591–608.

Kopanidis, Foula, Linda Robinson, and Michael Shaw. 2016. "'I'm Not Old Enough!' Why Older Single Women Are Not Engaging in Retirement Planning Services." In *Rediscovering the Essentiality of Marketing: Proceedings of the 2015 Academy of Marketing Science (AMS) World Marketing Congress,* edited by Luca Petruzzellis and Russell S. Winer (871–876). Cham (Switzerland): Springer International Publishing. https://doi.org/10.1007/978-3-319-29877-1_169.

Leenheer, Jorna, and Annette C. Scherpenzeel. 2013. "Does It Pay Off to Include Non-Internet Households in an Internet Panel?" *International Journal of Internet Science* 8(1): 17–29.

Lusardi, Annamaria, Anya Samek, Arie Kapteyn, Lewis Glinert, Angela Hung, and Aileen Heinberg. 2017. "Visual Tools and Narratives: New Ways to Improve Financial Literacy." *Journal of Pension Economics & Finance* 16(3): 297–323.

Mastrobuoni, Giovanni. 2011. "The Role of Information for Retirement Behavior: Evidence Based on the Stepwise Introduction of the Social Security Statement." *Journal of Public Economics* 95(7–8): 913–925.

Morgan, M. Granger, Baruch Fischhoff, Ann Bostrom, and Cynthia J. Atman. 2002. *Risk Communication: A Mental Models Approach.* New York, NY: Cambridge University Press.

Namey, Emily, Greg Guest, Kevin McKenna, and Mario Chen. 2016. "Evaluating Bang for the Buck: A Cost-Effectiveness Comparison Between Individual Interviews and Focus Groups Based on Thematic Saturation Levels." *American Journal of Evaluation* 37(3): 425–440.

Rabinovich, Lila, and Francisco Perez-Arce. 2019. "Improving Understanding of the Retirement Earnings Test." *Journal of Pension Economics & Finance* 20(4): 496–503. https://doi.org/10.1017/S1474747219000222.

Rabinovich, Lila, Francisco Perez-Arce, and Joanne Yoong. 2022. *Understanding America Study. UAS238: Retirement Planning—Wave 3.* Survey codebook. Los Angeles, CA: University of Southern California Center for Economic and Social Research.

Samek, Anya, Arie Kapteyn, and Andre Gray. 2022. "Using Vignettes to Improve Understanding of Social Security and Annuities." *Journal of Pension Economics & Finance* 21(3): 326–343. https://doi.org/10.1017/S1474747221000111.

Samek, Anya, and Justin R. Sydnor. 2020. "Impact of Consequence Information on Insurance Choice." NBER Working Paper No. 28003. Cambridge, MA: National Bureau of Economic Research.

Sass, Steven A. 2015. "Does the Social Security 'Statement' Add Value?" *Issue in Brief* No. 15-11. Chestnut Hill, MA: Center for Retirement Research at Boston College.

Shoven, John B., Sita Nataraj Slavov, and David A. Wise. 2018. "Understanding Social Security Claiming Decisions Using Survey Evidence." *Journal of Financial Planning* 31(11): 35–47.

Smith, Barbara A. 2020. "Can Informational Interventions Be Effective Policy Tools? An Initial Assessment of the *Social Security Statement.*" *Social Security Bulletin* 80(4): 1–22.

Smith, Barbara A., and Kenneth A. Couch. 2014. "How Effective Is the *Social Security Statement*? Informing Younger Workers About Social Security." *Social Security Bulletin* 74(4): 1–19.

Thomas, David R. 2006. "A General Inductive Approach for Analyzing Qualitative Evaluation Data." *American Journal of Evaluation* 27(2): 237–246.

Van Deursen, Alexander J. A. M., Ellen J. Helsper, and Rebecca Eynon. 2016. "Development and Validation of the Internet Skills Scale (ISS)." *Information, Communication & Society* 19(6): 804–823.

Yeager, David S., Jon A. Krosnick, LinChiat Chang, Harold S. Javitz, Matthew S. Levendusky, Alberto Simpser, and Rui Wang. 2011. "Comparing the Accuracy of RDD Telephone Surveys and Internet Surveys Conducted with Probability and Non-Probability Samples." *Public Opinion Quarterly* 75(4): 709–747.

Yoong, Joanne, Lila Rabinovich, and Saw Htay Wah. 2015. "What Do People Know About Social Security?" CESR-Schaffer Working Paper No. 2015-022. Los Angeles, CA: University of Southern California Center for Economic and Social Research.

The Alignment Between Self-Reported and Administrative Measures of Disability Program Application and Benefit Receipt in the Health and Retirement Study

by Jody Schimmel Hyde and Amal Harrati*

Longitudinal surveys offer a richness for studying the experiences of disability program applicants and beneficiaries that is not available from administrative data alone. Yet research suggests that individuals may not accurately report their Social Security Disability Insurance (DI) and Supplemental Security Income (SSI) application and benefit receipt. In this article, we examine the differences between self-reported data and administrative records of DI and SSI application and benefit receipt using Health and Retirement Study (HRS) survey data linked to the Social Security Administration's Form 831 records and Disability Analysis File. We compare application and receipt prevalence by calendar year, HRS sampling cohort, and age from 51 through full retirement age. We find that aggregate survey reports of DI and SSI application and receipt are lower than administrative records indicate and that individual-level misreporting is common, although both sources indicate similar trends by age, cohort, and survey wave.

Introduction

Understanding the circumstances that lead to disability program application and the postapplication outcomes for beneficiaries and denied applicants is important for assessing the effects of changes to the benefit determination process, program rules, and benefit generosity. The Social Security Administration (SSA) collects from applicants only the information that is necessary to make benefit determinations or to administer monthly benefits. This information includes work history, education, health status, income, and assets, but does not always include applicants' living arrangements, other income sources, or receipt of other forms of public or private assistance. SSA periodically requires beneficiaries to update the information on their health condition (to determine whether benefit eligibility will continue) and earnings (if they exceed the level that denotes substantial gainful activity), but, in general, the information available to the agency on beneficiary characteristics is limited.

Therefore, researchers and policymakers turn to other sources of information on disability program applicants and beneficiaries to understand their needs more fully. For example, surveys collect detailed information on a range of subjects including respondent disability status and benefit receipt. Many surveys compile only their respondents' self-reported information, but some link respondents' self-reported information to administrative data. SSA has used such data linkages to analyze its disability and retirement programs.

Selected Abbreviations

ADL	activity of daily living
CPS	Current Population Survey
DAF	Disability Analysis File
DI	Disability Insurance
FRA	full retirement age
HRS	Health and Retirement Study

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Selected Abbreviations—*Continued*

IPW	inverse probability weight
OASI	Old-Age and Survivors Insurance
SSA	Social Security Administration
SSI	Supplemental Security Income

Recent research has capitalized on administrative-data linkages to better understand the accuracy of self-reported survey data and to identify the best way to combine information from the two potentially differing sources. As we discuss later, the research findings vary by disability program and survey (for example, Meyer and Mittag 2019; Chen, Munnell, and Sanzenbacher 2018; Bee and Mitchell 2017).

In this article, we compare survey data from the University of Michigan's Health and Retirement Study (HRS) with administrative data from SSA on Social Security Disability Insurance (DI) and Supplemental Security Income (SSI) applicants and beneficiaries. The HRS is a nationally representative longitudinal survey of noninstitutionalized adults aged 51 or older. The study started in 1992 and is known for the richness of its data on the health, income, and other characteristics of older adults. After entering the survey sample, respondents are interviewed every other year until they die or otherwise exit the study. To maintain a consistent age distribution, the HRS replenishes the survey sample with a new cohort of respondents aged 51–56 every 6 years. During the initial interview and each subsequent survey wave, respondents report their own program participation history, including DI and SSI applications filed and benefit receipt. Respondents are periodically asked for consent to have their information linked to SSA records on earnings and benefits. Not all HRS respondents consent to the linkage, but for those who do, it is possible to compare their self-reports with their administrative records.

There are several reasons why comparing the HRS results with administrative records is important, even with the breadth of existing literature based on other survey data sources. First, health shocks occur more frequently with age (Smith 2003), so HRS respondents will be more likely to apply for and receive disability program benefits than the younger adults who are typically included in other national surveys. Second, the programs administered by SSA offer a critical—but potentially confusing—mix of benefits to an individual in the years just before retirement. Old-Age and Survivors Insurance (OASI) retired-worker benefits can be claimed on reaching age 62, and DI benefits are available to insured workers at any age until the worker's full retirement age (FRA—65 to 67, depending on year of birth), when they automatically convert to OASI benefits. Individuals may qualify for SSI payments at any age, although the eligibility requirements change at age 65. Thus, respondents misreporting their program participation may be more common in the HRS than in other national surveys.

This study examines the accuracy of self-reported disability program participation as collected in the HRS survey and the potential strengths and limitations of using matched administrative data. We answer the following questions:

- What share of HRS respondents consented to the data linkage to measure DI and SSI application and receipt? How did the likelihood of consenting vary by cohort and over time?
- How do HRS respondents who consented to the administrative-data linkage differ from those who did not, both sociodemographically and in their reporting of DI and SSI application and receipt?
- How does the prevalence of DI and SSI application and receipt vary by cohort, time, and age? How do the aggregate rates differ if a researcher uses the self-reported data instead of the administrative records, and what factors might explain the difference?
- Among respondents who consented to the linkage, how accurate are self-reports, and what are the characteristics of respondents whose reports are incorrect?

The majority of HRS respondents have consented to administrative-data linkages, but rates of consent differ by survey cohort and over time. This, in part, reflects changes to how the HRS has obtained consent over the years. Consistent with earlier studies (Olson 1999; Haider and Solon 2000), we find that demographic, employment, and health-related characteristics differ between respondents who consent to the linkage and those who do not.

We also find that the share of respondents who report having DI or SSI application or receipt is generally lower than SSA records indicate. The pattern of underreporting is generally consistent across respondent age groups (regardless of their cohort or the survey year); however, there is no consistent pattern across survey cohorts. As we saw with respondents consenting and not consenting to a data linkage, the demographic, socioeconomic, and health characteristics of respondents whose self-reports diverge from their administrative records differ from those whose self-reports agree with SSA data.

Background: The Accuracy of Self-Reported Disability Program Participation in National Surveys

Surveys offer a depth of information that is not available in administrative sources alone. Longitudinal surveys can provide a detailed look at the characteristics, outcomes, and trajectories of individuals before, during, and after application for or receipt of DI or SSI benefits. Davies and Fisher (2009) documented potential uses of SSA-and-survey linked data, while also assessing earlier work (Huynh, Rupp, and Sears 2002; Koenig 2003) on DI and SSI reporting in surveys versus administrative sources. They summarized the literature based on analysis of data from older adults in the 1990s as showing that Current Population Survey (CPS) respondents slightly underreported their Old-Age, Survivors, and Disability Insurance (OASDI) benefits and significantly underreported their SSI payments, while Survey of Income and Program Participation (SIPP) respondents slightly overreported their OASDI income and were mixed on reporting their SSI payments. Schimmel Hyde and others (2018) used 2008–2009 CPS and SIPP data for a working-age population and found that, compared with the administrative record, many beneficiaries misreported their beneficiary status and benefit income. The authors also found that discrepancies appeared to be larger than those in the earlier studies cataloged by Davies and Fisher.

More recent research has sought to augment survey self-reports with administrative data to better understand income received from government programs more broadly. Beginning with Meyer, Mok, and Sullivan (2015), these studies suggest that misreporting is not uncommon and that underreporting is more common than overreporting. Meyer and Mittag (2019) found that income from government benefits among working-age CPS respondents was dramatically understated. Bee and Mitchell (2017) similarly documented underreporting of income among older adults in the CPS, driven primarily by misreported defined benefit pension income and retirement account withdrawals. Chen, Munnell, and Sanzenbacher (2018) extended Bee and Mitchell's work to other data sources and found that the CPS was an outlier in terms of retirement income misreporting. For example, when compared with administrative data, the CPS captured 61 percent of retirement income, while the SIPP captured 93 percent and the HRS captured 96 percent.

Although the linkage to administrative data from SSA has been available for two decades, to our knowledge, no research to date has assessed the accuracy of HRS respondents' self-reported DI and SSI application and receipt (Schimmel Hyde and Stapleton 2017). This article bridges that gap by comparing HRS self-reports with administrative records. Although it is easy to assume that deviations between the two sources reflect respondent misreporting, self-reports may be more current or complete than the administrative records for several reasons. We discuss those reasons later in our findings to allow interested researchers to assess the relative strengths and limitations of self-reports versus administrative data.

Data and Measures

In this section, we further describe our data sources, the sample selection, the cohorts we include in our analysis, and the measures we use to document DI and SSI application and receipt. We also discuss how the HRS collects consent for the administrative linkage from its respondents, how nonconsent affects the sample size, and how we adjusted the sample weights to account for nonconsenters.

Data Sources

We combined information from publicly available HRS survey data with restricted-access SSA records for HRS respondents. The latter are available with permission from the HRS following an in-depth application and review process. We drew on four source files for our analysis.

The RAND-HRS Longitudinal File is a cross-wave, consistent file developed to facilitate research (Phillips 2003/2004; Bugliari and others 2021). Largely derived from the information in each HRS interview, it simplifies information collected about DI and SSI benefits over many years of the study. As we will discuss, the RAND-HRS file occasionally uses longitudinal information to impute or infer information across waves, particularly when survey design changes limit cross-wave comparisons. The RAND-HRS file is continually updated as new data become available; our analysis used the version of the file that contained data through 2018.

