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Articles

Perspectives

Insight into the Earned Income Tax Credit and Tax-Advantaged Retirement Savings

by David Rogofsky, Richard E. Chard, and Joanne Yoong*

Saving for retirement has traditionally been compared to a three-legged stool supported by Social Security benefits, workplace pensions, and household savings. As the prevalence of defined benefit pensions has diminished in recent decades, the importance of household savings has grown. To enable and encourage saving among lower-income Americans, policymakers have established several types of tax incentives. The Earned Income Tax Credit (EITC) provides an immediate reduction in income tax liability (or a larger refund) for eligible households. Additionally, certain types of retirement saving accounts and defined contribution saving plans lower current tax liability by deferring taxation of the amounts contributed until the funds are withdrawn in retirement. Using data from the Understanding America Study, this article compares the retirement-related financial behavior and preparedness of EITC-eligible and ineligible households and examines whether EITC eligibility affects the use of tax-advantaged retirement saving plans.

Introduction

Social Security benefits are central to retirement security. Hence, a robust understanding of how Social Security benefits change depending on individual choices—such as the age at which they are claimed—is a vital component of long-term financial planning and well-being (Gustman and Steinmeier 1999). However, Social Security was never intended to be the sole source of retirement income. Rather, retirement income has traditionally been described as a three-legged stool supported in roughly similar measures by Social Security benefits, workplace pensions, and private savings. For the average retiree, Social Security benefits replace about 40 percent of preretirement earnings, and although the relative importance of each "leg" has changed over the years (see, for example, Miller, Lavenberg, and MacKay 2014), supplementing Social Security benefits with pension income or other savings remains critical. The federal government has tried many ways to increase the public's long-term retirement security by encouraging greater household savings. In this article, we examine how two such federal initiatives combine to affect eligible participants. These efforts aim to encourage retirement saving by way of tax incentives of one kind or another. One initiative is the Earned Income Tax Credit (EITC); the other involves providing tax-advantaged retirement saving vehicles that exempt plan contributions from income tax until the funds are withdrawn. These plans include individual retirement accounts (IRAs) and tax-deferred defined contribution (DC) saving plans. The latter are named for the sections of

Selected Abbreviations

DB	defined benefit
DC	defined contribution
EBRI	Employee Benefit Research Institute
EITC	Earned Income Tax Credit
IRA	individual retirement account
UAS	Understanding America Study

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the United States Tax Code that describe them, as in 401(k) or 403(b).

For policymakers, the absence of long-term savings among many lower-income households is a major concern. According to the 2013 Survey of Consumer Finances, only 9 percent of the population in the lowest income quintile had a tax-advantaged DC plan or IRA. To protect lower-income households from falling into poverty, policymakers established the EITC in 1975. The EITC allows eligible low-income workers to retain resources by substantially reducing their tax burden. Over the years, it has become one of the most significant federal antipoverty programs: "By itself, the EITC lifted 6.7 million people (including 3.4 million children) above the poverty line in 2012" (Sherman and Trisi 2015). However, although the EITC provides current income tax relief, questions remain about the long-term savings and retirement preparedness of EITC-eligible households. A related question is whether the EITC inadvertently undermines the incentives to participate in tax-advantaged retirement saving plans.

In this article, we discuss the role of the EITC in increasing household savings and compare EITC-eligible and ineligible individuals in terms of their retirement preparedness. We examine in particular the extent to which EITC eligibility predicts retirement-related financial behavior patterns, independent of socioeconomic background and financial capability.[1] To do so, we use data collected by the University of Southern California's Understanding America Study (UAS), a longitudinal study using online surveys of a nationally representative sample of households.

This article consists of six sections. Following this introduction, the second section briefly reviews the relevant literature. The third section describes the UAS, our methods, the main sample characteristics, and the subsamples we use for comparative purposes. In the final three sections, we present our main results and conduct robustness checks, discuss policy implications, and conclude by describing study limitations and proposing future work.

Background and Literature Review

The EITC reduces or eliminates the income tax liability of qualifying low- to moderate-income working households (particularly those with children). In some instances, the dollar amount of the credit exceeds the worker's income tax liability; when that occurs, the worker receives the difference as a refund. At present, more than half of the states and the District of Columbia supplement the federal EITC with an additional credit.

In an earlier study, we showed that socioeconomic factors play a significant role in optimal financial decision making, and that individuals from disadvantaged groups (women, minorities, and those with lower income and educational attainment) are subjectively and objectively less prepared for retirement (Chard, Rogofsky, and Yoong 2017). EITC households may therefore be expected to be less prepared for retirement than are non-EITC households simply because of socioeconomic differences. In addition, EITC households may be less likely to work for employers who offer benefits such as 401(k) plans, or may be in work arrangements that make them ineligible for such benefits.

In this article, we examine certain aspects of the EITC that may be negatively associated with incentives to save for retirement. For example, the tax advantage experienced by EITC households may negate the benefits of typical tax-advantaged plans because the tax liability is immediately eliminated rather than deferred until retirement. Therefore, EITC households may be less likely to use tax-advantaged plans, relative to other forms of saving. Additionally, EITC households receive their credit in the form of a lump-sum refund each year, which they are more likely to spend than save. On the other hand, contributing to tax-advantaged accounts such as 401(k) plans reduces adjusted gross income, which can increase EITC eligibility (employer contributions, by contrast, do not affect taxable income, and thus do not affect eligibility). At the margin, therefore, EITC eligibility may be positively associated with saving in tax-advantaged accounts. Nevertheless, Weber (2016, 41) finds that in spite of tax-advantaged federal incentives for EITC-eligible households such as the Saver's Credit and Individual Development Accounts, the EITC

> provides a substantial disincentive for individuals to save and realize investment income because EITC benefits decline as investment income rises over certain income ranges…over the last two decades, an average of 17.6 percent of low-income individuals that claim the EITC have some dividend and interest income, but strikingly, the fraction has declined by more than 50 percent over time, from 26.2 percent in 1988 to just 12.3 percent in 2006.

Finally, many households may not fully understand the EITC and hence may not respond to the tax incentives it contains. The EITC's rules are complex, and tax preparers have to navigate a number of tests to determine eligibility. Given the complexity of the credit and the relatively low level of financial knowledge among Americans (FINRA Investor Education Foundation 2016), the presence of an empirical relationship between retirement preparedness and EITC participation (particularly as it relates to participation in tax-advantaged plans) is an open question.

Our primary research objective is to determine retirement preparedness among EITC-eligible and ineligible households. Specifically, we test the hypothesis that EITC-eligible households are subjectively and objectively less prepared for retirement than EITC-ineligible households are. We then explore whether differences in retirement preparedness reflect the fact that EITC-eligible households are socioeconomically disadvantaged, or whether EITC status itself is independently associated with differential preparedness, controlling for household socioeconomic characteristics.

Data and Methods

Our data are from the UAS, a panel study consisting of approximately 6,000 households representing the entire United States. The UAS is an Internet panel, which means respondents answer surveys on a computer, tablet, or smart phone, wherever they are and whenever they wish to participate. Panel members respond to surveys about once or twice a month and are paid a nominal fee. Individual surveys are restricted to about 30 minutes per interview. A given panel member's entire history of responses can be linked to provide a wealth of information about his or her financial knowledge and behavior, cognitive capability, and personality. Sampling weights for the UAS are generated using an iterative ranking algorithm tied to the Census Bureau's Current Population Survey Annual Social and Economic Supplement. The pool of UAS respondents is the noninstitutionalized U.S. population aged 18 or older, excluding military personnel. A detailed discussion of the UAS also appears in this issue of the *Social Security Bulletin* (see Alattar, Messel, and Rogofsky 2018).

Our study is based on data collected in three separate surveys (UAS 16, UAS 24, and UAS 26) designed and fielded in May–December 2015.[2] We analyzed only the subsample of nonretired individuals aged 18 to 65, comprising 2,682 respondents. Table 1 shows the demographic characteristics of the entire subsample, the EITC-eligible subsample, and the EITC-ineligible subsample. All values are weighted, here and throughout the analysis. Appendix A presents details on the weights.

We use a proxy measure for EITC eligibility based on reported family size and income, described below. Relative to EITC-ineligible individuals, the EITC population is more likely to be younger, less educated, nonwhite, female, and (by design) to have lower income.

A Proxy for Measuring EITC Eligibility

The UAS does not track EITC eligibility. Because of recall bias or lack of awareness among UAS respondents (many EITC claims are filed by third-party tax preparers), self-reported EITC take-up or eligibility would not necessarily be a useful indicator in any event. Therefore, we constructed a proxy measure of EITC eligibility by matching, as best we could, the eligibility rules for 2015 to UAS data on household income and family composition. A summary of that proxy measure follows.

EITC eligibility is determined by one set of income cutoffs for married taxpayers filing jointly and another set for taxpayers in all other filing statuses. Because the UAS does not directly collect data on filing status, we assume that all married respondents file jointly. The income cutoffs for EITC eligibility are also affected by the presence and number of qualifying children, defined as related children who meet the age criteria for individuals living in the household who are claimed as dependents. The UAS likewise does not directly collect this information, so we count all children, siblings, or grandchildren aged younger than 20 and residing in the UAS respondent's household as qualifying children. The EITC income cutoffs are specific dollar amounts (for example, $45,207 if married filing jointly with one qualifying child), but income data collected by UAS are nonspecific, defined only within broad ranges (such as $40,000–$49,999). Taking a conservative approach, we placed households in the EITC-eligible subsample only if they reported income within a range that is unambiguously below their EITC income threshold. Finally, because investment income of $3,400 or more disqualifies a household for the EITC, we used the total of all self-reported rental, annuity, stock, bond, certificate of deposit (CD), savings, and other asset income to determine if the household is EITC-eligible.

Measuring Retirement Preparedness

In earlier work (Chard, Rogofsky, and Yoong 2017), we used positive retirement saving–related indicators to construct a "Retirement Preparedness Index" and principal components analysis (PCA) to retain one

Table 1.
Percentage distribution of the working-age population, by selected sociodemographic characteristics: Full subsample and by EITC eligibility, 2015 (weighted estimates)

Characteristic	Full subsample	EITC status: Eligible	EITC status: Ineligible
Sex			
Men	50	41	52
Women	50	59	48
Race/ethnicity			
Non-Hispanic white	63	48	67
Non-Hispanic black	13	27	9
Hispanic (any race)	19	21	18
Other	5	3	5
Age			
34 or younger	40	58	35
35–54	43	34	46
55–65	17	8	19
Mean age (years)	40.17	34.87	41.54
Marital status			
Married	60	44	64
Other	40	56	36
Household income ($)			
Less than 30,000	23	78	9
30,000–49,999	17	22	16
50,000–74,999	18	0	23
75,000 or more	42	0	53
Educational attainment			
High school diploma or less	38	61	32
Some college	29	30	28
College degree or more	33	8	39
Employment status			
Employed	89	75	93
Unemployed [a]	11	25	7

SOURCE: Authors' calculations based on UAS data.

NOTES: Full subsample size = 2,682.

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

a. A currently unemployed worker may qualify for the EITC based on earnings from earlier in the year.

factor, from which the index is then derived using the factor loadings as weights, which we interpret as being correlated with an underlying principal factor of retirement preparedness. The detailed methodology underlying this index is described in the 2017 study and in Yoong, Chard, and Rogofsky (forthcoming). Although we are not aware of others using this approach for estimating retirement preparedness, it is similar in concept to the widespread use of PCA to estimate wealth or socioeconomic status from a vector of asset indicators (Filmer and Pritchett 2001; McKenzie 2005; Vyas and Kumaranayake 2006).

In this study, we explore retirement preparedness using several alternative measures of subjective individual perceptions as well as objective measures based on (self-reported) behavior and financial status. All respondents were asked how prepared they felt for retirement, assigning themselves a grade from A (very prepared) to D (not prepared at all). We converted the grades to a numerical scale ranging from A = 3 to D = 0. We also investigated general planning and saving behavior using questions similar to those used in other analyses of retirement planning (for example, Lusardi and Mitchell 2007). Respondents were asked whether they have ever tried to make a plan for retirement and if they have ever tried to save for retirement.

Objectively measuring retirement readiness is complicated. It requires making long-term projections not only about Social Security benefits, retirement savings, and pension plans, but also about other assets (including investments and housing), various insurance arrangements, the ability and intention to continue working, desired lifestyle changes, asset decumulation rates in retirement, household arrangements (accounting for spousal resources, joint decision making, and possible transfers and bequest motives), expectations about mortality and morbidity, and economic conditions. The simplest approach is to rely on highly simplified rules of thumb, such as whether the household has savings equivalent to a given number of years of earnings. To the other extreme, complex measures aim to account for detailed interactions among numerous factors that change over time. For example, the Employee Benefit Research Institute (EBRI) Retirement Readiness Rating[3] is derived from stochastic simulations of wealth from retirement-income sources (Social Security; defined benefit [DB] plan annuities, which provide a fixed income stream in retirement; DC plan or IRA balances, which are accumulated wealth rather than a guaranteed income stream; and housing equity), expenses of every category (particularly health-related expenses, which can vary widely with age and income), and their many possible intersections. Such a comprehensive approach is complicated by potential questions about the quality and quantity of available data.