SSA Form 831 Respondent Records (the "831 file") is an administrative data file that contains information on initial applications for DI and SSI benefits.[1] The file we used contained data from 1988 (when SSA began storing application information in the 831 file) through 2016.[2] Because the 831 file contains only applications from 1988 onward, it undercounts the number of applications filed by HRS respondents in all years, including those who filed before they joined the HRS sample. This mostly affects participants in earlier HRS waves. The discrepancy diminishes with each subsequent HRS cohort, as the number of respondents with initial applications before 1988 declines.

The 831 file is limited to initial applications that received a medical review. Although disability benefit applications can go through multiple levels of adjudication, the initial application is the "original" and therefore reflects the starting point for each disability claim. The 831 file, however, does not include initial applications that: (1) have not yet received an initial review, or (2) were denied for nonmedical reasons; that is, because they did not meet the financial eligibility criteria of SSA's disability programs ("technical denials"). Most initial reviews occur relatively quickly—within a few months—although a few HRS respondents could have filed an application that had not yet received an initial decision by the time of the interview. Technical denials, however, could account for many more undercounts in the 831 file. During our analysis period, technical denials represented up to one-third of initial DI applications each year (SSA 2022).[3] With a technical denial, an HRS respondent would correctly report an application that would not be recorded in the 831 file. We do not know how technical denial rates vary with age, but they might be lower for older DI applicants, who are more likely to have accumulated a work history necessary for benefit eligibility.

The Disability Analysis File (DAF) combines SSA data from multiple administrative sources to produce monthly information about the receipt of DI and SSI benefits for all beneficiaries with at least 1 month of benefits since 1996 (Mathematica 2022).[4] The file also includes information on monthly benefit amounts and a range of other factors related to the periodic continuing disability reviews that beneficiaries must undergo to retain benefit eligibility, but we do not include that information in our analysis. The version of the file we used contained data through 2018.

The HRS-SSA Permissions Consent History file provides information about whether an HRS respondent consented to having his or her information linked to SSA records and whether a matching administrative record was found (HRS 2021a). We used this file to determine which respondents might be expected to have information available on disability program participation in the administrative records. Respondents who did not consent to the administrative linkage will not have that information available.

Sample Selection

To align with the availability of administrative records, we use data for 1996–2016, spanning four HRS respondent cohorts: the original HRS cohort (born during 1931–1941, first interviewed in 1992), the War Baby cohort (born during 1942–1947, first interviewed in 1998), the Early Baby Boom cohort (born during 1948–1953, first interviewed in 2004), and the Middle Baby Boom cohort (born during 1954–1959, first interviewed in 2010).[5] We include age-eligible sample members in each cohort, meaning that younger spouses who were selected because they lived in a household with an older age-eligible respondent are included in our analysis once they themselves age into the survey. Members of the original HRS cohort were first interviewed when they were aged 51–61, but all younger cohorts were first interviewed when they were aged 51–56. To provide a study sample comprising four similarly structured cohorts, our analysis includes only the younger members of the original HRS cohort, born during 1936–1941 and first interviewed at ages 51–56 in 1992. For simplicity, we refer to this younger subset as the "original HRS cohort" hereafter, while noting that we found that the outcomes for the younger and older subsets of the full original HRS cohort differed.

For three of the four cohorts, we used the data collected every other year from the initial interview through 2016 (Table 1). The exception is the original HRS cohort, which initially was surveyed in 1992, but we excluded results from survey waves before 1996 to align with the availability of DAF data on disability benefit receipt. Because DI benefits are converted to OASI retired-worker benefits when the beneficiary reaches FRA, and SSI recipients transition from the "disabled" eligibility category to "aged" at age 65, we stop tracking respondents' DI or SSI status at FRA.[6] In comparing results across cohorts, we categorize respondents in each wave into four

Table 1.
Age range of HRS respondents, by cohort, birth year, and survey wave

Birth year	HRS survey wave												
	1992 [a]	1994 [a]	1996	1998	2000	2002	2004	2006	2008	2010	2012	2014	2016
							Original HRS						
1936–1937	55–56	57–58	59–60	61–62	63–64	65–66	67–68	69–70	71–72	73–74	75–76	77–78	79–80
1938–1939	53–54	55–56	57–58	59–60	61–62	63–64	65–66	67–68	69–70	71–72	73–74	75–76	77–78
1940–1941	51–52	53–54	55–56	57–58	59–60	61–62	63–64	65–66	67–68	69–70	71–72	73–74	75–76
							War Baby						
1942–1943	. . .	. . .	. . .	55–56	57–58	59–60	61–62	63–64	65–66	67–68	69–70	71–72	73–74
1944–1945	. . .	. . .	. . .	53–54	55–56	57–58	59–60	61–62	63–64	65–66	67–68	69–70	71–72
1946–1947	. . .	. . .	. . .	51–52	53–54	55–56	57–58	59–60	61–62	63–64	65–66	67–68	69–70
							Early Baby Boom						
1948–1949	. . .	. . .	. . .	. . .	. . .	. . .	55–56	57–58	59–60	61–62	63–64	65–66	67–68
1950–1951	. . .	. . .	. . .	. . .	. . .	. . .	53–54	55–56	57–58	59–60	61–62	63–64	65–66
1952–1953	. . .	. . .	. . .	. . .	. . .	. . .	51–52	53–54	55–56	57–58	59–60	61–62	63–64
							Middle Baby Boom						
1954–1955	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	55–56	57–58	59–60	61–62
1956–1957	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	53–54	55–56	57–58	59–60
1958–1959	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	51–52	53–54	55–56	57–58

SOURCE: HRS (2022).

NOTES: Ages in shaded cells are FRA or older. This analysis omits results for respondents who have reached FRA.

. . . = not applicable.

a. Because SSA did not compile the DAF administrative data until 1996, survey results for 1992 and 1994 are omitted from this analysis.

groups—(1) interviewed and younger than FRA; (2) interviewed, but reached FRA; (3) not interviewed (no indication of death); and (4) not interviewed (died before interview).[7]

HRS Consent Requirements and Implications for Sample Selection

The administrative data are available only for HRS respondents who consented to the linkage and who provided requisite information (accurate Social Security number, name, and date of birth). The HRS consent process has changed over the years. Importantly for our analysis, the SSA 831 file and DAF are available only for respondents who consented to the linkage in 2006 or later, when the HRS moved from a retrospective permission approach (consent covered all data through the consent year) to a prospective approach (consent allowed linkages with data for past years as well as for a prespecified number of years in the future). This change meant that members of earlier cohorts initially consented under a retrospective permission system but may not have provided the requisite prospective permission necessary to be in our analysis.[8]

Table 2 shows the full unweighted sample size for each cohort in our analysis, as well as the share of each cohort who consented, at any time or in 2006 or later, to the linkage to their administrative records. For each subsequent cohort, the share of cohort members consenting to a linkage at any time has declined, from 88.0 percent in the original HRS cohort to 78.7 percent of Middle Baby Boomers. Despite the overall decline, the rate of consent granted in 2006 or later increased across the cohorts, from 49.0 percent among the original HRS cohort to 77.4 percent of the Middle Baby Boomers. The lower rate in earlier cohorts reflects the fact that more time elapsed for those cohorts from survey entry through 2006, during which many respondents left the sample, died, or did not reconsent. In this article, we use "consenter subsample" to refer to respondents who consented in 2006 or later, noting that this excludes those who consented in an earlier year.[9]

Consistent with earlier work (HRS 2021a), we found that the characteristics of respondents in the consenter subsample differ from those of the full HRS sample. Consenters are more likely to be White, female, and employed, and to have higher educational attainment and lower rates of chronic conditions, including heart disease, lung disease, diabetes, and stroke. Consenters also report lower rates of smoking, fewer difficulties with activities of daily living (ADLs), and fewer hospital stays and doctor visits (Table 3).

Weighting Process

Because of the differences in the characteristics of consenters and the full HRS sample, simply using the administrative records without reweighting would undermine the comparability of the consenter subsample and the full HRS sample. To adjust the sample weights for our analysis, we followed the HRS process to develop analysis weights for its SSA data.[10] Specifically, we predicted the likelihood of consenting in 2006 or later using a logistic regression in each survey

Table 2.
Sample size of each HRS cohort, by consent status (unweighted)

Consent status	Cohort: Original HRS	War Baby	Early Baby Boom	Middle Baby Boom
Total	5,604	3,090	3,369	4,781
Never consented	670	473	578	1,019
Consented before 2006 [a]	2,186	656	449	59
Consented 2006 or later	2,748	1,961	2,342	3,703
Ever consented (%)	88.0	84.7	82.8	78.7
Consented in 2006 or later (%)	49.0	63.5	69.5	77.5

SOURCE: Authors' calculations using data from the HRS-SSA Permissions Consent History file.

NOTE: Sample sizes are based on the age-eligible cohort at survey entry year and do not include age-ineligible spouses or spouses added in subsequent survey waves.

a. Some respondents in the Early Baby Boom and Middle Baby Boom cohorts were initially interviewed as younger spouses of respondents in earlier cohorts. We included these respondents based on their own birth year cohort, but they were able to provide consent to the linkage before their birth year entry cohort.

wave. Our model included variables for sex, race and ethnicity (indicators for Black and Hispanic), marital status (indicators for married, divorced, and widowed), education (indicators for high school graduate, some college, college graduate, and advanced degree), being employed, categories of self-rated health status, and quintiles of household income and wealth.

We used the predicted values from the logistic regression models to generate inverse probability weights (IPWs) for each record in the consenter file. We then applied the IPWs and the HRS sampling weights to the consenter subsample. This allowed us to generate a consenter subsample that approximated the full HRS sample on the observable characteristics in the IPW model, and with the HRS sampling weight applied, it yielded a weighted sum of interviewed consenters in each wave that equals the weighted sample size of interviewed respondents in that wave from the full HRS. We use this IPW-adjusted survey weight to produce nationally representative estimates based on the administrative data. This allows us to compare our consenter subsample with nationally representative estimates based on self-reports (using the HRS sampling weights alone). Like all such weighting algorithms, our method does not fully account for unobserved variation in consenters and nonconsenters or for observed factors on which consenters differ but were not included in the model. To the extent that those differences also affect the likelihood of applying for disability program benefits, our weighted estimates might be biased. Because our analysis was designed to broadly replicate how HRS data users might use the HRS-provided weights, we did not explore more sophisticated weighting approaches.

Table 3.
Comparison of characteristics for the full HRS sample and consenter subsample (unweighted)

Characteristic	Full HRS sample	Consenter subsample	*p*-value [a]
	Demographic characteristics		
Race (percentage distribution)	100.0	100.0	<0.001***
White	74.0	76.2	. . .
Black	18.3	16.4	. . .
All other responses [b]	7.7	7.4	. . .
Ethnicity (percentage distribution)	100.0	100.0	0.457
Hispanic	12.1	11.7	. . .
Non-Hispanic	87.9	88.3	. . .
Sex (percentage distribution)	100.0	100.0	<0.001***
Men	41.0	38.4	. . .
Women	59.0	61.6	. . .
Marital status (percentage distribution)	100.0	100.0	0.166
Married	87.6	87.3	. . .
Divorced	6.5	7.1	. . .
Never married	5.9	5.6	. . .
Education (years completed)	12.5	12.7	<0.001***
	Socioeconomic characteristics and employment		
Respondent income (2020 $)	24,352	25,490	0.045*
Household income (2020 $)	70,411	71,186	0.651
Total household assets (2020 $)	278,602	277,852	0.932
Labor force status (percentage distribution)	100.0	100.0	<0.001***
In labor force	68.0	71.9	. . .
Retired	17.8	15.6	. . .
Disabled	5.3	4.3	. . .
Not in labor force	8.9	8.2	. . .
Years of tenure at current job	12.0	11.7	0.106
Years at longest held job	15.7	15.4	0.028
Total years worked	26.9	26.8	0.494

(Continued)

Table 3.
Comparison of characteristics for the full HRS sample and consenter subsample (unweighted)—*Continued*

Characteristic	Full HRS sample	Consenter subsample	*p*-value [a]
	Health characteristics and behaviors		
Self-reported health status			
(percentage distribution)	100.0	100.0	<0.001***
Excellent	16.8	18.1	. . .
Very good	30.6	32.1	. . .
Good	28.9	28.5	. . .
Fair	16.8	15.8	. . .
Poor	6.9	5.5	. . .
Self-reported probability (%) of—			
Living to age 75	64.3	65.6	0.002**
Working full time after age 62	46.3	46.3	0.976
Working full time after age 65	28.9	29.1	0.708
Work-limiting health problem in next decade	38.8	38.3	0.442
Health problems limit work (%)	24.1	21.5	<0.001***
Percentage ever diagnosed with—			
Arthritis	37.3	36.3	0.138
Cancer	6.1	5.6	0.086
Diabetes	12.5	10.6	<0.001***
Heart disease	11.1	9.5	<0.001***
High blood pressure	37.4	35.7	0.007***
Lung disease	5.7	4.5	<0.001***
Psychological problem	12.1	12.4	0.383
Stroke	3.2	2.5	0.001***
Total number of health conditions reported	1.3	1.2	<0.001***
Body mass index (above 30 indicates obesity)	28.2	28.4	0.007***
Self-reported tendency toward depression [c]	1.5	1.4	0.445
Number of difficulties with ADLs [d]	0.213	0.179	<0.001***
Number of difficulties with instrumental ADLs [d]	0.170	0.138	<0.001***
Any hospital stay in previous 2 years (%)	18.4	17.0	0.005*
Any doctor visit in previous 2 years (%)	89.9	90.4	0.205
Number of doctor visits in previous 2 years	8.3	8.0	0.091
Out-of-pocket medical expenditures (2020 $)	2,248	2,165	0.347
Ever smoked (%)	59.2	57.4	0.005
Current smoker (%)	23.2	21.8	0.007**
Ever drank alcohol (%)	57.9	60.2	<0.001***
Number of days per week drinking alcohol	1.1	1.2	0.020**
Number of alcoholic drinks per day	0.9	1.0	0.387

SOURCE: Authors' calculations using data from the HRS-SSA Permissions Consent History file.

NOTES: Figures are for respondents at the time they are first observed in the study sample.

. . . = not applicable.

* = statistically significant at the 0.05 level; ** = statistically significant at the 0.01 level; *** = statistically significant at the 0.001 level.

a. Test statistics are derived from chi-square tests (for the differences in the distributions of the full HRS sample and the consenter subsample) and on *t*-tests for the differences in means.

b. Other race responses available in the HRS include American Indian, Alaska Native, Asian, Native Hawaiian, Pacific Islander, other (open-ended), don't know, and refuse to answer.

c. Mean scores in an 8-item version of the Center for Epidemiological Studies—Depression Scale, with respondents reporting from 0 to 8 symptom indicators.

d. ADLs and instrumental ADLs are marked 0–5 to represent the number of ADLs or instrumental ADLs in which the respondent reports at least some difficulty.

Chart 1 shows the weighted distribution of respondents by interview and consent status in each cohort and wave, from the year of survey entry through 2016, applying the wave-specific IPW to the baseline weights for each cohort. In the chart, the dark green bar segments show the share of respondents interviewed in each wave who provided consent for the administrative-data linkages in 2006 or later, enabling their inclusion in our analysis. The IPW reweighting process for analyzing the administrative data means that the weighted sum of the post-2005-consenter subsample (dark green bar segments) equals the weighted sum of the total number interviewed in each wave who have not reached FRA (the combination of the dark blue, light blue, and dark green bar segments). Over time, the share of the non-FRA sample that is interviewed declines because of attrition via FRA attainment, death, or withdrawal from the HRS. All respondents in the original HRS and War Baby cohorts reached FRA before 2016, while only some in the Early Baby Boom cohort did (and none in the Middle Baby Boom cohort did). Because respondents in a 2-year birth cohort attain FRA over more than one survey wave, it is important to note that a cohort's age composition changes as its members approach FRA, as shown in Table 1.

Measuring DI and SSI Application and Receipt

In this subsection, we describe our approach to measuring applications for and receipt of DI and SSI benefits. Box 1 defines our measures. Self-reported values are defined using cross-wave, consistent measures in the RAND-HRS file. Administrative information on applications comes from SSA's Form 831 records linked to the HRS, while administrative records on benefit receipt are derived from the DAF. If HRS respondents consented to the SSA linkage but did not have information available in their 831 file for either DI or SSI, we conclude that they had not applied for benefits from the relevant program. We follow a similar approach if they consented to the administrative linkage but did not have a record in the DAF, counting those respondents as nonbeneficiaries for the relevant program.

Box 1.
Overview of key measures

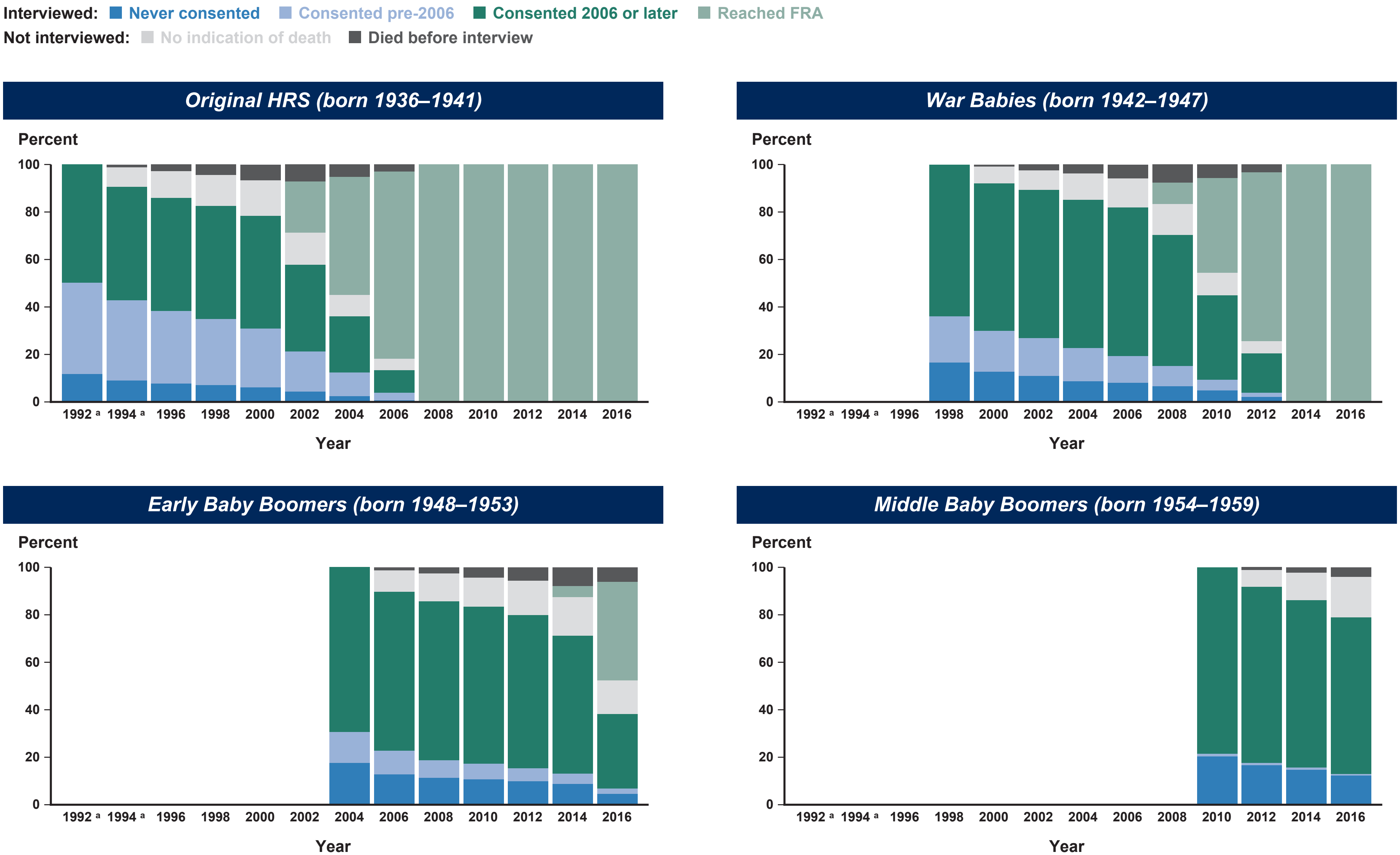
Ever applied for DI or SSI
The data indicate that the individual has ever applied for program benefits, either based on information directly related to an application being filed, or based on inferring an application for those receiving benefits.

Receipt of DI or SSI benefits
The data indicate that at the time of the HRS interview, the individual is receiving benefits from the program.

Application. For self-reported applications, we use the data available in the RAND-HRS file to identify whether the person had reported ever applying for DI and/or SSI by the date of the HRS interview. This information is based on the respondent's recollection of his or her application status, including the date of initial application. As described earlier, there are reasons why individual self-reports of application may not align with administrative records in the 831 file and why the 831 file undercounts applications that respondents might report. Based on the HRS questions, there are several scenarios under which a respondent would correctly report an application without having an analogous record in the 831 file. Although pending applications might eventually generate an 831 record in a future HRS wave, the 831 file will never include applications filed before 1988 nor does it include technical denials. Allowing for additional time to pass before analyzing the administrative data will not substantially reduce the magnitude of the disparity.

Conversely, the 831 file might also contain applications that respondents do not self-report. First, a respondent who applies for SSI may not know that SSA will also process an application for DI if the applicant meets the latter program's financial eligibility criteria. Second, SSA may consider the SSI eligibility of DI applicants based on information that SSA collects on that initial application.[11] In these cases, HRS respondents may report an application only for the program from which they sought benefits, even though the SSA record might show applications for both programs. Similarly, SSA may consider the DI eligibility of OASI retired-worker benefit claimants younger than FRA if their initial application indicates that they have a long-lasting impairment that limits their ability to work. As with concurrent applications, we believe that many HRS respondents may not report a DI application in this case, even though one might appear in the 831 file. Third, entities such as hospitals can file for SSI on behalf of uninsured patients who might be eligible for Medicaid once granted SSI; in these cases, an application may appear in the SSA record that HRS respondents are not aware of. We do not know the frequency of these scenarios, either in absolute terms or relative to the reasons that the 831 file might undercount applications.

Chart 1.
Interview and consent status of each HRS cohort, 1992–2016 (weighted)



SOURCE: Authors' calculations using data from the HRS-SSA Permissions Consent History file.

NOTE: Values are weighted using the HRS sampling weight from the initial interview in each cohort. Appendix Table A-1 presents analogous unweighted values.

a. Because SSA did not compile the DAF administrative data until 1996, survey results for 1992 and 1994 are omitted from this analysis.

Finally, until the 2016 survey wave, the HRS questions about DI and SSI application and receipt history were limited to respondents who reported having a health condition or impairment that limited their ability to work. Thus, some respondents who did not indicate a disability would not have been asked the question and therefore would be counted as non-applicants based on self-reporting. We return to this point later.

For both the self-reports and administrative data, we assume that if the respondent is a beneficiary in the current wave (based on the comparable self-report or administrative measure), then he or she applied for those program benefits at some point before that interview. We do so even when the survey and administrative data do not affirmatively indicate that the individual had applied. This may, to some extent, mitigate undercounts of applications. For example, applications filed before 1988 will be counted if they were approved and subsequently resulted in benefits (while denied applications will not).

Benefit receipt. We measured the receipt of DI and SSI benefits at the time of the HRS interview. For self-reports, we used wave-specific measures in the RAND-HRS file indicating that the respondent was currently receiving benefits from DI and/or SSI. For the administrative data, we used the DAF to measure benefit receipt, identifying individuals who were in current-payment status in the month or months of the HRS interview.[12] There are fewer reasons to expect misalignment between survey reports and administrative records on benefit receipt than there are for application data. Nonetheless, HRS self-reports undercount benefit receipt for beneficiaries who do not report a work-limiting health condition or impairment, because they are not asked about benefit receipt in that instance.

From 1992 through 2000, HRS respondents were asked about DI and SSI together. As such, respondents may have reported benefits from one of the programs but were unsure which one. We opted not to incorporate information on those whose responses were unsure. For example, respondents who did not clarify whether they received benefits from DI or SSI were classified as not being beneficiaries. After 2000, the survey questions on disability benefit receipt addressed the programs separately, so that an affirmative response was available separately for each program (we excluded information for respondents who replied "don't know" for both programs).[13] Based on our review of patterns over time, our exclusion of the "unsure" group through 2000 also understates program participation during that time, yet we found that the alternative of including the "unsure" group would have dramatically overstated program participation.[14]