For this article, we construct a set of (positive) retirement saving–related indicators using data from a UAS survey that is based on the Assets and Income questionnaire section of the University of Michigan's Health and Retirement Study. We first identify whether the respondent has a DB plan, DC plan, or IRA (or is named as a beneficiary of such a plan or account held by another household member). We then calculate the combined balances in these accounts (including up to three IRAs and/or DC plans). To estimate savings adequacy, we compare these total balances to present household income. We then calculate the ratio of retirement-savings balances to income and compare it against an age-specific rule-of-thumb threshold value developed by Fidelity Investments —1:1 at age 35, 3:1 at age 45, 5:1 at age 55, and 8:1 at age 67.[4] We select these ratios because they are cited in popular media[5] and may therefore be familiar to respondents as reasonable subjective savings goals. As these published values are provided only for selected discrete ages, we use linear interpolation to assign threshold values to all ages in between. We also compute the percentage of the total balance attributable to stock holdings for use in another age-based rule of thumb: 100 minus the individual's age. For example, a 40-year-old should invest 60 percent of retirement savings in stocks (Malkiel and Ellis 2010). We categorize the stock allocation as appropriate if it is within ±5 percentage points of the target percentage. Similarly, we account for prudent behaviors, such as making no early withdrawals from a retirement savings account (either the respondent's own or one on which the respondent is a beneficiary) and no early cash-ins (which is reported only for a respondent's own account).

Descriptive Statistics

We first test for differences between EITC-eligible and ineligible households in our measures of preparedness and behavior using simple chi-squared (χ^2) tests of independence and *t*-tests for comparisons of unconditional means. We then conduct a regression analysis for which the outcome measures are our binary indicators of planning and saving and our continuous measures of subjective and objective preparedness (the retirement preparedness perceptions scale and index, respectively). We regress these outcomes on the EITC proxy and a vector of sociodemographic control variables. We further analyze the effects on asset indicators individually, corrected appropriately for multiple hypotheses. Finally, we report the results of an Oaxaca decomposition to estimate the proportion of the gap (if any) that can be attributed to different socioeconomic endowments between the EITC-eligible and ineligible groups, versus the proportion that is due to different coefficients and their interaction effects.

After examining these initial measures, we investigate the effect of the EITC on our two measures of retirement preparedness (self-reported preparedness and the Retirement Preparedness Index) and on two measures of retirement planning (ever planned for retirement and ever tried to save for retirement). We use ordinary least squares to estimate the effect of the EITC using the following equations:

$$\begin{aligned}
\textit{Self-Assessed Preparedness} \text{ (equation 1)} &= \beta_0 \\
&+ \beta_1 \text{ Female} + \beta_2 \text{ Black} + \beta_3 \text{ Hispanic/Latino} \\
&+ \beta_4 \text{ Other ethnicity} + \beta_5 \text{ Age 35–54} + \beta_6 \text{ Age 55–64} \\
&+ \beta_7 \text{ Married} + \beta_8 \text{ Income \$30,000–\$49,999} \\
&+ \beta_9 \text{ Income \$50,000–\$74,999} \\
&+ \beta_{10} \text{ Income \$75,000 or more} + \beta_{11} \text{ Some college} \\
&+ \beta_{12} \text{ College degree or more} + \beta_{13} \text{ EITC proxy} \\
&+ \varepsilon.
\end{aligned}$$

Retirement Preparedness Index (equation 2) = $\beta_0 + \beta_1$ Female + β_2 Black + β_3 Hispanic/Latino + β_4 Other ethnicity + β_5 Age 35–54 + β_6 Age 55–64 + β_7 Married + β_8 Income \$30,000–\$49,999 + β_9 Income \$50,000–\$74,999 + β_{10} Income \$75,000 or more + β_{11} Some college + β_{12} College degree or more + β_{13} EITC proxy + ε.

Ever Planned for Retirement (equation 3) = $\beta_0 + \beta_1$ Female + β_2 Black + β_3 Hispanic/Latino + β_4 Other ethnicity + β_5 Age 35–54 + β_6 Age 55–64 + β_7 Married + β_8 Income \$30,000–\$49,999 + β_9 Income \$50,000–\$74,999 + β_{10} Income \$75,000 or more + β_{11} Some college + β_{12} College degree or more + β_{13} EITC proxy + ε.

Ever Tried to Save for Retirement (equation 4) = $\beta_0 + \beta_1$ Female + β_2 Black + β_3 Hispanic/Latino + β_4 Other ethnicity + β_5 Age 35–54 + β_6 Age 55–64 + β_7 Married + β_8 Income \$30,000–\$49,999 + β_9 Income \$50,000–\$74,999 + β_{10} Income \$75,000 or more + β_{11} Some college + β_{12} College degree or more + β_{13} EITC proxy + ε.

Results

Table 2 shows that less than 10 percent of subsample respondents consider themselves financially very well-prepared for retirement. Perceived levels of preparedness differ starkly between EITC-eligible and ineligible households, with the former being more than 2.5 times as likely to report being not prepared at all for retirement (63 percent) as are the latter (24 percent). Just under 40 percent of respondents report that they have tried to make a plan for retirement and slightly fewer (35 percent) report that they have actually tried to save (not shown).

Table 3 shows that very few subsample respondents have a DB pension plan (in the overall UAS sample [not shown], approximately 10 percent of respondents have a DB plan). A considerably larger share of members of the full subsample have their own IRAs (31 percent), and that share expands to 35 percent when including those who are named as a beneficiary on someone else's IRA. Table 3 also shows that EITC-eligible households are far less likely to participate in IRAs than ineligible households are.[6]

For ease of interpretation, we examine the association between EITC eligibility and retirement planning and preparedness using ordinary least squares regression analysis, which implies a linear probability model for discrete outcomes. The regression results in Table 4 confirm the descriptive results by showing that, when controlling for other sociodemographic factors, EITC-eligible households are significantly less prepared for retirement, whether measured by subjective means (self-perceptions) or objective indicators (our index of preparedness).

Table 2.
Subjective self-assessment of retirement preparedness: Full subsample and by EITC eligibility, 2015

Response	Full subsample	EITC status: Eligible	EITC status: Ineligible
How financially well-prepared for retirement are you?			
Very	6	2	7
Somewhat	33	12	39
Not too well	29	22	31
Not at all	33	63	24

SOURCE: Authors' calculations based on UAS data.

NOTE: Full subsample size = 2,682.

In Table 5, we regress our proxy variable and sociodemographic control variables on the binary indicators of ever planning and ever saving for retirement to test the hypothesis that EITC-eligible households are less prepared because they lack incentives or knowledge that would help enable planning and saving.

The key takeaways from these additional analyses, including our EITC proxy variable, is that general planning and saving behavior are *not* in fact correlated significantly with being eligible for the EITC.

Discussion

This article aims to contribute both methodologically and substantively to the literature on retirement policy and behavior. Toward the first purpose, we measure Social Security literacy with the Social Security Knowledge Index (Chard, Rogofsky, and Yoong 2017) and retirement preparedness with the Retirement Preparedness Index (Yoong, Chard, and Rogofsky forthcoming). The methodology for replicating these indices is straightforward and can be applied by other researchers using the same set of survey questions. Using these indexes and a rich set of other variables available for a representative sample of the adult

Table 3.
Percentages of UAS respondents reporting selected retirement saving behaviors: Full subsample and by EITC eligibility, 2015 (weighted estimates)

Behavior or characteristic	Full subsample	EITC status: Eligible	EITC status: Ineligible
Participates in a DB pension plan	1	0	1
Is entitled to retirement saving plan assets			
From own IRA	31	5	37
Including plans of which respondent is a beneficiary	35	5	41
IRA wealth exceeds age-adjusted household income threshold			
Own IRA only	5	1	6
Including IRAs of which respondent is a beneficiary	26	5	30
No early withdrawals from IRA			
Own IRA only	2	2	3
Including IRAs of which respondent is a beneficiary	4	2	4
No early cash-in on own IRA	99	98	99
Share of IRA wealth invested in stocks meets age-appropriate threshold			
Own IRA only	3	0	4
Including IRAs of which respondent is a beneficiary	3	0	4
Percentage of IRA assets invested in stocks			
Own IRA only	20	3	23
Including IRAs of which respondent is a beneficiary	21	3	24

SOURCE: Authors' calculations based on UAS data.

NOTE: Full subsample size = 2,682.

population from the UAS, we meet our second purpose by investigating a set of key hypotheses about the determinants of retirement saving behavior in the United States.

Weber (2016) has found that EITC-eligible individuals are less likely to hold interest-bearing savings accounts or investments that produce dividend or capital-gains income. Weber presented evidence that the EITC inadvertently provides its users with disincentives to earn extra income by those means. In this article, we examine whether EITC-eligible individuals have a similar disincentive to participate in tax-advantaged retirement saving plans. We find that they do and that, as Weber showed, they are also less likely to save by income-producing means.

Tax-advantaged retirement saving plans and the EITC reflect policies that would seem to operate at cross purposes, yet our results indicate the two in fact coexist quite well. Although retirement planning and saving behavior are not correlated significantly with the EITC proxy measure (Table 5), our EITC variable is a statistically significant negative predictor in our Retirement Preparedness Index (Table 4), which accounts for all the tax-related policy vehicles. This suggests that, conditional on other social and demographic controls, EITC households' propensity to plan and save is similar to that of non-EITC households. However, EITC households are significantly less likely to save in tax-advantaged vehicles specifically. EITC households also consider themselves less prepared for retirement than non-EITC households do (Table 2). This perception among EITC households may be an artifact of not fully understanding Social Security's progressive benefit formulas, under which lower-income individuals have higher preretirement-income replacement rates. This would be an interesting question to explore as more data become available.

Limitations and Future Research

The UAS sample size is small and our study parameters further limit the sample by age and retirement status. At the time our data were compiled, the sample of likely EITC-eligible individuals meeting our inclusion criteria numbered only approximately 1,000. The UAS currently has approximately 6,000 subjects and is expected to expand, which will enable future analysis to explore subgroup heterogeneity, regional effects, and related topics. For example, we will use data from

Table 4.
Ordinary least squares regression estimates of self-assessed retirement preparedness and Retirement Preparedness Index scores for EITC-eligible respondents, by selected sociodemographic characteristics

Characteristic	Self-assessed preparedness (subjective measure) Estimate	Self-assessed preparedness (subjective measure) *t*-statistic	Retirement Preparedness Index (objective measure) Estimate	Retirement Preparedness Index (objective measure) *t*-statistic
Sex				
Women	-0.014	-0.19	-0.200	-1.83*
Race/ethnicity				
Non-Hispanic black	0.005	-0.04	-0.342	-2.04**
Hispanic	-0.369	-3.51***	-0.768	-5.27***
Other [a]	0.122	1.18	-0.016	-0.08
Age				
35–54	0.329	4.12***	0.752	6.48***
55–64	0.347	3.48***	0.738	4.87***
Marital status				
Married	0.128	1.57	0.134	1.13
Household income ($)				
30,000–49,999	0.073	0.60	0.138	0.83
50,000–74,999	0.405	3.26***	0.419	2.02**
75,000 or more	0.575	4.47***	0.764	3.85***
Educational attainment				
Some college	-0.047	-0.52	0.271	1.90*
College degree or more	0.338	3.49***	0.594	3.53***
EITC proxy	-0.242	-2.22**	-0.312	-1.95*
Constant	0.561	4.39***	-1.091	-5.41***
R-squared	0.29		0.27	
F	21.750		27.354	
Observations	1,147		1,145	

SOURCE: Authors' calculations based on UAS data.

NOTE: * = $p < 0.10$, ** = $p < 0.05$, *** = $p < 0.01$.

a. Refers to race/ethnicities other than non-Hispanic white, non-Hispanic black, and Hispanic.

UAS survey 35, the Yodlee administrative record Internet banking project, to extend the findings of this study. In addition, the UAS surveys used in this study will be readministered at least every 2 years, allowing for time-series panel analysis.

A key limitation of our study is the reliance on self-reported survey data. Although we make every attempt to use validated measures, including the Assets and Income questionnaire section from the Health and Retirement Study, such data are still subject to bias. UAS designers are working to match survey data to financial transaction records, allowing researchers to compare self-reported and actual saving behavior and to evaluate financial behavior more accurately.

We will continue to refine the measurement and definition of critical variables. For instance, we use a pragmatic definition of retirement preparedness that incorporates several rules of thumb and a limited set of financial status indicators, which we will further develop and test in future studies. Our definition of nonretired is likewise pragmatic, as respondents are asked to indicate whether or not they are retired using a "yes" or "no" response. However, the interpretation of retirement is in fact complex and the relationship between work status and Social Security benefit claiming can be ambiguous, particularly for older adults who may experience transitions in and out of work, take up part-time employment, or work as volunteers. We also plan to examine differences in access to retirement saving plans and financial institutions. In addition, we will explore how low- to moderate-income households that are not eligible for the EITC because they have no qualifying children compare with households that have similar income levels but are eligible for the EITC because they do have at least one qualifying child.

Table 5.
Ordinary least squares regression estimates of self-reported history of planning to save and trying to save for retirement for EITC-eligible respondents, by selected sociodemographic characteristics

Characteristic	Ever planned to save		Ever tried to save	
	Estimate	*t*-statistic	Estimate	*t*-statistic
Sex				
Women	-0.015	-0.35	-0.037	-0.90
Race/ethnicity				
Non-Hispanic black	-0.124	-2.13**	-0.086	-1.56
Hispanic	-0.078	-1.24	-0.137	-2.34**
Other [a]	0.018	0.18	-0.070	-0.65
Age				
35–54	0.142	3.17***	0.080	1.86*
55–64	0.221	4.01***	0.145	2.67***
Marital status				
Married	0.062	1.38	0.040	0.89
Household income ($)				
30,000–49,999	-0.057	-0.94	-0.005	-0.08
50,000–74,999	0.143	2.06**	0.134	2.09**
75,000 or more	0.205	2.89***	0.235	3.50***
Educational attainment				
Some college	0.069	1.39	0.104	2.13**
College degree or more	0.186	3.25***	0.254	4.49***
EITC proxy	-0.035	-0.58	0.004	0.06
Constant	0.133	2.08**	0.109	1.85*
R-squared	0.18		0.19	
F	12.868		13.326	
Observations	1,148		1,148	

SOURCE: Authors' calculations based on UAS data.

NOTE: * = $p < 0.10$, ** = $p < 0.05$, *** = $p < 0.01$.

a. Refers to race/ethnicities other than non-Hispanic white, non-Hispanic black, and Hispanic.

Appendix

Table A-1 shows the weights for selected elements of the Retirement Preparedness Index. The highest weights are assigned to being an owner or the beneficiary of an IRA or being entitled to the assets of an IRA.

Table A-1.
Weights for selected individual Retirement Preparedness Index behaviors and characteristics, 2015

Behavior or characteristic	Weight
Participates in a DB pension plan	0.1576
Is entitled to retirement saving plan assets	
From own IRA	0.5184
Including plans of which respondent is a beneficiary	0.5427
IRA wealth exceeds age-adjusted household income threshold	
Own IRA only	. . .
Including IRAs of which respondent is a beneficiary	0.5217
No early withdrawals from IRA	
Own IRA only	. . .
Including IRAs of which respondent is a beneficiary	0.2343
No early cash-in on own IRA	0.0028
Share of IRA wealth invested in stocks meets age-appropriate threshold	
Own IRA only	. . .
Including IRAs of which respondent is a beneficiary	0.2449
Percentage of IRA assets invested in stocks	
Own IRA only	. . .
Including IRAs of which respondent is a beneficiary	0.1576

SOURCE: Authors' calculations based on UAS data.

NOTE: . . . = not applicable.

Notes

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[1] Financial capability—as distinct from the narrower concept of financial literacy—comprises "four components: knowledge, influences, access, and action" (University of Wisconsin-Extension 2013).

[2] For full descriptions of the three surveys, see https://uasdata.usc.edu/UAS-16, https://uasdata.usc.edu/UAS-24, and https://uasdata.usc.edu/UAS-26.

[3] EBRI initially developed the Retirement Readiness Rating in 2003 and publishes periodic Issue Briefs that update the Rating with new data from EBRI's proprietary Retirement Security Projection Model. For details on the modeling, see EBRI (2014).

[4] Fidelity revised these ratios in June 2017. For our analysis, however, we use the ratios given here, which were current at the time of the data collection.

[5] For example, Kadlec (2012) and Carrns (2012).

[6] The difference could in part reflect less access to financial institutions for EITC-eligible households, which we hope to study in future research.

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.

Carrns, Ann. 2012. "Suggested Retirement Savings Goals, by Age." *New York Times,* September 12. https://bucks.blogs.nytimes.com/2012/09/12/suggested-retirement-savings-goals-by-age/.

Chard, Richard, David Rogofsky, and Joanne Yoong. 2017. "Wealthy or Wise: How Knowledge Influences Retirement Savings Behavior." *Journal of Behavioral and Social Sciences* 4(3): 164–180.

[EBRI] Employee Benefit Research Institute. 2014. "What Causes EBRI Retirement Readiness Ratings™ to Vary: Results from the 2014 Retirement Security Projection Model®." Issue Brief No. 396. Washington, DC: EBRI. https://www.ebri.org/publications/ib/index.cfm?fa=ibDisp&content_id=5351.

Filmer, Deon, and Lant H. Pritchett. 2001. "Estimating Wealth Effects Without Expenditure Data—Or Tears: An Application to Educational Enrollments in States of India." *Demography* 38(1): 115–132.

FINRA Investor Education Foundation. 2016. *Financial Capability in the United States 2016.* Washington, DC: FINRA.

Gustman, Alan L., and Thomas L. Steinmeier. 1999. "Effects of Pensions on Savings: Analysis with Data from the Health and Retirement Study." *Carnegie-Rochester Conference Series on Public Policy* 50(1): 271–324.

Kadlec, Dan. 2012. "What You Should Save By 35, 45, and 55 To Be On Target." *Time,* September 21. http://business.time.com/2012/09/21/what-you-should-save-by-35-45-and-55-to-be-on-target/.

Lusardi, Annamaria, and Olivia Mitchell. 2007. "Financial Literacy and Retirement Planning: New Evidence from the Rand American Life Panel." MRRC Working Paper No. 2007-157. Ann Arbor, MI: University of Michigan Retirement Research Center.

Malkiel, Burton G., and Charles D. Ellis. 2010. *The Elements of Investing: Easy Lessons for Every Investor.* Hoboken, NJ: John Wiley & Sons.

McKenzie, David J. 2005. "Measuring Inequality with Asset Indicators." *Journal of Population Economics* 18(2): 229–260.

Miller, Rebecca J., Robert A. Lavenberg, and Ian A. MacKay. 2014. "ERISA: 40 Years Later." *Journal of Accountancy* 218(3): 86.

Sherman, Arloc, and Danilo Trisi. 2015. "Safety Net More Effective Against Poverty Than Previously Thought: Correcting for Underreporting of Benefits Reveals Stronger Reductions in Poverty and Deep Poverty in All States." Center on Budget and Policy Priorities Policy Futures. Washington, DC: CBPP. https://www.cbpp.org/research/safety-net-more-effective-against-poverty-than-previously-thought.

University of Wisconsin-Extension. 2013. "Analyzing the Financial Capability of People in Wisconsin." Issue Brief No. 2013-04. Madison, WI: University of Wisconsin. https://fyi.uwex.edu/financialseries/files/2013/04/April_2013_Fin_Cap1.pdf.

Vyas, Seema, and Lilani Kumaranayake. 2006. "Constructing Socio-Economic Status Indices: How to Use Principal Components Analysis." *Health Policy and Planning* 21(6): 459–468.

Weber, Caroline E. 2016. "Does the Earned Income Tax Credit Reduce Saving by Low-Income Households?" *National Tax Journal* 69(1): 41–76.

Yoong, Joanne, Richard Chard, and David Rogofsky. Forthcoming. "Using Informatics to Examine How Knowledge Influences Retirement Savings Behavior." *Proceedings of the 8th International Multi-Conference on Complexity, Informatics and Cybernetics.*

An Introduction to the Understanding America Study Internet Panel

by Laith Alattar, Matt Messel, and David Rogofsky*

This article provides an overview of the Understanding America Study (UAS), a nationally representative Internet panel of approximately 6,000 adult respondents that is administered by the University of Southern California. The UAS, which began in 2014, represents one of the richest sources of panel data available in the United States. It includes over 50 survey modules on topics such as retirement planning, economic well-being, and psychological constructs. This article reviews the UAS methodology; describes how external researchers may commission UAS surveys and incorporate their own survey questions and randomized controlled trials; highlights selected publicly available data from UAS surveys on cognition, personality, financial literacy and behaviors, political views, and other topics; and discusses opportunities for external parties to work with UAS administrators in developing new surveys and future lines of research.

Introduction

The Understanding America Study (UAS) is a nationally representative Internet panel of approximately 6,000 respondents aged 18 or older that is administered by the Center for Economic and Social Research (CESR) at the University of Southern California (USC). The UAS, which began in 2014, is supported by the Social Security Administration (SSA) and the National Institute on Aging through a cooperative agreement. Panel members are selected through address-based sampling and are compensated for their participation. Respondents are provided with a tablet computer and Internet access, if needed, to complete the surveys. The UAS includes over 50 survey modules on topics such as retirement planning, economic well-being, and various personality, cognitive, and other psychological constructs. The UAS also includes modules that correspond topically with most of the modules that comprise the University of Michigan's Health and Retirement Study (HRS). Although federal agencies, corporations, and academic research centers have commissioned many of these surveys, the collected data are available to the public either immediately or after a brief embargo. The UAS represents one of the richest sources of panel data available in the United States. In addition to offering breadth and accessibility, the UAS allows researchers to incorporate their own survey questions and methodological experiments, thereby providing greater flexibility than many other Internet panels.[1] Because many of the UAS surveys are regularly readministered, researchers can also use the UAS to conduct longitudinal panel analysis.[2] Finally, the UAS allows researchers to conduct randomized controlled trials (RCTs) to evaluate the efficacy of a wide array of interventions. Because the UAS is conducted online, researchers can receive survey and intervention data relatively quickly. On average, UAS administrators deliver data (weighted

Selected Abbreviations

ALP	American Life Panel
CDS	Computerized Delivery Sequence
CESR	Center for Economic and Social Research
CPS/ASEC	Current Population Survey Annual Social and Economic Supplement
FMS	Financial Management Survey

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Selected Abbreviations—*Continued*

HRS	Health and Retirement Study
LISS	Longitudinal Internet Studies for the Social Sciences
RCT	randomized controlled trial
SIS	Sequential Importance Sampling
SSA	Social Security Administration
UAS	Understanding America Study
USC	University of Southern California

to reflect the U.S. population) within 1 month of their collection.[3] Overall, the richness, flexibility, and timeliness of the UAS present significant opportunities for federal agencies, nonprofit organizations, and academic centers conducting research and analysis aimed at developing and improving programs and services.

Nationally representative Internet-based panels such as the UAS exemplify a relatively recent phenomenon in survey methodology. The oldest existing panel of this kind, CentERpanel, originated in the Netherlands in 1991. That panel enabled clients to receive results within a week of a survey being released to the respondents, a faster turnaround than had been possible with phone or written probability surveys. Today, a number of nationally representative Internet-based probability panels exist alongside the UAS. The GfK KnowledgePanel, initiated in 1999 as Knowledge Networks, is the largest ongoing Internet-based panel, with 55,000 participants. Both the Longitudinal Internet Studies for the Social Sciences (LISS) panel in the Netherlands and the American Life Panel (ALP) in the United States began in 2006; they have 7,500 and 6,000 panel members, respectively. Those panels administer surveys covering a wide range of topics, from health status to economic well-being to political views.[4]

This article provides an overview of the UAS. It first outlines the UAS methodology, then describes the process by which external parties such as researchers, policymakers, and corporations may commission UAS surveys. Finally, it highlights selected publicly available data (including a nearly complete replication of the HRS) and surveys on cognition, personality, financial literacy, retirement planning, political views, and voting behaviors, among other topics. The article also discusses opportunities for external parties to work with UAS administrators and CESR researchers in developing new surveys and future lines of research.

Methodology

This section covers UAS sampling, recruitment and survey collection, weighting procedures, standard variables, and the scope and treatment of missing data.

Sampling

In contrast with surveys that recruit panel members with random-digit dialing and face-to-face area sampling methodologies, the UAS uses address-based sampling. Random-digit dialing involves generating a list of telephone numbers at random. Researchers can stratify numbers by area code, telephone exchange, and other geographic identifiers when available. Although it has been a common method for generating survey samples since the 1970s, critics have in recent years questioned its ability to cover sampling frames adequately.[5] Furthermore, rates of landline telephone ownership decreased from 62 percent to 49 percent in the period 2012–2015, with 47 percent of U.S. households owning only cellular phones in 2015 (Blumberg and Luke 2016). Although some random-digit dialing samples now include cell phones, call-screening technologies and concerns about privacy among both cell phone and landline users may result in low response rates (Link and others 2008).