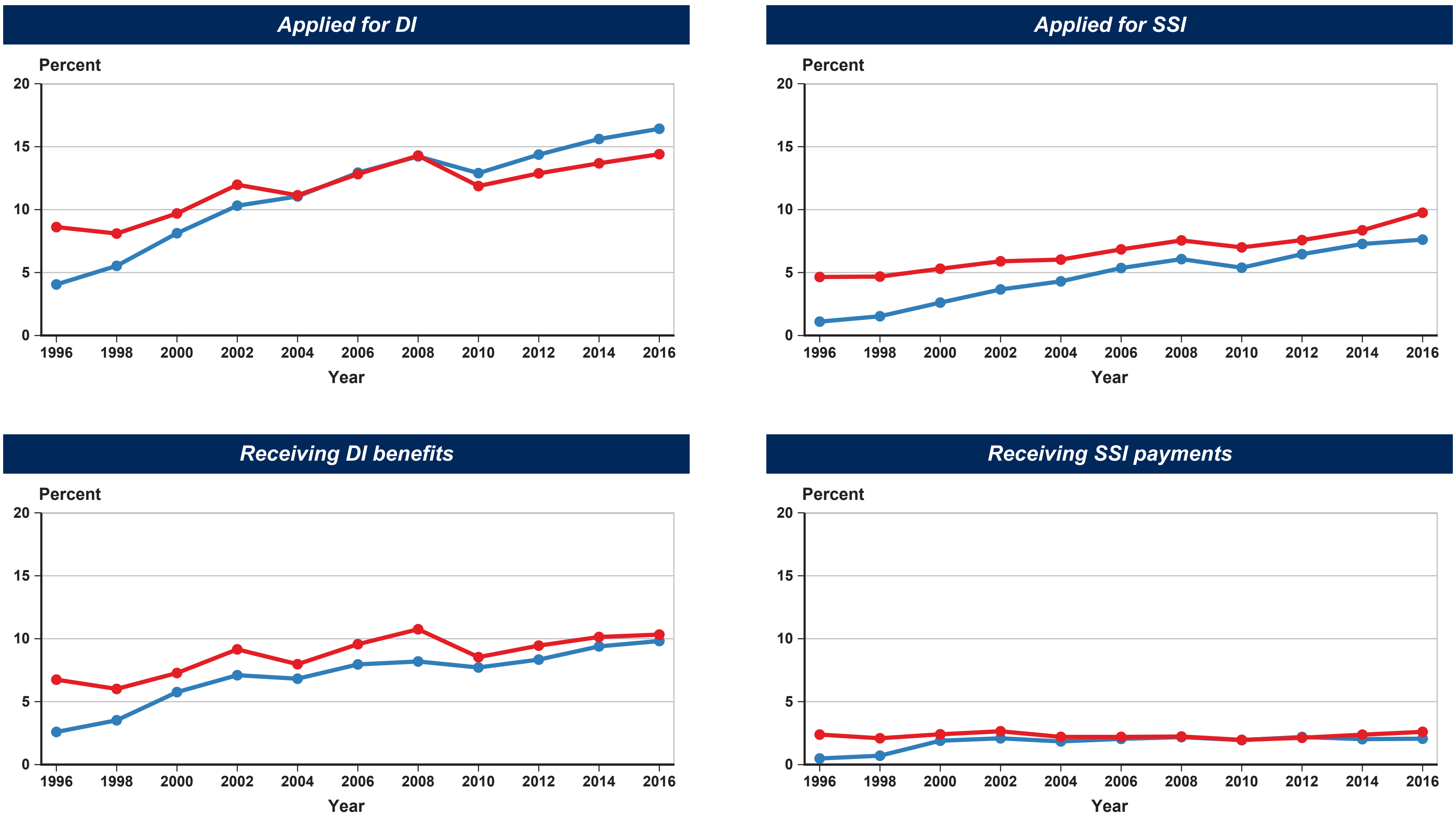
Patterns in DI and SSI Application and Receipt by Time and Cohort

To start, we consider the aggregate alignment of survey and administrative reports in each year, incorporating all four cohorts. This analysis shows the patterns of DI and SSI application and receipt derived from each data source over the years of the HRS. Chart 2 shows the results. The blue line shows self-reports, while the red line shows administrative data values; both have been weighted to produce nationally representative estimates of the sample in each year, as described earlier. Despite differences between survey and administrative data in the levels of DI and SSI applications and receipt, the rates of new applications and benefit receipt over time (indicated by the slopes of the lines) are generally similar. In other words, information on the prevalence of DI and SSI application and receipt from the two data sources differ, but the data on their incidence largely agree.

Both self-reported and administrative measures of DI benefit receipt generally increase over the period, as would be expected as a cohort ages and its members are more likely to meet the work-history and health-condition criteria for program eligibility. An individual receiving benefits in one survey wave might not receive benefits again in the next wave, but terminations for reasons other than death or reaching FRA are rare. Self-reported data on DI benefit receipt are always lower than the measure using administrative data at the same time, with the former increasing from about 3 percent in 1996 to just under 10 percent in 2016 and the latter increasing from 7 percent to just over 10 percent over the same period. The addition of new, younger cohorts in 1998, 2004, and 2010 obscures some of the patterns reflecting the aging of the earlier cohorts, shown by the small dip in DI receipt in those years when younger cohorts are added to the sample. Some of the lower levels of self-reported DI application and receipt in earlier years reflect our decision to include only those who reported benefit receipt for a specific program, although this was not an issue after 2000.

Chart 2.
DI and SSI application and benefit receipt in HRS survey waves from 1996 through 2016 (weighted)

■ Self-reported ■ Administrative data



SOURCE: Authors' calculations using HRS data linked to administrative data from SSA.

NOTE: Limited to HRS respondents born during 1936–1959 and part of the original HRS, War Baby, Early Baby Boom, and Middle Baby Boom cohorts.

The share of claimants who have ever applied for DI benefits is lower in self-reports than in administrative records each year through 2004, then quite close through 2008, after which the self-reported rates are higher than administrative data values. Our measure of having ever applied for benefits is cumulative through each year. Around 4 percent of respondents self-reported having applied for DI benefits in 1996 and around 16 percent self-reported having applied by 2016, while administrative records show that about 9 percent had applied in 1996 and about 14 percent had applied by 2016. The pattern over time is consistent with a growing share of technical denials over the period, meaning that administrative records would exclude an increasing share of applications in the later years of our analysis. It is also possible that toward the later years of the study period, respondents were reporting on applications for which an initial decision was still pending, although we expect this to represent relatively few applications.

Despite differences between survey and administrative data in the levels of DI application and receipt, both sources show similar patterns in new applications and benefit receipt over the period, which can be seen from the slopes of the lines. The slopes for DI receipt are relatively similar at most points after 2000 (when the HRS question scheme changed), except during the Great Recession of 2008, when the administrative data had more marked changes than the self-reports. After 2000, the slopes are quite similar for DI application as well.

In general, self-reported values of SSI application and receipt are also lower than those from the administrative data. The share of respondents who had ever applied for SSI increased from 1.1 percent in 1996 to almost 8 percent by 2016 based on self-reports compared with a change from 4.6 percent to nearly 10 percent based on administrative data. We suspect that the wider differences prior to 2000 largely reflect the HRS questions that combined DI and SSI. After 2000, the difference between self-reported and administrative data values narrows, fluctuating between 1.0 percent and 2.3 percent.

We next disaggregate the data shown in Chart 2 to highlight differences in self-reported and administrative data for each cohort in our analysis. The annual values in Chart 2 combine patterns over time based on secular patterns in experience with SSA's disability programs, differences in patterns across HRS cohorts (reflecting a range of factors including labor market conditions and sufficient labor force participation to be insured for DI), and the aging of HRS cohorts over time. Chart 3 highlights the same four outcome measures as Chart 2, but the horizontal axis replaces calendar years with HRS interview waves, starting with each cohort's respective first interview. Recall that the original HRS cohort was first interviewed in 1992, the War Baby cohort in 1998, the Early Baby Boom cohort in 2004, and the Late Baby Boom cohort in 2010. Because the DAF began in 1996, the first wave recorded in the chart for the original HRS cohort is its wave 3.

In Chart 3, the solid line for each cohort tracks the self-reported value over the successive waves, while the dashed line of the same color represents the value from the administrative data. The patterns by cohort are not consistent across all four measures, whether comparing across cohorts or comparing self-reports to administrative records. More recent cohorts tend to report higher rates of DI application than their administrative records show, aligning with the pattern shown in Chart 2, where self-reported application exceeds that of the administrative record in the later years.

Patterns are less clear for DI benefit receipt and for SSI application and receipt, which may reflect a combination of the factors discussed so far. Although there is modest evidence that the self-reports for the original HRS and War Baby cohorts "catch up" to the administrative records after 2000 following the introduction of the new survey question sequence (waves 5 and 2, respectively), a similar convergence in survey and administrative data is seen for the other cohorts, so that pattern may reflect other factors. Those cohorts also may be misreporting SSI as OASI at those points, although we did not explore that possibility.

Maestas, Mullen, and Strand (2015) found increased DI participation during and following the Great Recession of 2008; we would expect to see this reflected primarily in the 2010 wave given the HRS survey timing. This corresponds to wave 7 for the War Baby cohort and wave 4 for the Early Baby Boom cohort. We do not see notable deviations from the previous trend in DI or SSI application or receipt at that point for those cohorts, either in the self-reported or administrative data. By wave 7 for the War Baby cohort, much of the sample had passed the earliest age of retirement eligibility at 62, so it may be that much of the cohort claimed OASI early and did not meet the criteria for DI.

Chart 3.
DI and SSI application and benefit receipt for each HRS cohort from entry through FRA or 2016 (weighted)

SOURCE: Authors' calculations using HRS data linked to administrative data from SSA.

NOTE: Limited to HRS respondents born during 1936–1959 and part of the original HRS, War Baby, Early Baby Boom, and Middle Baby Boom cohorts.

a. The SSA administrative value for the War Baby cohort in wave 8 is suppressed to limit disclosure risk.

Age Profiles of DI and SSI Applicants and Beneficiaries

Next, we examine reporting of DI and SSI application and receipt by age, an alternative way to consider the HRS data. Because DI and SSI application and receipt are relatively rare events, some researchers may opt to combine data from multiple cohorts and look at a pooled sample of, say, all respondents aged 51–52. The results in this section highlight how similar survey responses would be to administrative records in that case, and they hold age constant while allowing the cohort to vary. We acknowledge that there are cohort and year differences in DI and SSI outcomes that may be important to account for in some contexts that we do not investigate in this exercise.

In Chart 4, we reorient the data such that all respondents are grouped by age,[15] regardless of the corresponding cohort or year. This structure allows direct comparisons by age but does not consider compositional effects of cohorts or time. These results are weighted using our IPW method, as described earlier. However, in this case, we reran the IPW model within age bands instead of by HRS survey wave. We then applied the IPWs to the wave weight available in the RAND-HRS file for the respondent at the relevant age. These estimates are therefore nationally representative of the age group across all the survey years—an artificial cohort, but one that allows for closer inspection of benefit patterns within ages and across cohorts.

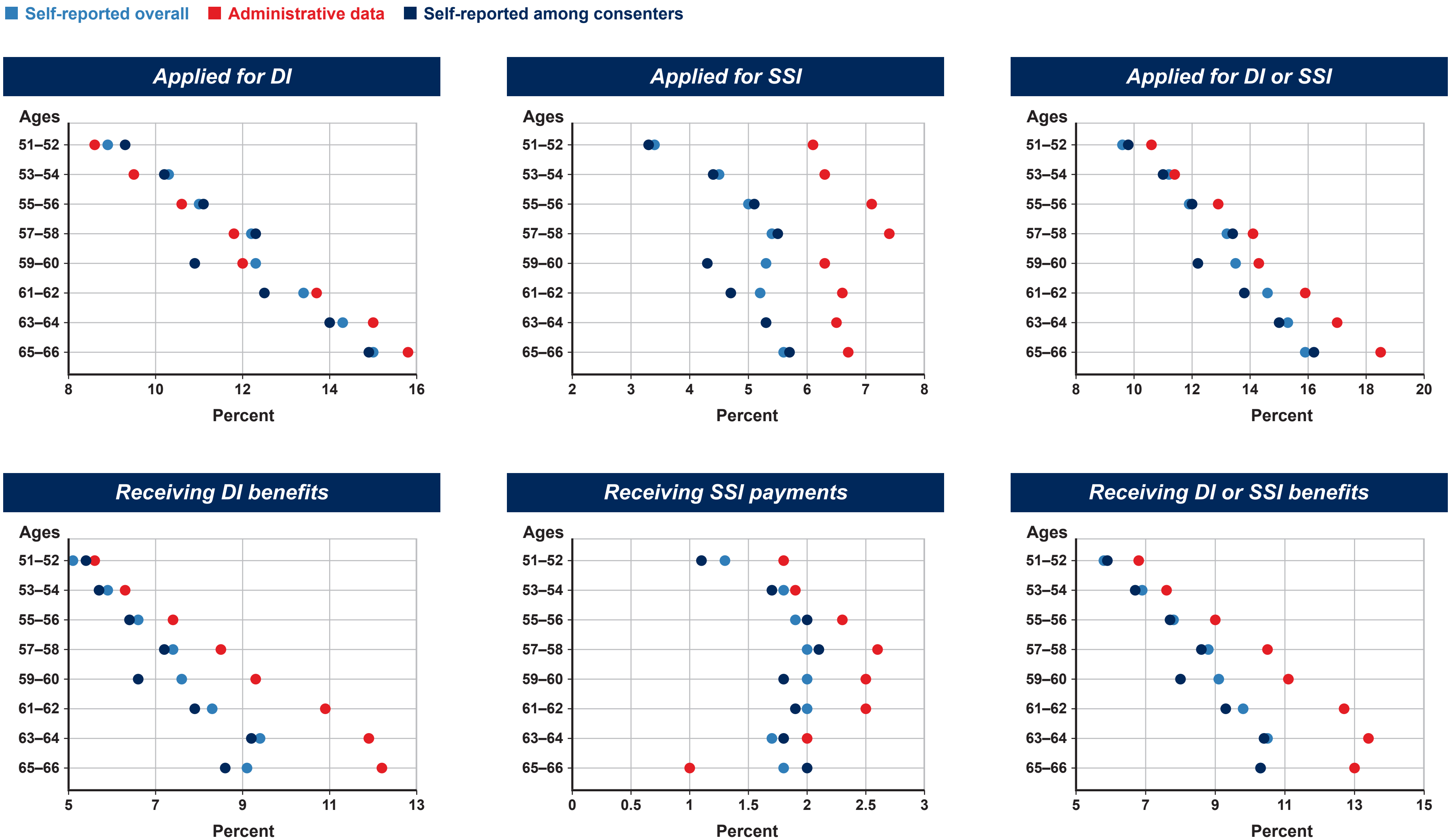
Chart 4 displays the percentage of respondents who self-reported DI and SSI application and/or receipt alongside corresponding percentages from administrative records at each age. One important caveat is that this restructuring does not yield a rectangular dataset—in our study design, we do not have data for each age in all four cohorts. Rather, the values shown include all respondents at each age for whom data were available. As we discussed earlier, Table 1 highlights the years from which we identified respondents of a particular age and cohort. For example, respondents aged 51–54 from the original HRS cohort were interviewed in 1992 and 1994 but are omitted from our analysis because the administrative data we use for comparison, the DAF, began in 1996. On the other end of the age range, the Middle Baby Boomers were last interviewed at ages 57–62. We include the information we have available for each age group, not all of which are represented in all four cohorts.