Face-to-face area sampling, in which researchers travel to households within a selected area, is an expensive alternative to random-digit dialing. Over the last decade, advancements in database technology have allowed compilers to create nationwide databases of addresses that researchers can use to construct sampling frames (Link and others 2009). The U.S. Postal Service created the most widely used database, the Computerized Delivery Sequence (CDS) file, which contains every postal address. In address-based sampling, researchers draw from one or more databases to recruit samples, often via mail.[6] In recruiting participants for the Massachusetts Health Insurance Survey, Sherr and Dutwin (2009) found that address-based sampling produced a lower response rate than random-digit dialing (34.7 percent versus 42.0 percent, respectively), but it also cost less and reduced coverage bias.[7] Additional limitations to address-based sampling include incomplete coverage of rural areas and the potential double counting of households with more than one mailing address.[8] Yet, the representativeness of address-based sampling continues to improve as survey methodologists address these issues (Iannacchione 2011; Iannacchione, Staab, and Redden 2003; Shook-Sa and others 2013). The UAS uses the CDS file, which includes 135 million residential addresses covering nearly 100 percent of U.S. households. The UAS also includes oversamples, such as Native Americans and residents of Los Angeles County and California.[9]

In its exclusive use of address-based sampling, the UAS differs from other studies. Although the GfK KnowledgePanel uses only address-based sampling (with data from the CDS file) to recruit panel members today, it used random-digit dialing prior to 2009. The ALP has used both address-based sampling and random-digit dialing. For the latter, it employs alternative sampling frames for landline and cellphone-only households in order to maximize coverage. The LISS panel uses a population-based registry, which is available in the Netherlands but not in the United States.

Like the other survey panels, the UAS draws a probability sample, as opposed to the convenience samples of some Internet-based surveys (Hays, Liu, and Kapteyn 2015). Convenience samples involve selecting the participants who are the easiest to locate and recruit; for a probability sample, on the other hand, researchers select participants randomly from a study population. Although researchers can recruit a large number of participants through convenience sampling, such a sample may not accurately represent study populations (Craig and others 2013; Tourangeau, Conrad, and Couper 2013).

An important feature of the UAS sampling procedure is sequential sample batching. The first batch is a simple random sample of addresses drawn from the CDS file. Subsequent batches are based on Sequential Importance Sampling (SIS), an algorithm developed by CESR designers.[10] SIS is a type of adaptive sampling (Groves and Heeringa 2006; Tourangeau and others 2017; Wagner 2013) that generates unequal sampling probabilities with desirable statistical properties. Specifically, before sampling an additional batch, the SIS algorithm computes the unweighted distributions of particular demographic characteristics (such as sex, age, marital status, and education) in the UAS at that time. It then assigns to each ZIP code a nonzero probability of being drawn, which is an increasing function of the degree of "desirability" of the ZIP code. The degree of desirability is a measure of how much, given its population characteristics, a ZIP code is expected to move the current demographic distributions in the UAS towards those of the U.S. population. For example, if at a particular juncture the UAS panel underrepresents women with a high school diploma, ZIP codes with a relatively high proportion of women with a high school diploma receive a higher probability of being sampled. The SIS is implemented iteratively. That is, after selecting a ZIP code, the distributions of demographics in the UAS are updated according to the expected contribution of this ZIP code towards the panel's representativeness, updated measures of desirability are computed, and new sampling probabilities for all other ZIP codes are defined. That procedure provides a list of ZIP codes to be sampled. From each ZIP code in the list, addresses are then sampled randomly from the CDS database.

Recruitment and Survey Collection

Administrators at CESR send an advance notification letter in English and Spanish to potential UAS respondents, followed by a mail survey to the randomly selected addresses, inviting residents aged 18 or older to participate. The mail survey includes a prepaid return envelope, a $5 incentive payment, and a promise of $15 for an individual who returns the completed survey by mail. The survey gathers demographic and economic information about the respondent and her or his household, as well as information about computer usage and other topics. At the end of the mail questionnaire, respondents may indicate their interest in participating in future surveys. If administrators do not receive a response within 2 weeks, they send a reminder post card. After another 2 weeks, they mail another questionnaire and provide the option to complete the survey online and an explanation that a different household member may complete the survey. If administrators receive no response within 3 weeks of mailing the second survey, they attempt to call the household, should a phone number be available.[11]

If a respondent returns the completed questionnaire and is not interested in participating in future surveys, administrators send a $15 payment, a thank-you letter, and a form inviting another household member to participate in the study. An individual who returns the survey and expresses interest in continued participation receives a brochure, a $15 prepaid debit card, and a welcome letter with information on how to start taking surveys online. The welcome letter notifies the individual that administrators will accept responses from all household members aged 18 or older who provide contact information. The letter also informs the individual that after logging into the UAS website and completing the "My Household" (demographic) survey, he or she will receive a bonus of $20. If the household does not have Internet service (as indicated in the mailed survey), the welcome letter will include a consent form (with return envelope) that permits administrators to provide a tablet and set up broadband Internet for the household. Once CESR receives the consent form, the UAS help desk calls the respondent to confirm his or her current address and the availability of broadband connectivity there. Participants are encouraged to use libraries or other free resources while they wait for their tablet or if they are hesitant to borrow equipment from the study. Tablets are set up per UAS specifications with a "quick link" to the survey site. Respondents whose participation lapses while in possession of a borrowed tablet are contacted and offered assistance to encourage them to resume participation.

When logging onto the UAS website, individuals are asked to complete an online consent form prior to beginning the My Household survey. They are also informed that the UAS has been granted a Certificate of Confidentiality by the Department of Health and Human Services. Households with at least one individual who submits My Household survey responses become part of the UAS panel. Thereafter, the UAS help desk invites respondents to participate in one or more surveys per month. The invitation includes a brief description of the survey, an estimate of the time it will take to complete the survey, the amount of compensation, and the deadline (if applicable). Panel members receive compensation on a monthly basis via a prepaid debit card provided by the survey team.

The UAS has a panel recruitment rate of 15–20 percent, similar to those of the GfK KnowledgePanel and the ALP.[12,13] The response rate is only an estimate, as it is not possible to definitively code how many mailed surveys arrived at their intended destination. Because initial surveys are sent by priority mail, the majority of mailings to bad addresses are assumed to be returned and coded as nondeliverable, but it is impossible to know how many bad addresses do not lead to a returned mailing. The calculation of response rates is therefore conservative, as any nonreturned survey is assumed to have gone to a valid address.[14]

Completion rates for individual UAS online surveys range between 70 percent and 95 percent.[15] Panel members typically spend 30 minutes, at most, completing a single survey. They are compensated $20 for a 30-minute survey.[16]

The UAS team administers surveys via the Internet in English and Spanish, using the NubiS data collection tool developed by CESR. The advantages of the Internet over other modes of conducting surveys (such as face-to-face, mail, or telephone) include lower costs and the ability to obtain survey data more quickly. However, Couper and others (2007) find that Internet access is unevenly distributed across certain demographic categories.[17] Internet usage is lower among Americans aged 65 or older and those with lower levels of education than it is among their younger and more educated counterparts (Table 1). In 2018, 66 percent of Americans aged 65 or older used the Internet, compared with 98 percent of those aged 18–29. Likewise, 65 percent of individuals with less than a high school diploma used the Internet, compared with 97 percent of those with a college degree (Anderson, Perrin, and Jiang 2018). The UAS addresses the variance in usage rates by providing Internet access and a tablet to any panel members who lack them.

Weighting

Researchers use weighting to allow the characteristics (such as race, sex, age, or education) of a sample to more closely reflect those of a study population. Respondents with characteristics that are underrepresented (or overrepresented) relative to the population receive larger (or smaller) survey weights. Each UAS survey is separately weighted. The target population is typically noninstitutionalized U.S. residents aged 18 or

Table 1.
Internet usage rates of U.S. adults, by selected demographic characteristics, January 2018

Characteristic	Percentage
Total	89
Sex	
Men	89
Women	88
Age	
18–29	98
30–49	97
50–64	87
65 or older	66
Race/ethnicity	
Non-Hispanic white	89
Non-Hispanic black	87
Hispanic	88
Educational attainment	
Less than high school diploma	65
High school diploma	84
Some college	93
Postsecondary degree	97
Household income	
Less than $30,000	81
$30,000–$49,999	93
$50,000–$74,999	97
$75,000 or more	98

SOURCE: Anderson, Perrin, and Jiang (2018).

older, although specific surveys may target particular segments of the population (for example, Medicare-eligible individuals). UAS surveys are weighted using a two-step process.

In the first step, statisticians create a base weight to address the fact that the SIS algorithm causes the probability of being sampled to vary from one ZIP code to another and from one household in a sampled ZIP code to another. Sampled ZIP codes are weighted to match their characteristics—such as Census region, urbanicity, and demographic composition (sex, age, education, race, and marital status)—with those of the ZIP codes covered by the Census Bureau's American Community Survey. This weight, indicated by w_1^b, is generated via logit regression. Then, the ratio of the number of all households to the number of sampled households in the ZIP code is computed. This can be denoted by w_2^b. The base weight is a ZIP code–level weight defined by the product of w_1^b and w_2^b.

In the second step, statisticians generate post-stratification weights to correct for differential survey nonresponse rates and to align the survey sample with the reference population in terms of a predefined set of demographic and economic variables (race, sex, age, education, household size, and total household income). The UAS uses estimates from the most recent available version of the Census Bureau's Current Population Survey Annual Social and Economic Supplement (CPS/ASEC) as the benchmark for population distributions of these variables. Specifically, UAS survey data collected from September 2015 to September 2016 are weighted using the 2015 CPS/ASEC, data collected from September 2016 to September 2017 are weighted using the 2016 CPS/ASEC, and so on. The poststratification weights are available for completed surveys and are part of the data file. Researchers may also request weights for ongoing surveys.[18]

Poststratification weights are created using a raking algorithm. The algorithm compares relative frequencies within the target population with relative frequencies in the survey sample by race, sex and age, sex and education, household size and total household income, census region, and urbanicity. When a researcher combines responses from two or more UAS surveys, the UAS team will provide weights unique to the combined data set based on the procedure described above. Alternatively, the UAS team can provide custom poststratification weights using specific raking factors chosen by the researcher.[19]

Standard Variables

In addition to survey weights, each UAS survey data set includes a set of standard variables. These include identifying variables, demographic variables, and survey metadata (for example, survey completion time, panel member's interest in the survey, and so on).

Identifying variables. Each panel member receives an individual identifier and two household identifiers. The individual identifier (*uasid*) is assigned to panel members at recruitment and remains with them through each survey in which they participate. Researchers may use this variable to merge data from different surveys. The UAS defines a household as all individuals living at the same address. The first household identifier (*uashhid*) matches the individual identifier for the primary panel member within the household.[20] Other panel members within the household are assigned the same household identifier. This identifier remains constant throughout a panel, so that researchers can always find the original household of each panel member. The second household identifier (*survhhid*) indicates the household in which a panel member lives at the time of the survey. This identifier may change; for example, if a household member moves to another household.

Demographic variables. Each data set also includes current demographic information about the panel member. Every quarter, panel members must update the My Household survey to complete additional surveys.[21] This survey covers a range of demographic information, which UAS administrators merge into all other surveys. Variables include sex, age, race and ethnicity, highest level of education, household size, household income, state of residence, marital status, citizenship, and place of birth, as well as additional variables related to employment. Table 2 summarizes demographic and employment characteristics reported in the My Household survey as of June 30, 2017. It shows the unweighted and weighted demographic characteristics of UAS panel members along with weighted figures from the 2016 CPS/ASEC, which serves as the U.S. population benchmark for the UAS surveys that began collecting data in September 2016. The sample includes 5,319 respondents from 9 nationally representative recruitment batches (therefore, it excludes the Los Angeles County and Native American oversamples).

Individuals who are female, middle-aged (40 to 59), non-Hispanic whites, married, U.S. citizens, and

Table 2.
Demographic characteristics of the UAS 2017 panel members: Unweighted, weighted, and compared with the benchmark 2016 CPS/ASEC, as of June 30, 2017

Characteristic	UAS 2017 panel			2016 CPS/ASEC percentage distributions [a]
	Number	Percentage distributions		
		Unweighted	Weighted to 2016 CPS/ASEC	
Sex				
Men	2,337	43.9	48.3	48.3
Women	2,982	56.1	51.7	51.7
Age				
18–39	1,533	28.8	38.2	38.2
40–49	1,020	19.2	16.3	16.3
50–59	1,170	22.0	18.0	18.0
60 or older	1,596	30.0	27.5	27.5
Race/ethnicity				
Non-Hispanic white	4,152	78.1	64.4	64.4
Non-Hispanic black	452	8.5	11.8	11.8
Hispanic	377	7.1	15.8	15.8
Other	338	6.3	8.0	8.0
Educational attainment				
High school diploma or less	1,367	25.7	40.6	40.7
Some college, no degree	1,242	23.3	17.8	19.1
Associate's degree	813	15.3	10.7	9.5
Bachelor's degree	1,110	20.9	17.7	19.5
Postgraduate/professional degree	787	14.8	13.2	11.2
Household income				
Less than $30,000	1,440	27.1	26.0	25.4
$30,000–$59,999	1,447	27.2	26.1	27.2
$60,000–$99,999	1,309	24.6	25.1	22.9
$100,000 or more	1,123	21.1	22.8	24.5
U.S. citizenship				
Yes	5,244	98.6	96.9	91.6
No	75	1.4	3.1	8.4
Born in United States				
Yes	5,014	94.3	90.3	82.7
No	305	5.7	9.7	17.3
Marital status				
Married	3,202	60.2	56.0	53.1
Separated, divorced, or widowed	1,150	21.6	20.3	18.6
Never married	967	18.2	23.7	28.3
Number of persons in household				
1	777	14.6	14.8	14.8
2	2,318	43.6	36.1	34.3
3–4	1,654	31.1	34.1	35.8
5 or more	570	10.7	15.0	15.1
Employment status				
Working	3,135	59.0	61.1	59.6
Self-employed	402	12.2	11.0	10.1
Unemployed	320	6.0	6.5	3.2
Retired	964	18.1	15.8	17.7
Other	900	16.9	16.6	19.5

SOURCES: UAS 2017 panel; 2016 CPS/ASEC.

a. Values are weighted using person-level weights.

U.S.-born are more heavily represented in the UAS panel than in the U.S. population. In most cases, survey weighting minimizes the aggregate differences between the UAS panel and the U.S. population. By construction, distributions of raking factors align with their benchmarks. The alignment matches exactly for sex, age, and race/ethnicity because the algorithm uses the same categories as those reported in Table 2 to generate the poststratification weights. However, the raking algorithm uses three education, household income, and household size categories instead of the four (or five) reported in Table 2. Because of this, the distributions among the weighted UAS values and the benchmark CPS/ASEC values differ slightly for these three variables. For most domains, survey weights diminish differences between sample and population distributions. Even after weighting, UAS panel members are slightly more likely than the U.S. population to have postgraduate education, to be self-employed, or to be unemployed. Differences are greater still in the distributions by citizenship, place of birth, and marital status.

Timing. Researchers may wish to use UAS data on demographic characteristics that were collected in multiple surveys. The interval between the data collection and its availability can range from a few moments to several months, depending on the promptness of a given survey's respondents and the length of time between surveys. Each UAS survey contains timestamps to indicate when the panel member began and finished the survey. These timestamps can help researchers to establish temporal aspects of study variables, when relevant.

Missing Data

Demographic data collected in the UAS are relatively complete. Table 3 shows the frequency of missing data for key demographic variables. Variables such as sex, citizenship, and place of birth have no missing values out of 5,319 respondents. Variables such as age, race/ethnicity, educational attainment, household income, marital status, and state of residence each have fewer than 10 missing values. Data on household size were missing for 3.5 percent of respondents. For weighting purposes, missing demographic variables are first categorized (if continuous or taking more than 10 values) and then imputed using a sequential imputation procedure.[22,23] Missing data on the respondent's sex are never imputed; information for such individuals do not receive a weight. In the data files, the extension ".e" represents questions that the respondent saw but did not answer; ".a" represents questions that the respondent never saw.[24] Respondents may not have seen a question either because they intentionally or inadvertently skipped over it or because they began but did not finish the survey.

Table 3.
Frequency of missing data on demographic characteristics in the UAS 2016 panel

Characteristic	Missing data rate (%)
Sex	0.00
Age	0.08
Race/ethnicity	0.19
Educational attainment	0.04
Household income	0.17
U.S. citizenship	0.00
Born in United States	0.00
Marital status	0.04
State of residence	0.06
Number of persons in household	3.48
Employment status	0.04

SOURCE: UAS.

External Research Examples and Commissioning Research

In addition to using UAS data that are already available, researchers, policymakers, and corporations may commission their own surveys or methodological experiments with the nationally representative UAS panel. The CESR research team will administer these surveys either once (for cross-sectional analysis) or multiple times (for panel analysis), depending on the research need of the client. A number of government agencies and private entities have used the UAS to conduct primary research that expands academic and policy-relevant knowledge. For instance, SSA worked with CESR to develop two questionnaires for use in annual surveys measuring the public's knowledge of Social Security and identifying the communication channels by which individuals prefer to receive information about the agency and the programs. SSA plans to use these surveys to improve their public outreach and communication efforts. Among other entities, Princeton University and the Roybal Center for Health Decision Making and Financial Independence in Old Age have commissioned surveys through the UAS. Similarly, the Federal Reserve Bank of Boston began conducting its annual Survey of Consumer Payment Choice with the UAS panel in 2015. For that survey, the longitudinal structure of the UAS allows researchers to understand not only which payment instruments

Americans use most frequently, but also how these payment behaviors change over time and in relation to microeconomic and macroeconomic phenomena.

When an individual or organization commissions a UAS survey, CESR designers provide support through programming and testing, finalizing the draft survey instrument, selecting the survey sample, translating the survey instrument into Spanish (if desired), collecting data, and providing a final weighted data set. CESR also provides other services: survey development and questionnaire design, item/survey testing, human-subject research advice, application development, visual displays, graphical interface, sample management design, data cleaning, and data analysis. Clients also gain access to NubiS, the web-based software developed by UAS programmers to conduct online surveys. The pricing structure of externally commissioned surveys depends on the survey length and sample size.

Each survey or methodological experiment requires approval from the USC human subjects committee internal review board (IRB) before data collection may begin. CESR researchers submit the survey to the IRB on behalf of the investigator and act as the intermediary between the investigator and the board.

Investigators also have the opportunity to embargo data temporarily. By default, survey questions and data, including those commissioned by external investigators, are publicly available through the UAS website. However, to allow investigators to analyze and write results before public release, CESR researchers will provide them exclusive access to the data for a period generally not exceeding 6 months after survey completion.

Available Panel Data

CESR administers a number of core UAS surveys on an ongoing basis, typically with an annual or biennial frequency. Examples include surveys on Social Security program knowledge and preferred communication channels; HRS-based survey modules; and surveys on psychological (cognitive and personality) variables, financial management and knowledge, and political preferences and voting behaviors. Panel members completed the first wave of most of these surveys in 2016. In future years, they will complete successive waves developed by CESR and external clients.

Social Security Program Knowledge and Preferred Communication Channels

UAS survey 16 (UAS16) asks panel members about their knowledge of Social Security, and UAS survey 26 (UAS26) asks them about the channels through which they prefer to receive information from SSA. UAS16 and UAS26 expand on the Social Security module of the ALP. Among others subjects, the two surveys address:

- knowledge about Social Security retirement and spousal benefits,
- knowledge about eligibility age and delayed retirement credits,
- understanding of the *Social Security Statement* and use of the *my* Social Security online account,
- views on what Social Security should provide and the adequacy of benefits, and
- views on the solvency of the Social Security trust funds.

Yoong, Rabinovich, and Wah (2015) provide initial findings from UAS16, and Rabinovich and Yoong (2015) provide findings from UAS26.

Beyond the wide range of topics included in the two Social Security surveys, researchers and policymakers may expand understanding of the public's interaction with SSA and the programs it administers by matching these data to surveys covering related topics such as wealth or financial knowledge. CESR will work with SSA to develop the surveys and will administer them every 2 years.

UAS-HRS Surveys

Since its inception in 1992, the HRS has proven useful for studying both national trends and individual-level changes among Americans aged 50 or older.[25] Studies using HRS data have played a crucial role in understanding changes in the health, wealth accumulation, and retirement planning of older Americans. The HRS has shed light on retirement planning and saving behavior, the role of health in labor force participation and retirement timing, and income and wealth trends in retirement, among myriad other research topics.[26]

The UAS extends these knowledge bases by administering biennial HRS survey modules that collect a breadth of data on retirement planning and saving from panel members aged 18 or older. Over time, HRS-based UAS data may also inform researchers about health, wealth, and retirement-planning trends of Americans over the entire course of adulthood. Furthermore, researchers and policymakers using the UAS may explore the relationships between data collected in the HRS, other UAS surveys, and their own survey instruments. In this way, researchers may extend their analysis to a broad range of topics while developing surveys that are focused and succinct. Finally, researchers and policymakers may use HRS-based measures to test the effectiveness of interventions targeting behaviors such as retirement planning or financial decision making. For example, researchers can test or compare the efficacy of new interventions using RCTs because the UAS allows different versions of a survey to be administered to randomly selected panel subsamples.

The UAS-HRS surveys differ from the official HRS surveys in several important ways. First, the UAS-HRS surveys are administered to all panel members, not only those aged 50 or older. (Panel members are invited to participate in UAS-HRS surveys only after they have completed at least three other UAS surveys.) Second, the timing of UAS-HRS surveys differs from that of the official HRS surveys. For the latter, panel members enter the study as part of a cohort; they complete all survey modules at the same time, with the first wave of surveys conducted within a single calendar year and additional surveys completed every 2 years thereafter. In the UAS-HRS, panel members may complete survey modules at different times. They too must complete the modules every 2 years, but they do not necessarily complete them at the same time that other UAS panel members do. Box 1 shows the correspondence between official HRS modules and the first round of UAS-HRS surveys. Each round of UAS surveys reflects the most recent HRS wave; for example, the first UAS round corresponds with the 2014 HRS and the second round with the 2016 HRS.[27]

The UAS-HRS modules use variables that are named using a convention consistent with that of the RAND HRS data file and codebook (Chien and others 2015). CESR designers adopted this naming convention to enable an easy transition for individuals who are familiar with RAND HRS data to the HRS-based data in the UAS. Income data are reported at the individual level and wealth data are reported at the household level. Although each participating HRS household includes only one financial respondent, more than one UAS respondent may provide financial data for his or her household.

Surveys on Cognitive and Personality Variables

UAS survey 1 (UAS1) measures numeracy, risk perception, personality, and financial literacy. Previous research found that these constructs significantly predict patterns of financial, health, retirement, and other behaviors (for example, Banks and Oldfield 2007; Lusardi and Mitchell 2011a, 2011b). Nevertheless, few surveys have included cognitive or personality measures in a panel design.[28] By collecting these measures on a regular basis, the UAS allows researchers to evaluate changes in cognition and personality over time, as well as to establish temporal patterns in cognition and personality as they relate to financial, health, and retirement planning and decision making. The UAS-HRS surveys, for instance, will query respondents every 2 years about current savings, saving plans, and expectations for retirement.

Box 1.
Topics covered in UAS surveys and corresponding HRS modules

UAS survey number	Topics	HRS modules
20	Personal background; household characteristics; health history; cognitive abilities	A, B, C, D
21	Family characteristics; health condition; caregiving; living arrangements	E, F, G, H
22	Current job status; job history; health-related work impairments	J, J2, K, L, M
23	Health insurance; health care service use; health event probabilities	N, O, P
24	Income and assets	Q, R
25	Wills, trusts, and life insurance policies	T, U, V

SOURCE: UAS.

NOTE: HRS modules not included in the UAS cover physical measures and biomarkers (I), widowhood and divorce (S), and Internet use (W).

Numeracy. Numeracy refers to the "ability to understand numerical information" (Reyna and others 2009, 943) and plays an important role in financial and health care decision making. The UAS measures numeracy through a Rasch-based scale developed by Weller and others (2013). The UAS scale combines five items drawn from the numeracy scale of Lipkus, Samsa, and Rimer (2001) with one item from the Peters and others (2007) scale and two items from the Cognitive Reflection Test (Frederick 2005). A number of studies find that numeracy and cognitive reflection—the latter defined by Sinayev and Peters (2015, 1) as the "tendency to check and detect intuitive errors"—represent a similar underlying concept (Låg and others 2014; Liberali and others 2012;[29] Weller and others 2013). The UAS website includes information on scale items and the development of the final scale score.

The UAS enables researchers to expand the study of numeracy and decision making across the life course. In particular, the UAS-HRS surveys contain information on health care and retirement saving and planning behaviors. The UAS also allows researchers and policymakers to test hypothetical health care or retirement interventions. Because the UAS samples are larger than those observed in many previous studies of numerical ability,[30] researchers may use UAS to study numeracy in subsamples (such as young adults) or to test the effectiveness of interventions across the spectrum of numerical ability.