Chart 4 consists of panels for each of six measures. Each panel contains three sets of dots for each age group. The light blue dots represent the application or receipt rate, as applicable, reported by the full HRS sample; this is the value that is available to HRS data users without access to the administrative linkage. The red dots represent the corresponding rate as shown in the administrative data, which are limited to consenters. The light blue and red dots mirror information shown by year (in Chart 2) and by cohort (in Chart 3), instead shown by age. The dark blue dots represent the self-reported rate among only those HRS respondents who consented to the administrative-data linkage. This set of dots allows us to compare the self-reports of consenters with both the self-reports of the full HRS sample and the consenters' administrative records. Although researchers are unlikely to study this group, we include them here to highlight the accuracy of consenters' self-reports.

Chart 4 shows that HRS respondents' self-reported DI and SSI application and receipt rates are generally lower than those reflected in the administrative records for both the full sample and for the subset who have consented to the administrative-data linkage. This is most notable for SSI applications, for which we expected the administrative data counts to be lower than the self-reports. The pattern is similar for DI and SSI benefit receipt, except for SSI receipt at age 65 or older.[16] For DI applications, self-reported rates are higher than those in the administrative records at ages younger than 60, after which the pattern switches. This may reflect DI applications that are considered because the applicant reported a work-limiting health impairment when claiming OASI retired-worker benefits, which can occur as early as age 62. Despite finding that respondents who consent to the SSA data linkage differ on several demographic and health characteristics, the aggregate patterns of reporting on disability program application and benefit receipt do not differ substantially between consenters and the full HRS sample.

Chart 4's dark blue dots show that, in general, consenters are less likely to self-report DI application and receipt than the members of the full HRS sample are. For SSI, the rates are more similar than those for DI, and in some cases, consenters are more likely to self-report application or receipt. Chart 4 also shows results for measures that combine DI and SSI application and receipt. These combined measures account for individuals who may know they have interacted

Chart 4.
Comparisons of percentage of DI and SSI application and benefit receipt, by age (weighted)



SOURCE: Authors' calculations using HRS data linked to administrative data from SSA.

NOTES: Limited to HRS respondents born during 1936–1959 and part of the original HRS, War Baby, Early Baby Boom, and Middle Baby Boom cohorts.

"DI or SSI" refers to the total number of respondents who report either program; some respondents report only one program and some report both.

with a disability program administered by SSA but may incorrectly recall the program. If misreporting reflects respondent confusion between the programs, this combined measure will more closely align with SSA records than either of the individual program measures.

There is not a significant age gradient in the observed gaps between self-reports and administrative records, in either the individual or combined program measures. There is some evidence that misreporting of DI benefits increases as respondents reach the earliest age of eligibility for Social Security retirement benefits (62). For example, self-reports and administrative records of DI benefit receipt are much closer for respondents aged 55–56 than for those aged 63–64 or 65–66. We do not observe a similar pattern for SSI, nor do we see that combining DI and SSI results in differences between self-reported and administrative data that are substantially smaller. This again may reflect applicants who initially claim OASI benefits but are ultimately awarded DI benefits. Unlike OASI benefits, DI benefits claimed before FRA are not actuarially reduced. Further, Medicare coverage is available to DI beneficiaries after a 2-year waiting period, potentially before age 65, but not to OASI beneficiaries before age 65. Given these facts, it would be unlikely that a DI-eligible claimant would prefer OASI benefits.[17] Nonetheless, it is possible that DI beneficiaries who initially claimed OASI benefits may misreport their benefit status when interviewed. Because the composition of the sample is changing with age (given the availability of data at older ages for more recent cohorts), we cannot definitively conclude that self-reports at older ages reflect (or do not reflect) confusion over the program from which benefits are being claimed.

Accuracy of Individual Self-Reported DI and SSI Application and Benefit Receipt Responses

Having described patterns of reporting in the aggregate—by wave, cohort, and age—we now describe the accuracy of individual self-reports. We focus on results for two specific ages: 55, the age for which data are likely to be available for the greatest number of respondents; and 63, which is past the earliest retired-worker benefit eligibility age (62) but is younger than FRA for all cohorts. The misreports we discuss are not weighted; we are interested solely in the likelihood of misreporting by groups of respondents, and nationally representative estimates are not appropriate in that context.

Examining responses separately for DI and SSI as well as for application and receipt, we categorize the accuracy of self-reports into one of four groups:

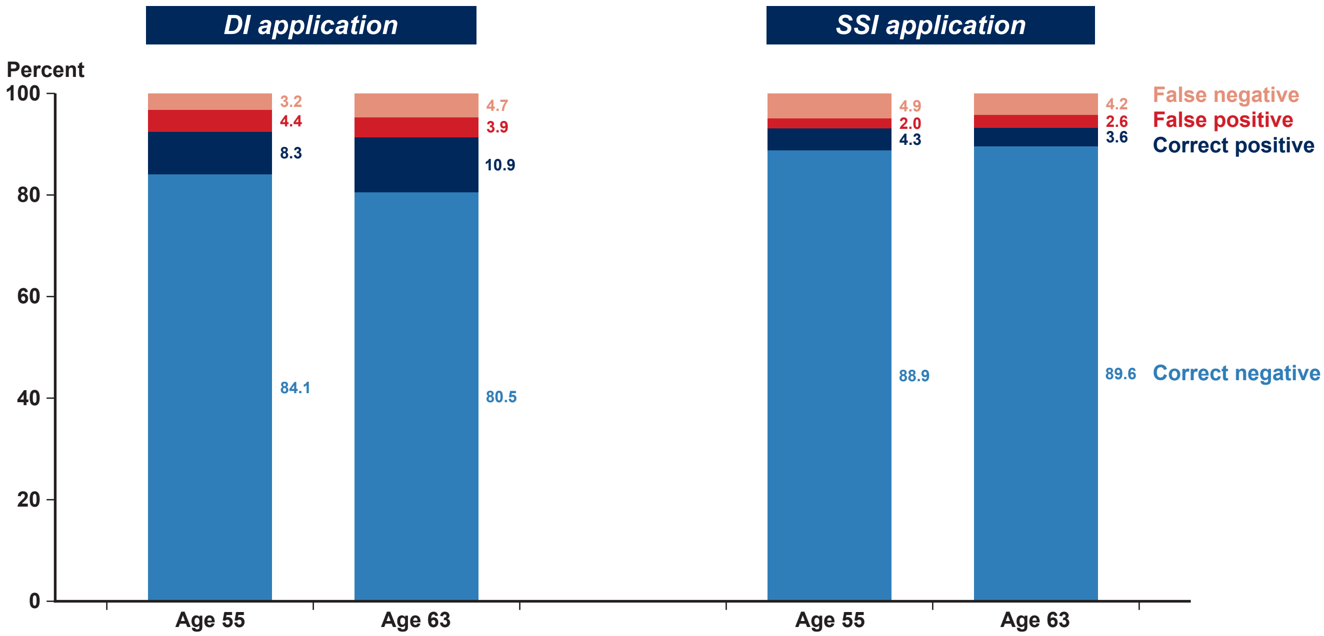
- ***Correct negative*** means that a respondent reports not having applied for or received DI or SSI benefits, and the corresponding administrative record concurs.
- ***Correct positive*** means a concurrence in self-reports and administrative records for respondents who report they have applied for or received benefits.
- ***False positive*** indicates that a respondent reports having applied for or received benefits, but the administrative record does not.
- ***False negative*** indicates that a respondent reports not having applied for or received benefits, but the administrative record indicates application or receipt.

When interpreting these values, we assume that the administrative record is correct—although, as noted earlier, there are reasons why this may not be true, especially for applications.

Chart 5 displays the distribution of respondents aged 55 and 63 who reported ever submitting a DI or SSI application, by accuracy category. Because most adults do not interact with disability programs, correct negatives constitute the largest of the four categories, representing 81–90 percent of the respondents, depending on the program and respondent age. Correct positives are the second largest category, but they occur far less frequently than correct negatives simply because relatively few adults apply for benefits. Together, the false positives and false negatives represent the share of respondents who misreported their benefits, which is small relative to the full sample; 7 percent to 9 percent of HRS respondents misreport DI and SSI application at ages 55 and 63.

Another way to consider the magnitude of misreporting is to consider false reports as a share of total positive or negative reports. This allows for a much closer inspection of the effect of misreporting on aggregate values. For example, consider DI applications reported at age 63: 15.6 percent of respondents either self-reported having applied (10.9 percent) or had a false negative (4.7 percent), meaning that the administrative record indicated that the respondents filed but they did not report an application. The share of false positives (3.9 percent) is close to the share of false negatives (4.7 percent) overall; yet

Chart 5.
The accuracy of self-reported DI and SSI application at ages 55 and 63 (unweighted)



SOURCE: Authors' calculations using HRS data linked to administrative data from SSA.

NOTES: Limited to HRS respondents born during 1936–1959 and part of the original HRS, War Baby, Early Baby Boom, and Middle Baby Boom cohorts.

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

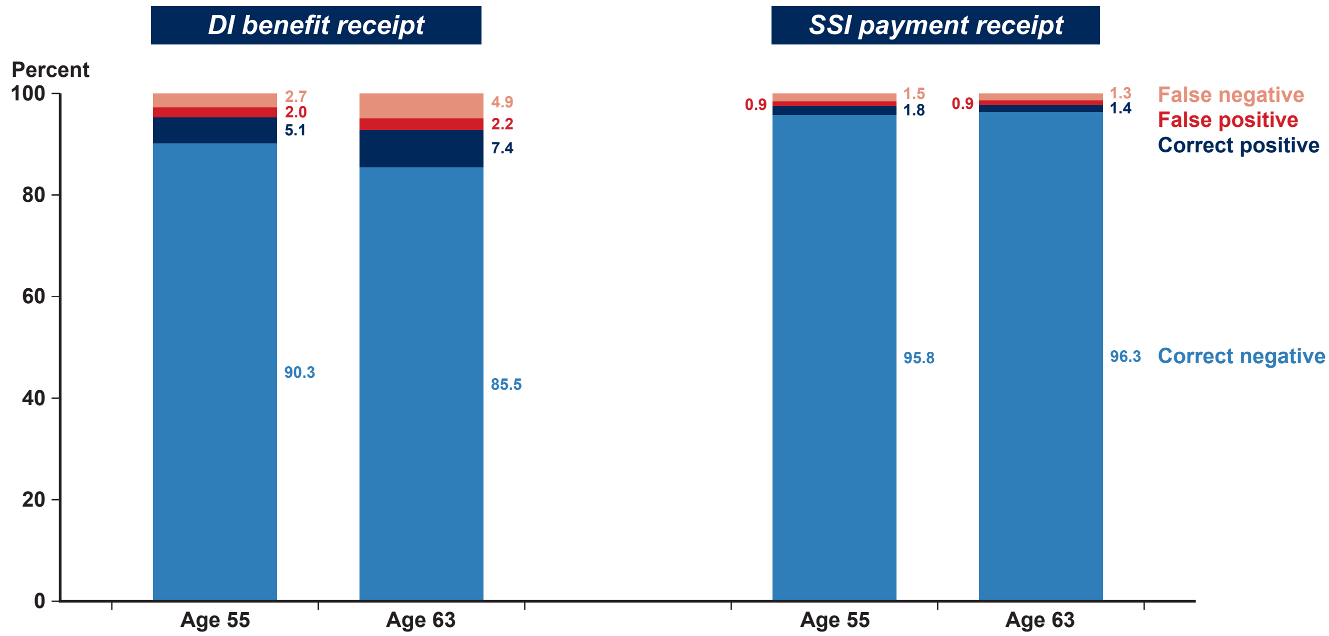
false negatives as a percentage of total self-reported negatives is far lower than false positives as a share of total self-reported positives. This means that positive self-reports are more likely to be wrong relative to the administrative record; 26.4 percent of positive self-reports were incorrect (3.9 percent of 14.8 percent) compared with only 5.5 percent of negative self-reports (4.7 percent of 85.2 percent). We can consider false negatives to be the share of actual applications that were not reported and led to an undercount of total applications. Conversely, false positives represented an opposite influence, toward overcounting; but other than DI applications reported at age 55, false negatives constituted larger shares of the self-reports than false positives.

Chart 6 displays similar results and patterns for benefit receipt for respondents aged 55 and 63. Overall, correct negatives are the largest category of self-reports, consistent with the relative infrequency of disability program participation. Misreports are a smaller share of total reports for benefit receipt than for application (reflecting that many applicants do not ultimately become beneficiaries), but false positives again constitute a much greater share of total positive reports than false negatives relative to all negative self-reports. As with applications, false negative reports of benefit receipt are more common than false positives.

It is helpful to compare the distributions in Charts 5 and 6 with the total misreports indicated in Chart 4. In Chart 6, actual receipt is the sum of correct positives and false negatives. For example, the percentage of respondents aged 55 who reported receiving DI benefits from Chart 6 is 7.1 percent—5.1 percent (correct positives) plus 2.0 percent (false positives). The most proximate value in Chart 4 is represented by the dark blue dot indicating self-reported DI receipt among respondents aged 55–56 who consented to the linkage (and therefore have a corresponding administrative record from which we can assess misreporting). In Chart 4, 6.4 percent of respondents aged 55–56 receive DI benefits. Because the values in Chart 4 are weighted and those in Charts 5 and 6 are unweighted, we expect these values to be similar—as they are—but not necessarily identical.

As we alluded to in discussing Chart 4, it may be useful to consider the overlap in misreporting across

Chart 6.
The accuracy of self-reported DI and SSI receipt at ages 55 and 63 (unweighted)



SOURCE: Authors' calculations using HRS data linked to administrative data from SSA.

NOTES: Limited to HRS respondents born during 1936–1959 and part of the original HRS, War Baby, Early Baby Boom, and Middle Baby Boom cohorts.

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

programs to try to determine whether misreports reflect confusion about the multiple programs administered by SSA. To evaluate whether a respondent may be correct in reporting receipt of some disability benefit but mistaken on which program, we considered a false positive in one program and a false negative in the other (Table 4). Although there is some overlap that might suggest that respondents are misreporting participation in one program as participation in the other, the share of respondents in this category is relatively small and without a clear pattern. Among false positives for DI receipt, more respondents aged 55–56 reported a false negative for SSI receipt than a correct positive for SSI. Considering the opposite scenario—a false positive report for SSI receipt—we do not see a clear concentration of false negative reports for DI. It appears likely that respondents who misreport benefit receipt for one program may report correctly for the other. Thus, we find some evidence that misreports are the result of respondents mistaking the program from which they receive benefits.

Tables 5 and 6 examine whether misreporting is concentrated in certain demographic and health condition subgroups. It is possible, for example, that misreporting is more (or less) common among those who are less healthy, as they may have had more opportunities to interact with (or learn about) disability programs. In Table 5, we compare characteristics of respondents aged 55–56 and 63–64 with correct positive and false positive reports of DI and SSI benefit receipt. In Table 6, we compare characteristics of those with correct negative and false negative reports.

The tables contain several simplifications to aid in interpretation. First, we omit results for application to focus on benefit receipt.[18] Second, we focus on characteristics in which we identified statistically significant differences between those who report correctly and those who misreport in at least one of the outcomes we considered. To simplify further, we focus on groups of variables (for example, race includes White, Black, and "all other responses," where we tested the difference in the racial distribution of the groups). A check indicates that the mean or distribution of the variable category shown was statistically different between the correct- and false-report groups.[19]

Table 4.
Cross-comparisons of self-reports of DI and SSI benefit receipt, by age and accuracy category

SSI receipt report	DI receipt report: Total	Correct negative	Correct positive	False positive	False negative
	Respondents aged 55–56				
Total	8,627	7,795	437	173	222
Correct negative	8,273	7,615	361	110	187
Correct positive	147	88	44	15	(X)
False positive	79	22	20	17	20
False negative	128	70	12	31	15
	Respondents aged 63–64				
Total	6,598	5,655	489	136	318
Correct negative	6,370	5,541	448	102	279
Correct positive	83	52	31	(X)	(X)
False positive	60	19	10	10	21
False negative	85	43	(X)	24	18

SOURCE: Authors' calculations using HRS data linked to administrative data from SSA.

NOTE: (X) = suppressed because of small sample size; category totals exclude the omitted group.

Table 5 shows that there are differences between respondents who misreported receiving benefits (false positives) and those who correctly reported receiving benefits (correct positives). We do not observe consistent patterns in the characteristics correlated with misreporting across program or age. Respondents aged 55–56 who misreported DI receipt differed from respondents who reported correctly by ethnicity and educational attainment. Respondents aged 55–56 with false positive reports for DI had worked for fewer years and were more likely to report poorer health (with a higher prevalence of high blood pressure). Respondents aged 63–64 with a false positive report of DI receipt were twice as likely to be Hispanic, had less education (by almost 1 year, on average), and were employed for 6 fewer years (on average).

We also observe demographic and health differences between respondents aged 55–56 with false positive and correct positive reports of SSI receipt, but they are not the same differences we find for DI beneficiaries. SSI misreporters differ from correct reporters by race and ethnicity, as well as by average income and assets. Notably, false positive reporters are more likely to have higher incomes and assets (which might be expected, given the income and assets limits for SSI). There are also health differences between respondents who reported false positives and correct positives; those with false positive reports tend to have better health behaviors but report worse health. Specifically, those with false positive reports are less likely to be smokers, report drinking fewer alcoholic drinks per day, and are less likely to report having a psychological problem, but they have had more hospital stays in the last 2 years and higher out-of-pocket medical expenditures. In general, the patterns of differences between correct reporters and false reporters for SSI receipt among respondents aged 63–64 reflect a different set of characteristics than those for respondents aged 55–56.

Table 6 reveals that there are consistent differences between false negative and correct negative reporters, across ages and programs. We find statistically significant differences across most individual characteristics, which may not be particularly surprising for two reasons. The first is sample size; correct negatives include all respondents who have no interaction with DI or SSI, which, as shown in Chart 6, is most of the sample. As such, the larger sample sizes may better detect statistically significant differences in characteristics. The second reason involves the eligibility factors underlying program participation. False negative reporters receive benefits, meaning that their financial and health characteristics meet the program eligibility requirements. Because beneficiaries have significant health and functional impairments and are generally out of the labor force, the differences in socioeconomic and health characteristics are to be expected.

Table 5.
Characteristics of respondents aged 55–56 and 63–64 reporting DI and SSI benefit receipt with statistically significant differences between correct positives and false positives

Characteristic	Age 55–56		Age 63–64	
	DI	SSI	DI	SSI
Number of correct positives	437	147	489	83
Number of false positives	173	79	136	60
	Demographic characteristics			
Race		✓		
Ethnicity	✓	✓		
Marital status			✓	
Education (years completed)	✓		✓	
	Socioeconomic characteristics and employment			
Respondent income		✓		✓
Total household assets		✓		✓
Working for pay			✓	✓
Total years worked	✓		✓	✓
	Health characteristics and behaviors			
Self-reported probability of work-limiting health problem in next decade			✓	
Body mass index (above 30 indicates obesity)				✓
Self-reported tendency toward depression [a]	✓			✓
Number of hospital stays in previous 2 years		✓		✓
Out-of-pocket medical expenditures		✓	✓	✓
Current smoker		✓		
Number of alcoholic drinks per day		✓	✓	✓

SOURCE: Authors' calculations using HRS data linked to administrative data from SSA.

NOTE: A check mark indicates a statistically significant difference, based on chi-square tests for differences in the distributions of respondents reporting correct positives and false positives and *t*-tests for differences in the means.

a. Mean scores in an 8-item version of the Center for Epidemiological Studies—Depression Scale, with respondents reporting from 0 to 8 symptom indicators.

Discussion

We began this project seeking a definitive answer to whether researchers should use the HRS self-reported data or the administrative records from SSA. Based on our analysis, the answer is that it depends. In many cases, the self-reported data may be accurate enough—if receipt of SSI is simply a control variable, the difference between 2.0 percent (self-reported data) and 2.5 percent (administrative records), for example, may not be important (Chart 4). Moreover, the consistency of benefit self-reporting along with other self-reported data in the HRS may make the potential bias relative to administrative records derived from another source acceptable. Administrative records may contain information that differs from a respondent's correct self-report, especially on application data, for known reasons. For example, SSA data do not track applications that result in technical denials, which has the effect of undercounting applications. Because administrative data are available only for a subset of HRS respondents who consent to the linkage—and especially for targeted population subsets that can constitute a small sample—using the self-reported data is a sensible choice in many cases, despite its limitations.

If the research question involves establishing beneficiary status, administrative data from SSA should, on their own, provide an accurate representation; however, the administrative linkage to the HRS may be tremendously powerful. Because tracking an individual's disability program interactions is notoriously complex, especially for interactions after reaching retirement age, administrative data about the application process may be valuable. For research projects that intend to use information about denied or allowed

Table 6.
Characteristics of respondents aged 55–56 and 63–64 not reporting DI and SSI benefit receipt with statistically significant differences between correct negatives and false negatives

Characteristic	Age 55–56		Age 63–64	
	DI	SSI	DI	SSI
Number of correct negatives	7,795	8,273	5,655	6,370
Number of false negatives	222	128	318	85
	Demographic characteristics			
Race	✓	✓	✓	✓
Ethnicity	✓	✓	✓	✓
Sex		✓		✓
Marital status	✓	✓	✓	✓
Education (years completed)	✓	✓	✓	✓
	Socioeconomic characteristics and employment			
Respondent income	✓			✓
Total household assets	✓	✓	✓	✓
Working for pay	✓	✓	✓	✓
Years at longest held job	✓	✓	✓	✓
Total years worked	✓	✓	✓	✓
	Health characteristics and behaviors			
Self-reported health status	✓	✓	✓	✓
Self-reported probability of—				
Living to age 75 and/or working to age 65	✓	✓	✓	
Work-limiting health problem in next decade		✓	✓	
Health problems limit work	✓	✓	✓	✓
Ever diagnosed with—				
Arthritis	✓	✓	✓	✓
Back problems	✓	✓	✓	✓
Diabetes	✓	✓	✓	✓
Heart disease	✓		✓	✓
High blood pressure	✓	✓	✓	✓
Lung disease	✓	✓	✓	✓
Memory problem	✓		✓	
Psychological problem	✓	✓	✓	✓
Stroke	✓	✓	✓	
Total number of health conditions reported	✓	✓	✓	✓
Self-reported tendency toward depression [a]	✓	✓	✓	✓
Number of difficulties with ADLs or instrumental ADLs [b]	✓	✓	✓	
Any hospital stay in previous 2 years	✓	✓	✓	
Number of doctor visits in previous 2 years			✓	
Out-of-pocket medical expenditures	✓	✓	✓	
Ever smoked and/or current smoker	✓	✓	✓	✓
Number of alcoholic drinks per day	✓			✓

SOURCE: Authors' calculations using HRS data linked to administrative data from SSA.

NOTE: A check mark indicates a statistically significant difference, based on chi-square tests for differences in the distributions of respondents reporting correct negatives and false negatives and *t*-tests for differences in the means.

a. Mean scores in an 8-item version of the Center for Epidemiological Studies—Depression Scale, with respondents reporting from 0 to 8 symptom indicators.

b. ADLs and instrumental ADLs are marked 0–5 to represent the number of ADLs or instrumental ADLs in which the respondent reports at least some difficulty.

applications, such as time to initial decision or reason for denial, administrative data are almost certainly preferable. Yet even then, the 831 file does not contain information on all benefit applications submitted to SSA, nor does it contain the full determination path for those applications. In the next several years, SSA intends to incorporate more complete information on disability applications from its Structured Data Repository into the DAF, which would provide substantially more complete information about applications than is currently available in that file or in the Form 831 records, although it would encompass only applications from 2007 forward (Mathematica 2022).

We found that among the approximately 15 percent of HRS respondents who indicated interactions with SSA's disability benefit programs, about half of their responses to survey questions about DI or SSI application or receipt do not align with the administrative record maintained by SSA for that individual. In general, we found that it is more likely that respondents fail to report benefits they are receiving than to report benefits they are not receiving. As a result, on net, the overall prevalence of DI and SSI application and receipt (when weighted to be nationally representative in the HRS) is lower if based on self-reports than if based on the administrative data. We found that this is generally true across HRS respondent ages and cohorts.

Despite differences between survey and administrative data in the prevalence of reported interactions with SSA's disability benefit programs, the patterns of incidence—new applications and new benefit receipt—across ages and interview waves in the self-reported and administrative data look generally similar. In other words, the differences between self-reported and SSA data that we observe for respondents when they first enter the survey appear generally to remain over future waves, although we observe some differences by HRS cohort that may be important to consider in some research contexts. Overall, we found that the availability of OASI early retirement benefits at age 62 likely does not seem to exacerbate misreporting. We found some evidence that suggested that respondents were reporting DI program interactions when they meant SSI.

We do not fully understand the causes of misreporting beyond those caused by known issues such as changes in some of the HRS questions over the years and the omission of pending applications and technical denials in the 831 administrative file. In some instances, information in the administrative record may not match what is salient to an individual. For example, an applicant may not know that he or she was also considered for DI when applying for SSI or that the lack of a cash payment in a given month does not mean beneficiary status has ended. As we described, most of the reasons we might expect a mismatch between the data sources would result in self-reports of program interactions that are higher than the administrative records indicate, but we generally found the opposite. We found that misreports are nonrandom and differ across race, sex, income, employment history, and several health conditions and behaviors.

We also found—as others have with older versions of the files—that consenting to the administrative-data linkage is nonrandom. We attempted to account for this using a simple IPW scheme that the HRS also uses for its other SSA data linkages, although a more in-depth approach to reweighting, such as exactly matching participants on certain characteristics, may be warranted in other research contexts. More importantly, though, researchers considering using the linked data should be able to use our analysis to take stock of the effects on sample size. The richness of the HRS questionnaire should not be understated, but the small sample for low-frequency events such as disability program benefit receipt becomes still smaller as some respondents decline consent to the data linkage, which may make certain research studies infeasible. Understanding the sample size loss may lead some researchers to accept the loss of precision in the self-reports to preserve record count.