Risk perception. UAS1 also measures consistency in risk perception, a subtest of the larger adult decision-making competence scale (Bruine de Bruin, Parker, and Fischoff 2007). Consistency in risk perception involves uniformly determining the probability of events over different time spans or in different contexts. For instance, it refers to an individual's ability to assess the risk of an event occurring within the next year versus the next 5 years, or of a specific event context (such as visiting the dentist to fill a cavity) versus a more general one (visiting the dentist for any reason). By testing consistency in risk perception, the UAS may open multiple avenues for research. Before the UAS, researchers tested the adult decision-making competence scale in controlled settings with relatively limited sample sizes. Over time, the UAS will allow for longitudinal measurement of a larger sample. Researchers may also be able to measure the consistency-in-risk-perception scale in relation to real-life financial, health, and retirement decisions by employing items from the UAS-HRS surveys. For example, policymakers could use these data to understand how changes in policy or the economy shape the investment strategies, health care decisions, or retirement plans of Americans based on differing levels of consistency in risk perception.

Personality. Alongside cognitive scales, a 44-item version of the "Big Five" personality inventory (John 1990) is included in the UAS. The inventory measures five personality traits: openness to experience, conscientiousness, agreeableness, extroversion, and neuroticism. A large body of research focuses on the relationship between big five personality profiles, job satisfaction, and career success (for example, Barrick and Mount 1991; Judge and others 1999; Judge, Heller, and Mount 2002; Seibert and Kraimer 2001; Soldz and Vaillant 1999; and Thoresen and others 2004). The UAS offers opportunities to expand the understanding of personality in relation to retirement, financial decision making, and health. In particular, the relationship between personality and financial decision making bears further exploration. The UAS allows researchers to match personality data with an array of self-reported financial decisions and facilitates the exploration of these personality/behavior relationships in respondents from young adulthood to beyond retirement age. The UAS also enables longitudinal studies linking measures of personality and health. Shanahan and others (2014) theorize about how personality relates to health over the life course, yet few studies have had the opportunity to study this relationship empirically. The UAS-HRS includes health-related items covering topics such as perceived health, disability, and health care expenditures.

Financial literacy. The role of financial literacy in retirement planning, saving, and making informed financial decisions is central (for example, Hilgert, Hogarth, and Beverly 2003; Lusardi and Mitchell 2011b; and Utkus and Young 2011). The UAS adopts a measurement of financial understanding that was developed for the ALP; prior research on financial literacy had relied on a limited set of questions and samples that excluded younger individuals (Lusardi and Mitchell 2011b). UAS1 adopts some of the basic questions from previous surveys on financial literacy[31] and includes many additional items that test respondents' knowledge of stocks, bonds, and savings accounts, among other financial topics. Lusardi and Mitchell (2017) find that knowledge of these specific financial instruments, terms, and concepts predicts time devoted to retirement planning more strongly than does knowledge of more basic concepts such as interest rates, inflation, and risk diversification. The survey also includes a scale of respondents' confidence in their own financial knowledge.[32]

The UAS allows for additional research in financial literacy. The wide array of survey data available in the study will allow researchers to explore the relationship between financial knowledge and demographic, economic, cognitive, and personality variables. For instance, researchers may combine UAS data to study the ways in which financial literacy and personality interact to shape retirement saving behavior across the life course. Furthermore, the UAS may allow researchers and policymakers to test online financial education interventions.

Financial Management Survey (FMS)

CESR designed the FMS to provide updates to the 2012 Older Adult Survey, which was administered by the Federal Reserve Board of Governors to a sample of ALP respondents.[33] The 2012 survey explored the financial well-being of Americans aged 40 or older in the wake of the Great Recession. Specifically, it investigated how older adults use financial products, how they make financial decisions and to whom they turn for advice, and the primary sources of their financial stress. The FMS, which is fielded as UAS survey 18, enables researchers not only to understand how the financial situation of Americans has changed since the Great Recession, but also to assess the financial well-being and decision making of individuals aged 18 or older. CESR will administer the FMS every 2 years, which will allow researchers to explore how households' financial status changes over the life cycle. Specific topics addressed in the FMS include use of financial products and services, including credit cards, mortgages, student loans, bank accounts, and alternative financial services (such as payday lenders); financial decisions, such as refinancing, investment, retirement planning, and planning for incapacity; confidence in financial decisions; and financial stress and well-being. Researchers can match FMS data to results of other UAS surveys, such as those on financial knowledge, financial well-being, and numeracy, further expanding the avenues for research.

Political Data

The UAS also collects data on respondents' political views through its USC Dornsife/*Los Angeles Times* Presidential Election "Daybreak" poll, which is funded by nonfederal sources. These data are collected continuously during each presidential election cycle. The UAS poll differs from most election polls in that it surveys the same individuals every week from July to November of the election year. First, CESR invites panel members to participate in the poll. Participants take a baseline survey between May and early July, in which they indicate the candidate for whom they voted the previous presidential election, the U.S. congressional candidates for whom they voted in the previous midterm election, and whether they are currently registered to vote. A brief follow-up survey is administered to each participant every week until the election. CESR administers the weekly survey to one-seventh of the participants each day, and weights the responses to demographic characteristics from the Current Population Survey and to 2012 election data.

Each week, Daybreak poll participants indicate the percentage likelihood that (1) they will vote in the presidential election; (2) they will vote for the Democratic candidate, the Republican candidate, or another candidate; and (3) the Democratic candidate, the Republican candidate, or another candidate will win the election. Thus, the survey questions are probabilistic rather than the verbal questions (such as, "For which candidate will you vote?") typical of most election surveys. In assessing ALP 2008 election data, Delavande and Manski (2010) found that probabilistic items predicted actual voting behavior more accurately in early August, while verbal questions predicted more accurately in late October. However, responses to both probabilistic and verbal items largely agreed over the election cycle as a whole.

The Daybreak poll provides two broad research opportunities. First, it allows researchers to track changes in voter preference and likelihood of voting over time. Second, researchers can match political preference and voting data to results from other UAS surveys.

Discussion, Limitations, and Future Research

The UAS presents researchers with unique reach and flexibility in conducting survey-based and experimental research, including access to a large, nationally representative sample; customizable surveys and RCTs; and rich, publicly available data sets. The UAS also provides unique information to broaden SSA's understanding of U.S. retirement security and to enable the agency to help workers plan for retirement. In addition to the two surveys on Social Security program knowledge and preferred communication channels mentioned earlier, other UAS surveys will examine various aspects of the retirement-benefit claiming decision. Some UAS surveys also allow the agency to learn how American families save over time and how much they rely on Social Security income in retirement. Data from these surveys enable the agency to target program-knowledge outreach campaigns to key subgroups—particularly, to those most reliant on Social Security income. For SSA's disability programs, the UAS, in conjunction with the HRS, can identify patterns and predictors of impairments and functional limitations from young adulthood to old age. Additionally, the UAS is working to establish permissions and procedures for matching survey results with administrative data from SSA and the Centers for Medicare and Medicaid Services. To explore ways to reduce respondent burden and enhance accuracy, a CESR pilot study encourages respondents to use a financial aggregator service. The aggregator provides daily electronic financial transaction data to CESR, which can be compared against self-reported information.

Limitations

The UAS addresses a number of limitations of other Internet-based panels, such as accessibility and random sampling; yet certain challenges remain. Although an address-based sampling frame is comprehensive, it may fail to include an adequate number of population subgroups such as ethnic and racial minorities. In the past, UAS administrators have targeted ZIP codes with high proportions of Native American residents as part of a special-purpose sample. They continue to explore methods that ensure the inclusion of ample numbers of minority households in the UAS panel.

Given the breadth and volume of UAS surveys, another potential concern is survey fatigue. CESR and collaborating researchers ensure reasonable survey loads by monitoring the frequency and length of surveys administered to participants. For example, analysis of timestamp data might show that a given respondent tends to take longer to complete successive surveys, which may indicate incipient survey fatigue. Similarly, the fact that panel members are willing to take so many surveys (and spend so much time taking them) may mean that respondents are more conscientious in this regard than the average American. UAS administrators can address this potential selection bias by measuring and controlling for self-reported conscientiousness and other relevant variables.

A final limitation of surveys that are repeated at regular intervals is that continued participation may trigger knowledge, awareness, and behavior in the respondent that might not otherwise have occurred, which might be seen as artificially altering the extent to which the panel members are representative of the population. Fortunately, the continuing expansion of the UAS panel gives researchers the option of limiting data analysis to "fresh" samples of participants with only a single exposure to a particular survey. Conversely, researchers may choose to capitalize on panel members' changing knowledge and incorporate it into their research variables.

Future Research

As the UAS panel expands, CESR and other researchers continue to develop surveys to address more complex research questions across and within larger population samples. For example, SSA and CESR researchers are working on using UAS data in the development of innovative indexes related to retirement. Chard, Rogofsky, and Yoong (2017) introduce the retirement planning index, which combines a set of positive retirement savings–related indicators from the UAS-HRS Income and Asset module. Other ongoing research also aims to develop a retirement satisfaction index, which will measure levels of satisfaction, regret, and well-being among retirees, focusing retrospectively on their retirement-related decisions.

The expansion of the UAS panel will also allow researchers to study specific segments of the population, such as low-income households or individuals with disabilities. Further, it will allow analysis of defined geographic areas. SSA researchers will analyze trends in Social Security program knowledge and preferred methods of communication across the agency's 10 administrative regions. SSA regional offices may use this research to better understand the populations that they serve. With this information, the agency may also tailor communication efforts and deliver them through more effective platforms. Because the sample sizes will be small in some SSA regions, however, it may be difficult for researchers to provide subanalysis at the regional level.

As noted earlier, the flexibility and continued expansion of the UAS also enable researchers to conduct RCTs to evaluate the efficacy of various program and communication interventions. For example, SSA and CESR are studying how the use of alternative terminology in discussing Social Security benefit claiming affects respondent understanding, claiming intentions, and other outcomes.

In addition, CESR specialists have started building a user-friendly public-use data file similar to that of the HRS. The core components of the UAS public-use file are the cognitive ability, financial knowledge, big five personality inventory, Social Security program knowledge, and Social Security preferred communication channel modules; the FMS; and data on key UAS-HRS topics. The public-use file will include longitudinal data for many of these components. In the future, the data file may, with sponsoring agency approval, also include federally funded data sets. Data file documentation will indicate when each of the various UAS modules and surveys was administered and, when applicable, readministered.

Future researchers may be able to match UAS panel results to SSA and Internal Revenue Service (IRS) administrative data. Work is under way to determine how many panel members will consent to provide their Social Security number to match UAS and Social Security administrative data. If enough panel members consent to match their UAS survey responses and SSA/IRS administrative data, CESR will create a restricted-use file and house it in a secure location. If matched data are available, researchers will send their project proposals to SSA and IRS. Researchers will also require approval from USC to use the restricted matched data. The approval procedure will be similar to that for obtaining restricted HRS data.

This article outlined the methodological features of the UAS, including its sampling and weighting procedures. It provided information on how researchers can customize their own surveys and incorporate them into the UAS panel. It also highlighted some of the recurring UAS surveys, such as UAS-HRS surveys and modules on cognitive and personality variables, financial management, financial knowledge, Social Security program knowledge and preferred communication channels, and political views.

Future articles will provide additional detail on aspects of the UAS panel such as the public-use data file, the retirement preparedness index, the retirement satisfaction index, and additions to the panel as it expands.

Notes

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[1] Some other studies, such as the RAND American Life Panel, allow such interactivity.

[2] Panel analysis involves studying the same individuals over an extended period with a series of repeated observations. In the UAS, these observations include various survey modules. Although researchers regularly add new modules to the study, panel members also take many of the core surveys on a repeated follow-up basis. This allows researchers to understand how the knowledge and perspectives of panel members change over time or, in certain cases, after an experimental intervention.

[3] Although receiving initial results in a month is typical, researchers may receive weighted data sooner, depending on how quickly panel members respond to the survey and when the survey is closed. If a high response rate is achieved within a few days of the survey release, the researcher may request the weighted data at that point.

[4] For more information on CentERpanel, see https://www.centerdata.nl/en/databank/centerpanel-data-0; on GfK KnowledgePanel, see http://www.gfk.com/products-a-z/us/knowledgepanel-united-states/; on LISS, see https://www.lissdata.nl/about-panel/; and on ALP, see https://alpdata.rand.org/.

[5] Sampling frames represent all units in a population that a researcher intends to study. For the UAS, the sampling frame includes individuals aged 18 or older living in the United States.

[6] In some cases, however, researchers contact households via telephone after matching telephone numbers to addresses (Dekker and Murphy 2009).

[7] Coverage bias occurs when a sampling methodology draws its sample from a population subset that differs from the entire population in a systemic way (for example, the income level of the subset differs substantially from that of the entire population).

[8] This may occur if a household maintains seasonal residences, merges two apartment units at the same address, or uses a Post Office box in addition to a home mailing address.

[9] CESR designers draw these oversamples to produce sample sizes that are statistically sufficient to support studies covering those specific populations. The oversamples of Native Americans and a subgroup of Los Angeles county residents with young children, recruited using information from state birth records, are omitted from the UAS weighting computations that allow each survey sample to be representative of the target population. Both groups are appropriately flagged in the data files. For more information on the construction of the oversamples, see https://uasdata.usc.edu/index.php.

[10] The SIS algorithm is implemented to recruit respondents for the nationally representative main sample as well as for the oversamples of Los Angeles County and California residents. Different sampling procedures are adopted to recruit respondents for the Native American oversample and for the oversample of a subgroup of Los Angeles

County residents with young children. Because of their specific sampling procedures, these two groups receive zero weight.

[11] Administrators make up to 15 attempts to contact the household about completing the survey.

[12] The UAS response rate is provided by the American Association for Public Opinion Research's Response Rate calculator.

[13] The LISS panel, employing both telephone and face-to-face recruiting methods for its population registry-based sample, has an initial response rate of 45 percent.

[14] For complete details on recruitment per sample wave, see https://uasdata.usc.edu/index.php.

[15] For comparison, 2015 ALP surveys based on probability samples had completion rates of 60 percent or higher (Pollard and Baird 2017) and one of the GfK KnowledgePanel surveys had a completion rate of 85 percent (Callegaro and DiSogra 2008).

[16] Some surveys take less than 30 minutes. The amount of compensation is proportional to the length of the survey.

[17] Hays, Liu, and Kapteyn (2015) discuss other drawbacks of Internet-based surveys, such as respondents inadvertently giving the same response to consecutive items or, in the case of convenience panels, taking the same survey more than once.

[18] Researchers may send the request to uas-weights-l@mymaillists.usc.edu.

[19] For more information on the raking algorithm, refer to UAS documentation (https://uasdata.usc.edu/addons/documentation/UAS%20Weighting%20Procedures.pdf).

[20] The primary panel member is the resident who first responded to the initial survey mailed to the address.

[21] Items in the My Household survey are prepopulated with the respondent's answers from the previous survey iteration. If a particular item remains the same, the panel member does not change it.

[22] In sequential imputation, the missing values of a given variable (for example, household income) are imputed using a regression of observed cases of that variable with a set of other variables (such as age or sex). When the missing values of the first variable are imputed, those values are used in a regression imputation for a second variable. The process repeats until all variables have been imputed.

[23] For more information on sequential imputation and all other UAS weighting procedures, see https://uasdata.usc.edu/addons/documentation/UAS%20Weighting%20Procedures.pdf.

[24] ".a" may also represent data that contain errors.

[25] For more information on the HRS, see http://hrsonline.isr.umich.edu/.

[26] The HRS website includes a full list of publications (https://hrs.isr.umich.edu/publications).

[27] For the UAS-HRS survey codebooks, see https://uasdata.usc.edu/surveys; for the original HRS survey codebook, see http://hrsonline.isr.umich.edu/index.php?p=showcbk.

[28] The HRS, which includes repeated measures of cognitive ability, is a notable exception.

[29] The authors report that outcome in one of the two studies they conducted.

[30] UAS1 has about 6,000 respondents versus between 100 and 200 respondents in previous studies.

[31] UAS designers drew these questions from the National Council of Economic Education Survey, the Financial Industry Regulation Authority's Investor Knowledge Quiz, the HRS module on financial literacy and planning, the Survey of Financial Literacy in Washington State, and the Survey of Consumers.

[32] Lusardi and Mitchell (2007) observe that confidence generally exceeds financial literacy. Few studies, however, have investigated the relationship between financial literacy and confidence in financial decision making (see Asaad 2015).

[33] Additional information about the Older Adult Survey may be found at https://www.federalreserve.gov/econresdata/older-adults-survey/July-2013-Appendix-A-Older-Adult-Survey-Methodology.htm.

References

Anderson, Monica, Andrew Perrin, and Jingjing Jiang. 2018. "11% of Americans Don't Use the Internet. Who Are They?" Pew Research Center FactTank (March 5). http://www.pewresearch.org/fact-tank/2018/03/05/some-americans-dont-use-the-internet-who-are-they/.

Asaad, Colleen Tokar. 2015. "Financial Literacy and Financial Behavior: Assessing Knowledge and Confidence." *Financial Services Review* 24(2): 101–117.

Banks, James, and Zoe Oldfield. 2007. "Understanding Pensions: Cognitive Function, Numerical Ability and Retirement Saving." *Fiscal Studies* 28(2): 143–170.

Barrick, Murray R., and Michael K. Mount. 1991. "The Big Five Personality Dimensions and Job Performance: A Meta-Analysis." *Personnel Psychology* 44(1): 1–26.

Blumberg, Stephen J., and Julian V. Luke. 2016. *Wireless Substitution: Early Release of Estimates from the National Health Interview Survey, January–June 2016.* Hyattsville, MD: National Center for Health Statistics.

Bruine de Bruin, Wändi, Andrew M. Parker, and Baruch Fischoff. 2007. "Individual Differences in Adult Decision-Making Competence." *Journal of Personality and Social Psychology* 92(5): 938–956.

Callegaro, Mario, and Charles DiSogra. 2008. "Computing Response Metrics for Online Panels." *Public Opinion Quarterly* 72(5): 1008–1032.

Chard, Richard E., David Rogofsky, and Joanne Yoong. 2017. "Wealthy or Wise: How Knowledge Influences Retirement Savings Behavior." *Journal of Behavioral and Social Sciences* 4(3): 164–180.

Chien, Sandy, Nancy Campbell, Chris Chan, Orla Hayden, Michael Hurd, Regan Main, Joshua Mallett, Craig Martin, Colleen McCullough, Erik Meijer, Michael Moldoff, Philip Pantoja, Susann Rohwedder, and Patricia St. Clair. 2015. *RAND HRS Data Documentation, Version O.* Santa Monica, CA: RAND Center for the Study of Aging.

Couper, Mick P., Arie Kapteyn, Matthias Schonlau, and Joachim Winter. 2007. "Noncoverage and Nonresponse in an Internet Survey." *Social Science Research* 36(1): 131–148.

Craig, Benjamin M., Ron D. Hays, A. Simon Pickard, David Cella, Dennis A. Revicki, and Bryce B. Reeve. 2013. "Comparison of US Panel Vendors for Online Surveys." *Journal of Medical Internet Research* 15(11): e260.

Dekker, Katie, and Whitney Murphy. 2009. "Address Based Sampling and Address Matching: Experience from REACH U.S." Paper presented at the Proceedings of the American Statistical Association, Section on Survey Research Methods.

Delavande, Adeline, and Charles F. Manski. 2010. "Probabilistic Polling and Voting in the 2008 Presidential Election: Evidence from the American Life Panel." *Public Opinion Quarterly* 74(3): 433–459.

Frederick, Shane. 2005. "Cognitive Reflection and Decision Making." *Journal of Economic Perspectives* 19(4): 25–42.

Groves, Robert M., and Steven G. Heeringa. 2006. "Responsive Design for Household Surveys: Tools for Actively Controlling Survey Errors and Costs." *Journal of the Royal Statistical Society: Series A (Statistics in Society)* 169(3): 439–457.

Hays, Ron D., Honghu Liu, and Arie Kapteyn. 2015. "Use of Internet Panels to Conduct Surveys." *Behavior Research Methods* 47(3): 685–690.

Hilgert, Marianne A., Jeanne M. Hogarth, and Sondra G. Beverly. 2003. "Household Financial Management: The Connection between Knowledge and Behavior." *Federal Reserve Bulletin* 89(7): 309–322.

Iannacchione, Vincent G. 2011. "The Changing Role of Address-Based Sampling in Survey Research." *Public Opinion Quarterly* 75(3): 556–575.

Iannacchione, Vincent G., Jennifer M. Staab, and David T. Redden. 2003. "Evaluating the Use of Residential Mailing Addresses in a Metropolitan Household Survey." *Public Opinion Quarterly* 67(2): 202–210.

John, Oliver P. 1990. "The 'Big Five' Factor Taxonomy: Dimensions of Personality in the Natural Language and in Questionnaires." In *Handbook of Personality: Theory and Research,* edited by Oliver P. John, Richard W. Robins, and Lawrence A. Pervin (66–100). New York, NY: Guilford Press.

Judge, Timothy A., Daniel Heller, and Michael K. Mount. 2002. "Five-Factor Model of Personality and Job Satisfaction: A Meta-Analysis." *Journal of Applied Psychology* 87(3): 530–541.

Judge, Timothy A., Chad A. Higgins, Carl J. Thoresen, and Murray R. Barrick. 1999. "The Big Five Personality Traits, General Mental Ability, and Career Success across the Life Span." *Personnel Psychology* 52(3): 621–652.

Låg, Torstein, Lars Bauger, Martin Lindberg, and Oddgeir Friborg. 2014. "The Role of Numeracy and Intelligence in Health-Risk Estimation and Medical Data Interpretation." *Journal of Behavioral Decision Making* 27(2): 95–108.

Liberali, Jordana M., Valerie F. Reyna, Sarah Furlan, Lilian M. Stein, and Seth T. Pardo. 2012. "Individual Differences in Numeracy and Cognitive Reflection, with Implications for Biases and Fallacies in Probability Judgment." *Journal of Behavioral Decision Making* 25(4): 361–381.

Link, Michael W., Michael P. Battaglia, Martin R. Frankel, Larry Osborn, and Ali H. Mokdad. 2008. "A Comparison of Address-Based Sampling (ABS) Versus Random-Digit Dialing (RDD) for General Population Surveys." *Public Opinion Quarterly* 72(1): 6–27.

Link, Michael W., Gail Daily, Charles D. Shuttles, Tracie L. Yancey, and H. Christine Bourquin. 2009. "Building a New Foundation: Transitioning to Address-Based Sampling after Nearly 30 Years of RDD." Paper presented at the 64th annual conference of the American Association for Public Opinion Research, Hollywood, FL, May 14–17.

Lipkus, Isaac M., Greg Samsa, and Barbara K. Rimer. 2001. "General Performance on a Numeracy Scale among Highly Educated Samples." *Medical Decision Making* 21(1): 37–44.

Lusardi, Annamaria, and Olivia S. Mitchell. 2007. "Financial Literacy and Retirement Preparedness: Evidence and Implications for Financial Education." *Business Economics* 42(1): 35–44.

———. 2011a. "Financial Literacy and Planning: Implications for Retirement Wellbeing." In *Financial Literacy: Implications for Retirement Security and the Financial Marketplace,* edited by Olivia S. Mitchell and Annamaria Lusardi (17–39). New York, NY: Oxford University Press.

———. 2011b. "Financial Literacy and Retirement Planning in the United States." *Journal of Pension Economics and Finance* 10(4): 509–525.

———. 2017. "How Ordinary Consumers Make Complex Economic Decisions: Financial Literacy and Retirement Readiness." *Quarterly Journal of Finance* 7(3).

Peters, Ellen, Judith Hibbard, Paul Slovic, and Nathan Dieckmann. 2007. "Numeracy Skill and the Communication, Comprehension, and Use of Risk-Benefit Information." *Health Affairs* 26(3): 741–748.

Pollard, Michael, and Matthew D. Baird. 2017. *The RAND American Life Panel: Technical Description.* Santa Monica, CA: RAND Labor and Population. https://www.rand.org/content/dam/rand/pubs/research_reports/RR1600/RR1651/RAND_RR1651.pdf.

Rabinovich, Lila, and Joanne Yoong. 2015. "How Do People Want to Learn About Social Security?" CESR-Schaeffer Working Paper No. 2015-021. Los Angeles, CA: University of Southern California Center for Economic and Social Research.

Reyna, Valerie F., Wendy L. Nelson, Paul K. Han, and Nathan F. Dieckmann. 2009. "How Numeracy Influences Risk Comprehension and Medical Decision Making." *Psychological Bulletin* 135(6): 943–973.

Seibert, Scott E., and Maria L. Kraimer. 2001. "The Five-Factor Model of Personality and Career Success." *Journal of Vocational Behavior* 58(1): 1–21.

Shanahan, Michael J., Patrick L. Hill, Brent W. Roberts, Jacquelynne Eccles, and Howard S. Friedman. 2014. "Conscientiousness, Health, and Aging: The Life Course of Personality Model." *Developmental Psychology* 50(5): 1407–1425.

Sherr, Susan, and David Dutwin. 2009. "Comparing Random Digit Dial (RDD) and United States Postal Service (USPS) Address-Based Sample Designs for a General Population Survey: The 2008 Massachusetts Health Insurance Survey." Paper presented at the Proceedings of the American Statistical Association, Section on Survey Research Methods.