Another reason that researchers may avoid using administrative records is a very high barrier to entry. Although the HRS has streamlined and simplified the process to access the linked SSA data in recent years, the documentation required to understand and link the files to the core survey remains complex and limited. Even with the addition of the DAF—which was designed to support research on disability programs by linking information contained in SSA's other administrative files (many of which can also be accessed by HRS users with permissions)—a detailed knowledge of SSA programs and program data is required to work with the linked data. We have attempted to fill some of that gap with this article. However, the administrative records were not designed primarily to support research, and utmost caution is required to avoid misinterpretation of the information they contain.

Because of the high barriers of access to administrative records, we suspect that self-reported HRS survey results will remain the dominant source of information on disability program benefit receipt. Despite their misalignment with the administrative records, there are several reasons why this may be advantageous. First, the HRS is continually improving the information it collects from respondents. For example, in 2016, the HRS began asking all new respondents—not only those reporting a health-related work limitation—about their receipt of DI and SSI benefits, recognizing that a share of beneficiaries would not report such limitations. Beginning with the 2022 survey wave, all respondents are asked these questions. Second, the HRS collects a large volume of information about disability onset that goes beyond program participation. For example, the survey asks respondents about the nature of their limitations, the timing of new onsets, and their own and their employer's responses to new health conditions. To the extent that self-reported information about program participation aligns with the respondent's recall about the other disability measures, self-reported data across the board may be preferable to information combined from other sources.

A third advantage of using self-reported information is that the RAND-HRS files have converted data drawn from a complex question sequence that has varied over the three decades of HRS data collection to a streamlined, quickly accessible set of measures of DI and SSI program participation. The herculean effort that went into producing cross-wave, consistent measures of program participation should not be understated, and we suspect that many studies of those measures would not have been conducted if the researchers had been faced with developing the measures independently, using the core HRS files. The HRS has significantly advanced knowledge about older workers with new disabling conditions because of its rich, longitudinal data collection and its care in preserving measures as much as possible over time to produce cross-wave consistency. The RAND-HRS files have built on that extensive data collection to make the information widely accessible to the research community. Without both components, we suspect that our understanding of disabilities among older workers would be substantially less robust.

Conclusion

In this article, we investigated differences between HRS survey results and administrative data on DI and SSI application and benefit receipt, as well as differences between those who consent to having their survey responses linked with administrative data and those who do not. We find that aggregate self-reported percentages of DI and SSI application and benefit receipt are lower than those reported in linked HRS-SSA data at nearly all ages, but patterns of new applications and benefit receipt are similar over time and across ages. Moreover, there are cohort differences in the self-reported and administrative data on DI and SSI application and benefit receipt, but no consistent pattern in the difference between the two data sources across the cohorts. Individual misreporting represents a minority of cases, and false negatives (that is, reporting no application or receipt despite administrative records indicating otherwise) tend to be more common than false positives, especially at older ages. For respondents whose administrative data indicate that they misreported their program interactions, some characteristics differ from those whose self-reports concur with administrative records. Those differences depend on the program and the respondent age, but include race, income, assets, education, health conditions, and health behaviors.

Taken together, we find that both data sources can be useful for research pertaining to DI and/or SSI applicants or beneficiaries, depending on the research question. Using HRS self-reported data is likely to result in lower estimates of program application and receipt than linked HRS-SSA data would provide. Estimated distributions of applicants and beneficiaries by demographic, employment, income, and health characteristics might also differ. As such, care should be taken in interpretations of applicant or beneficiary characteristics when using self-reports. Still, the use of linked data may not be feasible for some research purposes. When data linkage may not be practical, self-reports can still be informative in many research applications. These can include, and are not limited to, longitudinal analysis of employment or health characteristics in relation to SSA programs, or the use of beneficiary status as a covariate or control in statistical analysis.

Appendix A

Table A-1.
Interview and consent status of HRS respondents by cohort and wave (unweighted)

Status	HRS survey wave												
	1992 [a]	1994 [a]	1996	1998	2000	2002	2004	2006	2008	2010	2012	2014	2016
	Original HRS (born 1936–1941)												
Interviewed													
Younger than FRA	5,604	5,045	4,788	4,578	4,336	3,207	1,981	723	. . .	. . .	. . .	. . .	. . .
Never consented	670	508	439	394	346	248	139	40	. . .	. . .	. . .	. . .	. . .
Consented pre-2006	2,186	1,902	1,730	1,565	1,389	950	550	170	. . .	. . .	. . .	. . .	. . .
Consented 2006 or later	2,748	2,635	2,619	2,619	2,601	2,009	1,292	513	. . .	. . .	. . .	. . .	. . .
Reached FRA	. . .	. . .	. . .	. . .	. . .	1,213	2,796	4,435	5,604	5,604	5,604	5,604	5,604
Not interviewed													
No indication of death	. . .	487	645	760	877	750	513	269	. . .	. . .	. . .	. . .	. . .
Died before interview	. . .	72	171	266	391	434	314	177	. . .	. . .	. . .	. . .	. . .
	War Baby (born 1942–1947)												
Interviewed													
Younger than FRA	. . .	. . .	. . .	3,090	2,834	2,752	2,634	2,526	2,141	1,290	569	. . .	. . .
Never consented	. . .	. . .	. . .	473	358	313	250	232	189	133	61	. . .	. . .
Consented pre-2006	. . .	. . .	. . .	656	571	528	472	381	285	146	55	. . .	. . .
Consented 2006 or later	. . .	. . .	. . .	1,961	1,905	1,911	1,912	1,913	1,667	1,011	453	. . .	. . .
Reached FRA	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	322	1,365	2,290	3,090	3,090
Not interviewed													
No indication of death	. . .	. . .	. . .	. . .	227	257	337	379	395	264	139	. . .	. . .
Died before interview	. . .	. . .	. . .	. . .	29	81	119	185	232	171	92	. . .	. . .

(Continued)

Table A-1.
Interview and consent status of HRS respondents by cohort and wave (unweighted)—*Continued*

Status	HRS survey wave												
	1992 [a]	1994 [a]	1996	1998	2000	2002	2004	2006	2008	2010	2012	2014	2016
							Early Baby Boom (born 1948–1953)						
Interviewed													
Younger than FRA	. . .	. . .	. . .	. . .	. . .	. . .	3,369	3,019	2,892	2,803	2,683	2,394	1,299
Never consented	. . .	. . .	. . .	. . .	. . .	. . .	578	419	372	346	327	290	159
Consented pre-2006	. . .	. . .	. . .	. . .	. . .	. . .	449	349	265	225	190	155	75
Consented 2006 or later	. . .	. . .	. . .	. . .	. . .	. . .	2,342	2,251	2,255	2,232	2,166	1,949	1,065
Reached FRA	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	162	1,390
Not interviewed													
No indication of death	. . .	. . .	. . .	. . .	. . .	. . .	. . .	311	388	416	487	538	463
Died before interview	. . .	. . .	. . .	. . .	. . .	. . .	. . .	39	89	150	199	275	217
							Middle Baby Boom (born 1954–1959)						
Interviewed													
Younger than FRA	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	4,781	4,393	4,124	3,813
Never consented	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	1,019	834	761	658
Consented pre-2006	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	59	44	45	38
Consented 2006 or later	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	3,703	3,515	3,318	3,117
Reached FRA	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
Not interviewed													
No indication of death	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	333	537	761
Died before interview	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	55	120	207

SOURCE: Authors' calculations using data from the HRS-SSA Permissions Consent History file.

NOTE: . . . = not applicable.

a. Because SSA did not compile the DAF administrative data until 1996, survey results for 1992 and 1994 are omitted from this analysis.

Table A-2.
Comparison of characteristics of respondents aged 55–56 who correctly report and misreport receipt of DI benefits (linked respondents, unweighted)

Characteristic	Positive report			Negative report		
	Correct	False	*p*-value [a]	Correct	False	*p*-value [a]
Number of respondents	437	173	. . .	7,795	222	. . .
Percentage of respondents	5.1	2.0	. . .	90.4	2.6	. . .
	Demographic characteristics					
Race (percentage distribution)	100.0	100.0	0.085	100.0	100.0	<0.001***
White	72.8	63.2	. . .	81.7	70.4	. . .
Black	22.0	29.9	. . .	12.7	22.4	. . .
All other responses [b]	5.3	6.9	. . .	5.6	7.2	. . .
Ethnicity (percentage distribution)	100.0	100.0	0.007**	100.0	100.0	0.006**
Hispanic	7.3	14.6	. . .	10.4	15.2	. . .
Non-Hispanic	92.7	85.4	. . .	89.6	84.8	. . .
Sex (percentage distribution)	100.0	100.0	0.448	100.0	100.0	0.176
Men	45.9	42.4	. . .	41.5	45.3	. . .
Women	54.1	57.6	. . .	58.5	54.7	. . .
Marital status (percentage distribution)	100.0	100.0	0.147	100.0	100.0	<0.001***
Married	70.7	60.8	. . .	83.1	68.6	. . .
Divorced	23.6	30.4	. . .	13.1	25.8	. . .
Never married	5.8	8.8	. . .	3.9	5.7	. . .
Education (years completed)	12.0	11.2	0.003**	13.0	11.6	<0.001***
	Socioeconomic characteristics and employment					
Respondent income (2020 $)	17,712	14,396	0.716	41,328	17,279	0.003**
Household income (2020 $)	36,829	30,062	0.119	79,372	33,277	<0.001***
Total household assets (2020 $)	234,448	215,537	0.749	546,320	182,006	<0.001***
Working for pay (%)	5.1	9.0	0.079	55.1	7.8	<0.001***
Total years worked	29.1	25.1	0.002**	35.6	31.6	<0.001***

(Continued)

Table A-2.
Comparison of characteristics of respondents aged 55–56 who correctly report and misreport receipt of DI benefits (linked respondents, unweighted)—*Continued*

Characteristic	Positive report			Negative report		
	Correct	False	*p*-value [a]	Correct	False	*p*-value [a]
			Health characteristics and behaviors			
Self-reported probability of work-limiting health problem in next decade (%)	73.3	57.5	0.554	44.6	52.5	0.423
Health problems limit work (%)	93.9	89.4	0.088	19.0	80.0	<0.001***
Percentage ever diagnosed with—						
High blood pressure	70.1	75.5	0.204	50.9	63.7	<0.001***
Lung disease	22.0	23.6	0.683	5.5	15.2	<0.001***
Psychological problem	42.1	38.9	0.496	14.5	32.7	<0.001***
Total number of health conditions reported	3.2	3.4	0.290	1.7	2.8	<0.001***
Body mass index (above 30 indicates obesity)	31.2	31.5	0.710	28.5	31.1	<0.001***
Self-reported tendency toward depression [c]	2.6	3.2	0.008**	1.1	2.6	<0.001***
Any hospital stay in previous 2 years (%)	40.0	45.1	0.275	17.0	39.6	<0.001***
Any doctor visit in previous 2 years (%)	96.8	93.1	0.049	92.0	93.5	0.335
Out-of-pocket medical expenditures (2020 $)	5,233	4,498	0.576	2,865	3,913	0.003**
Number of days per week drinking alcohol	0.6	0.6	0.952	1.2	62.9	<0.001***
Number of alcoholic drinks per day	0.5	0.6	0.510	0.8	0.5	0.004**

SOURCE: Authors' calculations using HRS data linked to administrative data from SSA.

NOTES: . . . = not applicable.

* = statistically significant at the 0.05 level; ** = statistically significant at the 0.01 level; *** = statistically significant at the 0.001 level.

a. Test statistics are derived from chi-square tests (for the differences in the distributions of respondents who correctly report and misreport benefit receipt) and on *t*-tests for the differences in means.

b. Other race responses available in the HRS include American Indian, Alaska Native, Asian, Native Hawaiian, Pacific Islander, other (open-ended), don't know, and refuse to answer.

c. Mean scores in an 8-item version of the Center for Epidemiological Studies—Depression Scale, with respondents reporting from 0 to 8 symptom indicators.

Table A-3.
Comparison of characteristics of respondents aged 63–64 who correctly report and misreport receipt of DI benefits (linked respondents, unweighted)

Characteristic	Positive report: Correct	Positive report: False	Positive report: *p*-value [a]	Negative report: Correct	Negative report: False	Negative report: *p*-value [a]
Number of respondents	489	136	. . .	5,655	318	. . .
Percentage of respondents	7.4	2.1	. . .	85.7	4.8	. . .
			Demographic characteristics			
Race (percentage distribution)	100.0	100.0	0.601	100.0	100.0	<0.001***
White	45.3	51.7	. . .	81.3	53.4	. . .
Black	43.2	35.0	. . .	13.3	38.6	. . .
All other responses [b]	11.6	13.3	. . .	5.5	8.0	. . .
Ethnicity (percentage distribution)	100.0	100.0	0.949	100.0	100.0	<0.001***
Hispanic	22.1	21.7	. . .	10.0	28.4	. . .
Non-Hispanic	77.9	78.3	. . .	90.0	71.6	. . .
Sex (percentage distribution)	100.0	100.0	0.217	100.0	100.0	0.025
Men	24.2	33.3	. . .	42.6	30.7	. . .
Women	75.8	66.7	. . .	57.4	69.3	. . .
Marital status (percentage distribution)	100.0	100.0	0.004*	100.0	100.0	<0.001***
Married	30.8	62.0	. . .	82.3	38.7	. . .
Divorced	46.2	32.0	. . .	13.9	46.8	. . .
Never married	23.1	--	. . .	3.8	14.5	. . .
Education (years completed)	10.1	11.3	0.024*	13.0	9.1	<0.001***
			Socioeconomic characteristics and employment			
Respondent income (2020 $)	0	18,167	. . .	40,731	9,125	0.212
Household income (2020 $)	11,486	28,336	<0.001***	75,058	12,775	<0.001***
Total household assets (2020 $)	39,800	256,063	0.107	512,484	52,141	0.003**
Working for pay (%)	0.0	--	0.028**	49.8	--	<0.001***
Total years worked	15.5	21.9	0.009**	35.4	14.7	<0.001***

(Continued)

Table A-3.
Comparison of characteristics of respondents aged 63–64 who correctly report and misreport receipt of DI benefits (linked respondents, unweighted)—*Continued*

Characteristic	Positive report			Negative report		
	Correct	False	*p*-value [a]	Correct	False	*p*-value [a]
			Health characteristics and behaviors			
Self-reported probability (%) of—						
Living to age 75	47.4	55.3	0.195	65.7	44.6	<0.001***
Working full time after age 65	3.0	--	0.173	29.6	4.9	<0.001***
Health problems limit work (%)	84.0	98.2	0.007**	26.4	74.7	<0.001***
Percentage ever diagnosed with—						
Diabetes	39.0	38.3	0.940	19.3	37.5	<0.001***
Heart disease	39.4	38.3	0.899	16.7	38.6	<0.001***
High blood pressure	77.9	68.3	0.188	52.7	69.3	0.002**
Lung disease	28.4	16.7	0.096	7.1	13.6	0.018*
Stroke	22.1	15.0	0.278	4.8	14.8	<0.001***
Total number of health conditions reported	3.6	3.2	0.172	1.8	3.2	<0.001***
Body mass index (above 30 indicates obesity)	32.0	29.4	0.052	28.8	32.0	<0.001***
Self-reported tendency toward depression [c]	3.5	3.4	0.810	1.3	3.5	<0.001***
Number of difficulties with ADLs [d]	1.2	1.3	0.705	0.2	1.1	<0.001***
Any hospital stay in previous 2 years (%)	44.2	36.7	0.356	19.7	36.4	<0.001***
Any doctor visit in previous 2 years (%)	92.6	93.3	0.869	92.4	92.1	0.899
Number of doctor visits in previous 2 years	17.3	18.9	0.762	9.1	18.4	<0.001***
Out-of-pocket medical expenditures (2020 $)	1,201	4,130	0.003**	3,185	375	<0.001***
Ever drank alcohol (%)	23.2	50.0	0.001***	55.3	25.0	<0.001***
Number of alcoholic drinks per day	0.4	1.0	0.010**	0.8	0.5	0.036

SOURCE: Authors' calculations using HRS data linked to administrative data from SSA.

NOTES: . . . = not applicable; -- = not available.

* = statistically significant at the 0.05 level; ** = statistically significant at the 0.01 level; *** = statistically significant at the 0.001 level.

a. Test statistics are derived from chi-square tests (for the differences in the distributions of respondents who correctly report and misreport benefit receipt) and on *t*-tests for the differences in means.

b. Other race responses available in the HRS include American Indian, Alaska Native, Asian, Native Hawaiian, Pacific Islander, other (open-ended), don't know, and refuse to answer.

c. Mean scores in an 8-item version of the Center for Epidemiological Studies—Depression Scale, with respondents reporting from 0 to 8 symptom indicators.

d. ADLs are marked 0–5 to represent the number of ADLs in which the respondent reports at least some difficulty.

Notes

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[1] Form 831 is SSA's Disability Determination and Transmittal form.

[2] Because the HRS continually updates its administrative-data linkages, the 831 file currently available includes information for years since 2016 (https://hrs.isr.umich.edu/data-products/restricted-data/available-products/9695).

[3] Although it is not relevant to our analysis, the 831 file includes only the initial and reconsideration decisions in SSA's five-step sequential disability determination process (Wixon and Strand 2013). Thus, an applicant whose claim appears to have been denied in the 831 file may ultimately appear in SSA's beneficiary files if the individual appealed the initial denial and was awarded benefits at a higher level of adjudication. This is not uncommon among older HRS respondents (Schimmel Hyde, Wu, and Gill 2020).

[4] DAF documentation is updated online with each iteration of the file. The documentation currently available covers a more recent version of the DAF than that available to HRS users, but the contents are largely unchanged.

[5] Because respondents in the Late Baby Boom cohort (born 1960–1965) were first interviewed in 2016, data for only one survey wave was available when we conducted our analysis.

[6] To align the cohorts, we tracked SSI payments through the respondent's FRA rather than age 65; we discuss the implications of this decision in the results section.

[7] For the respondents in our analysis, the FRA ranges from 65 to 66 and 10 months. The FRA is 65 for respondents born before 1938. It increases in 2-month increments for each birth year from 1938 to 1942, is 66 for those born from 1943 through 1954, again increases in 2-month increments for each birth year from 1955 to 1959, and is 67 for those born in 1960 or later.

[8] Given this change in consent regimes and the survey years we analyzed, we were not able to use the HRS-supplied weights for nationally representative analyses using the linked SSA data. Instead, we created new nationally representative weights for our analytical sample, based on the HRS approach, which we describe later.

[9] Appendix Table A-1 provides detail on the interview and consent status of each cohort by HRS wave.

[10] The HRS develops survey weights for many of its restricted data products using administrative-data linkages but it focuses on benefit receipt rather applications (HRS 2021b). Therefore, it does not provide weights for Form 831 records, nor do the available weights account for the fact that certain files were linked only for those who consented in 2006 or later. As such, we followed the process used by the survey generally, but applied it only to the files of interest in our analysis.

[11] An 831 file record that is linked to the HRS contains a variable that indicates whether applications for both programs were initially filed concurrently. In many cases, the variable indicates concurrent applications, but a medical decision was made for only one program. In these cases, it would be possible to determine that a technical denial was decided for the program for which there was no 831 record. Because we would still be missing technical denials for applications from one or both programs and we do not have a way to estimate the magnitude of that effect, we did not use this additional information in our analysis.

[12] For respondents whose HRS interview spanned multiple months, we looked for benefit receipt in any of those months in the administrative data. This could be especially important for SSI, for which payment receipt is more likely to change on a monthly basis.

[13] Where possible, RAND-HRS "backfills" records with uncertain program status in the earlier years based on later reports of benefit receipt (for example, an early report of "DI or SSI" might be replaced with "DI" if that is the only disability program benefit reported later). This backfilling was not possible in all cases (for example, if a respondent died or left the sample), and it is possible that later information would not align with one's status at the time. We opted to maintain the RAND-HRS approach because we think it most closely resembles how HRS users would typically work with that file.

[14] In the earliest years of the survey (1992 and 1994), many of the application and receipt reports were not reconciled. DI application and benefit receipt prevalence estimates that included the "unknown" program responses were 2–3 times higher than those we report, and SSI application and receipt rates were 7–10 times higher. The magnitude of the difference declined each year through 2000, presumably reflecting a higher likelihood of reinterviewing respondents in 2000 or later that allowed for the record to be updated.

[15] Note that the "age" we use is based on HRS survey wave and birth year, rather than actual age at interview, to avoid complications arising from HRS interview dates that are not necessarily exactly 2 years apart. For example, a respondent born on May 15, 1947, would have been 53 when interviewed for the HRS on May 31, 2000, but would be 54 if next interviewed on April 1, 2002. We would classify this respondent in the 53–54 age bin in 2000 and the 55–56 age bin in 2002.

[16] The pattern at age 65–66 for SSI should be interpreted with caution; the SSI payments after age 65 may be based on age rather than on disability. To be consistent and to align with the DAF Suspension or Termination of Cash Benefits for Work measure, we used this value through FRA, but there are reasons to think this comparison may reflect a different set of considerations than it does for respondents at younger ages.

[17] There are several financial reasons why a small percentage of DI beneficiaries choose to convert to OASI benefits prior to FRA. For example, if a beneficiary has part of his or her DI program benefit offset because of Workers' Compensation benefits, the OASI program benefit (which would not be offset) can be higher. Also, the family maximum benefit is higher under OASI than under DI, providing an incentive for affected beneficiaries.

[18] The results of our analysis for program applications are available on request (jschimmel@mathematica-mpr.com).

[19] Appendix Tables A-2 and A-3 contain full results of these comparisons for DI benefit receipt.

References

Bee, Adam, and Joshua Mitchell. 2017. "Do Older Americans Have More Income Than We Think?" SEHSD Working Paper No. 2017-39. Washington, DC: Census Bureau, Social, Economic, and Housing Statistics Division. https://www.census.gov/content/dam/Census/library/working-papers/2017/demo/SEHSD-WP2017-39.pdf.

Bugliari, Delia, Joanna Carroll, Orla Hayden, Jessica Hayes, Michael Hurd, Adam Karabatakis, Regan Main, Joyce Marks, Colleen McCullough, Erik Meijer, Michael Moldoff, Philip Pantoja, Susann Rohwedder, and Patricia St. Clair. 2021. "RAND HRS Longitudinal File 2018 (V1) Documentation." Santa Monica, CA: RAND Corporation. https://hrsdata.isr.umich.edu/data-products/rand-hrs-longitudinal-file-2018.

Chen, Anqi, Alicia H. Munnell, and Geoffrey T. Sanzenbacher. 2018. "How Much Income Do Retirees Actually Have? Evaluating the Evidence from Five National Datasets." Working Paper No. 2018-14. Chestnut Hill, MA: Center for Retirement Research at Boston College.

Davies, Paul S., and T. Lynn Fisher. 2009. "Measurement Issues Associated with Using Survey Data Matched with Administrative Data from the Social Security Administration." *Social Security Bulletin* 69(2): 1–12.

Haider, Steven, and Gary Solon. 2000. "Nonrandom Selection in the HRS Social Security Earnings Sample." Report No. DRU-2254-NIA. Labor and Population Program Working Paper No. 00-01. Santa Monica, CA: RAND Corporation.

[HRS] Health and Retirement Study. 2021a. "Permissions Consent History." https://hrs.isr.umich.edu/data-products/restricted-data/available-products/11516.

———. 2021b. "Social Security Weights (2004–2016): Data Description and Usage." https://hrs.isr.umich.edu/sites/default/files/restricted_data_docs/SSWgts_JP_DD%20v2.pdf.

———. 2022. "HRS Survey Design and Methodology: Longitudinal Cohort Sample Design." https://hrs.isr.umich.edu/documentation/survey-design.

Huynh, Minh, Kalman Rupp, and James Sears. 2002. "The Assessment of Survey of Income and Program Participation Benefit Data Using Longitudinal Administrative Records." Survey of Income and Program Participation Report No. 238. Washington, DC: Census Bureau.

Koenig, Melissa L. 2003. "An Assessment of the Current Population Survey and the Survey of Income and Program Participation Using Social Security Administrative Data." Paper presented at the Federal Committee on Statistical Methodology Research Conference, Washington, DC (November 18).

Maestas, Nicole, Kathleen J. Mullen, and Alexander Strand. 2015. "Disability Insurance and the Great Recession." *American Economic Review* 105(5): 177–182.

Mathematica. 2022. *Disability Analysis File 2020 (DAF20) Documentation: Data from January 1994 through December 2020*. Washington, DC: Mathematica. https://www.ssa.gov/disabilityresearch/documents/daf/V10.%20DAF20_Admin%20Source%20File%20Documentation.pdf.

Meyer, Bruce D., and Nikolas Mittag. 2019. "Using Linked Survey and Administrative Data to Better Measure Income: Implications for Poverty, Program Effectiveness, and Holes in the Safety Net." *American Economic Journal: Applied Economics* 11(2): 176–204.

Meyer, Bruce D., Wallace K. C. Mok, and James X. Sullivan. 2015. "Household Surveys in Crisis." *Journal of Economic Perspectives* 29(4): 199–226.

Olson, Janice A. 1999. "Linkages with Data from Social Security Administrative Records in the Health and Retirement Study." *Social Security Bulletin* 62(2): 73–85.

Phillips, John. 2003/2004. "The RAND HRS Data File: A User-Friendly Version of the Health and Retirement Study." *Social Security Bulletin* 65(2): 97–98.

Schimmel Hyde, Jody, Sarah Croake, Alex Bryce, and Matthew Messel. 2018. "Developing Income-Related Statistics on Federal Disability Beneficiaries Using Nationally Representative Survey Data." DRC Working Paper No. 2018-05. Washington, DC: Mathematica Policy Research.

Schimmel Hyde, Jody, and David C. Stapleton. 2017. "Using the Health and Retirement Study for Disability Policy Research: A Review." *Forum for Health Economics and Policy* 20(2).

Schimmel Hyde, Jody, April Yanyuan Wu, and Lakhpreet Gill. 2020. "The Benefit Receipt Patterns and Labor Market Experiences of Older Workers Who Were Denied Social Security Disability Insurance Benefits on the Basis of Work Capacity." *Social Security Bulletin* 80(2): 25–48.

Smith, James P. 2003. "Consequences and Predictors of New Health Events." NBER Working Paper No. 10063. Cambridge, MA: National Bureau of Economic Research.

[SSA] Social Security Administration. 2022. *Annual Statistical Report on the Social Security Disability Insurance Program, 2021*. Publication No. 13-11826. Washington, DC: SSA. https://www.ssa.gov/policy/docs/statcomps/di_asr/2021/index.html.

Wixon, Bernard, and Alexander Strand. 2013. "Identifying SSA's Sequential Disability Determination Steps Using Administrative Data." Research and Statistics Note No. 2013-01. Washington, DC: SSA.