Shook-Sa, Bonnie E., Douglas B. Currivan, Joseph P. McMichael, and Vincent G. Iannacchione. 2013. "Extending the Coverage of Address-Based Sampling Frames Beyond the USPS Computerized Delivery Sequence File." *Public Opinion Quarterly* 77(4): 994–1005.

Sinayev, Aleksandr, and Ellen Peters. 2015. "Cognitive Reflection vs. Calculation in Decision Making." *Frontiers in Psychology*, 6(532): 1–16.

Soldz, Stephen, and George E. Vaillant. 1999. "The Big Five Personality Traits and the Life Course: A 45-Year Longitudinal Study." *Journal of Research in Personality* 33(2): 208–232.

Thoresen, Carl J., Jill C. Bradley, Paul D. Bliese, and Joseph D. Thoresen. 2004. "The Big Five Personality Traits and Individual Job Performance Growth Trajectories in Maintenance and Transitional Job Stages." *Journal of Applied Psychology* 89(5): 835–853.

Tourangeau, Roger, Michael Brick, Sharon Lohr, and Jane Li. 2017. "Adaptive and Responsive Survey Designs: A Review and Assessment." *Journal of the Royal Statistical Society: Series A (Statistics in Society)* 180(1): 203–223.

Tourangeau, Roger, Frederick G. Conrad, and Mick P. Couper. 2013. *The Science of Web Surveys*. New York, NY: Oxford University Press.

Utkus, Stephen P., and Jean A. Young. 2011. "Financial Literacy and 401(k) Loans." In *Financial Literacy: Implications for Retirement Security and the Financial Marketplace,* edited by Olivia S. Mitchell and Annamaria Lusardi (59–75). New York, NY: Oxford University Press.

Wagner, James. 2013. "Adaptive Contact Strategies in Telephone and Face-to-Face Surveys." *Survey Research Methods* 7(1): 45–55.

Weller, Joshua A., Nathan F. Dieckmann, Martin Tusler, C. K. Mertz, William J. Burns, and Ellen Peters. 2013. "Development and Testing of an Abbreviated Numeracy Scale: A Rasch Analysis Approach." *Journal of Behavioral Decision Making* 26(2): 198–212.

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

PERSPECTIVES

Accounting for Geographic Variation in Social Security Disability Program Participation

by John Gettens, Pei-Pei Lei, and Alexis D. Henry*

There is wide geographic variation in Social Security Disability Insurance and Supplementary Security Income participation across the United States. Some policymakers and members of the public may assume that interregional administrative inconsistencies are a major reason for the geographic variation. To test this assumption, and to reveal other potential explanations for the variation, we decompose the total variation into components by examining regional differences in disability prevalence and in program participation among persons with disabilities as well as the correlation between those two factors. We further decompose the variation in participation among persons with disabilities into socioeconomic components. Our findings strongly suggest that geographic variation in program participation is mainly an indication of geographic variation in disability prevalence and socioeconomic characteristics and that inconsistency in program administration is not a major reason for the variation.

Introduction

There is wide geographic variation in Social Security Disability Insurance (DI) and Supplementary Security Income (SSI) participation rates (participants as a percentage of the working-age population). For the period 2009–2011, we calculate DI participation rates ranging from 0.4 percent in Aleutians West County, Alaska to 21.0 percent in Buchanan County, Virginia. SSI participation rates range from 0.1 percent in Pitkin County, Colorado to 21.0 percent in Owsley County, Kentucky.[1] The variation is large; however, what accounts for the variation is not well understood, and its significance for DI/SSI is not known.[2]

One potential explanation is inconsistent program administration. The Social Security Advisory Board (2001, 2012a, 2012b) has reported geographic inconsistencies in DI/SSI program administration—specifically, in allowance and denial rates, bases for initial awards and denials, and disability examiner salary levels and attrition rates—and these inconsistencies could underlie geographic variation in program participation. The Board has expressed concern that the Social Security Administration (SSA) lacks the information needed to determine whether the inconsistencies in program administration cause inconsistent outcomes—and this in turn raises questions about program integrity (Social Security Advisory Board 2001). Besides inconsistent program administration, other plausible explanations for geographic variation in DI/SSI participation include variations in disability prevalence, demographic characteristics, employment opportunities for people with disabilities, and health care and public assistance program access.

Selected Abbreviations

ACS	American Community Survey
CAPUMA	county-aligned Public Use Microdata Area
DI	Disability Insurance
PUMA	Public Use Microdata Area
SSA	Social Security Administration
SSI	Supplemental Security Income

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In the absence of empirical analysis explaining the geographic variation in program participation, some policymakers and members of the public assume that administrative inconsistency is a major underlying cause.[3] In this study, we decompose the geographic variation in participation into its component variations. This approach allows us to determine the relative importance of each component. We find that nearly all of the variation in program participation is explained by variation in disability prevalence and certain socioeconomic factors. This finding strongly suggests that inconsistent program administration is not a major cause of the geographic variation.

Participation in DI/SSI is contingent on severe disability; conceptually, participants are thus restricted to the subpopulation of persons with disabilities and cannot be part of the subpopulation of persons without disabilities. For this reason, the geographic variation in DI/SSI participation is the composite of two component geographic variations: that of the prevalence of disability and that of DI/SSI participation *among persons with disabilities.* We therefore seek to determine how much of the overall variation is attributable to each of those two components. In addition, we further decompose the variation in DI/SSI participation among persons with disabilities into subcomponents defined by selected demographic and labor market characteristics.

To the best of our understanding, this research is the first to use variance decomposition methods to analyze the geographic variation. Prior research has generally used regression methods, which are well-suited to describing associations and to estimating the total explained variance. However, regression methods do not account for the relative importance of the components to the total variation. Also to the best of our understanding, our research is among the first to examine the geographic variation in participation specifically among persons with disabilities.[4] Prior research examined the variation among all persons, with and without disabilities. As we discuss in the Methods section, the interpretation of results and assessment of policy implications are more straightforward when based on analysis of persons with disabilities.

This article consists of eight sections, including this introduction. The second section reviews the prior literature. The third section discusses our methods and describes the variance decomposition measures. The fourth section discusses our data. The fifth section presents our results. It includes statistical tables and thematic maps that describe the geographic variations in DI/SSI participation, disability prevalence, and DI/SSI participation among persons with disabilities. It also includes the variance decomposition estimates. The final three sections respectively discuss the findings, consider the limitations of the study, and summarize the implications of the analysis.

Previous Literature

Conceptually, participation in DI or SSI is determined by the interaction of the demand for DI/SSI among people with disabilities and the supply of benefits from the federal government (Rupp and Stapleton 1998). Demand is driven by the relative costs and benefits of individuals' participation versus nonparticipation. The supply of benefits is determined by program policy and operational procedures. Abundant literature examines factors that affect the demand and supply of benefits. Much of that research was conducted to explain the growth in the DI caseload, which has approximately doubled in the last 30 years (Daly, Lucking, and Schwabish 2013). A substantial majority of the growth can be attributed to changes in the size and age/sex composition of the labor force (Liebman 2015; Zayatz 2015; Pattison and Waldron 2013; Daly, Lucking, and Schwabish 2013); however, studies indicate that other factors also affect the supply of and demand for disability benefits. The literature informs our study by identifying factors affecting supply or demand that vary across geographic regions.

The geographic variation in DI/SSI participation was first described in the early 1990s in studies such as McCoy, Davis, and Hudson (1994) and Nelson (1994). Many subsequent studies have found that area differences in labor markets affect benefit demand (for example, McVicar 2006). Using local-area labor market variations based on a coal boom and subsequent bust, Black, Daniel, and Sanders (2002) found that permanent job creation and destruction have a larger effect on DI and SSI use than transitory local-area labor market changes do. A number of studies have found that adverse state conditions such as high unemployment or employment contractions are associated with increases in DI application (Autor and Duggan 2003; Burkhauser, Butler, and Weathers 2001/2002; Rupp and Stapleton 1995; Soss and Keiser 2006; Guo and Burton 2012; Coe and others 2011). In research indirectly related to demand, studies have found a negative association between state unemployment rates and disability program allowance rates, suggesting that areas with higher unemployment have a lower proportion of DI applicants with severe disabilities and that administrative procedures are likely to screen out applications filed by claimants without severe disabilities (Rupp 2012; Strand 2002; Rupp and Stapleton 1995).

State policies and programs may also affect the demand for DI. Studies have found that state variation in health insurance availability and cost, mandated employer-sponsored disability insurance, general assistance, unemployment benefits, and workers' compensation affect DI application rates (Maestas, Mullen, and Strand 2013; Coe and others 2011; Guo and Burton 2012; Rupp and Stapleton 1995; Rutledge 2012).

Studies have also investigated possible inconsistencies in program administration and whether state-by-state variations could affect DI/SSI supply. Strand (2002) estimated that approximately half of the interstate variation in allowance rates is associated with economic, demographic, and health factors external to program administration. Studies have suggested that allowance rates are affected by political or bureaucratic factors, as governors and other state officials exert influence on program administration (Iyengar and Mastrobuoni 2014; Keiser 2001). Woehl (2015) found that increasing workloads among disability determination workers and administrative law judges resulted in greater likelihood that the disability decision would err "on the side of awarding benefits."

Using regression methods, some studies have decomposed the state variation in DI/SSI application or participation rates into "explained" and "unexplained" components. Rupp (2012) estimated that demographic factors, diagnostic factors, unemployment rates, state fixed effects, and time fixed effects accounted for approximately 75 percent of the state variation in DI and SSI allowance rates. Coe and others (2011) estimated that health status, demographics, and employment status explain over 70 percent of the state variation in DI application rates. Soss and Keiser (2006) estimated that differences in disability prevalence, demographic factors, unemployment, poverty, the availability of civil society organizations, the political ideology of state officials, and the generosity of state public assistance explain 59 percent of state variation in DI application volume and 75 percent of state variation in SSI application. Ruffing (2015) estimated that differences in socioeconomic characteristics such as education, median age, foreign-born share of the population, industry mix, poverty rate, and unemployment rate account for 84 percent of state variation in persons participating in either DI or SSI. The fact that these studies estimate comparable percentages of explained variation using different explanatory variables suggests high correlations between observed and unobserved explanatory factors. It is therefore difficult to determine the relative importance of discrete components in accounting for the overall variation. As we discuss below, the variance decomposition methods used in this study better account for the contributions of the discrete components.

Geographic variation in disability prevalence and health condition may also affect DI and SSI demand. Some studies control for disability or health when estimating the effects of supply or demand factors. Other research has estimated state-level variation in health or disability effects directly. Rutledge and Wu (2014) found that poor health increases SSI application and participation. Similarly, Coe and others (2011) found that poor health increases DI application. Soss and Keiser (2006) found that DI and SSI application rates are positively associated with disability prevalence. These studies include health or disability as an independent factor in regression models of DI/SSI participation. Below, we discuss the advantages of separately analyzing the variations in disability prevalence and in program participation among the population with disabilities.

Methods

We decompose the variation in DI/SSI participation in three operations. We first decompose the overall variation in participation into two component variations: in disability prevalence and in the participation rate among persons with disabilities. Second, we decompose the variation in program participation among persons with disabilities into socioeconomic subcomponents. We do this by using principal-components analysis to determine uncorrelated components, for which the variance contribution of each subcomponent can then be calculated. Finally, we decompose the unexplained variation from the second decomposition into two factors, within-state and between-state variation, using fixed-effect regression methods.

The variance decomposition methods apply equally to the DI and SSI programs. However, because DI is a social insurance program and SSI is a means-tested program, we expect that the variance decomposition accounting for them will differ and we produce separate variance decomposition estimates for each. Nevertheless, recall that we use the term "DI/SSI participation" in this article to refer to participation in either program. Thus, to reiterate, it may include but is not restricted to concurrent participation in both programs.

Disability Prevalence and Program Participation Decomposition

We define the variable g as the geographic area index for each applicable measure of geographic variation. The DI/SSI participation rate (*part*) in a geographic area is defined by equation 1:

$$part_g = \frac{npart_g}{ntotal_g}, \tag{1}$$

where *npart* is the number of DI/SSI participants and *ntotal* is the total number of working-age persons.

The DI/SSI participation rate among persons with disabilities (*partdis*) is defined by equation 2:

$$partdis_g = \frac{npart_g}{ndisability_g}, \tag{2}$$

where *ndisability* is the number of working-age persons with disabilities.

Disability prevalence (*disprev*) is defined by equation 3:

$$disprev_g = \frac{ndisability_g}{ntotal_g}. \tag{3}$$

By definition, $part_g$ is equal to the product of $disprev_g$ and $partdis_g$ (equation 4):

$$part_g = disprev_g \times partdis_g. \tag{4}$$

The variance relationship is given in equation 5:

$$Var(part) = Var(disprev \times partdis), \tag{5}$$

which indicates that the variance of *part* is the variance of the product of *disprev* and *partdis*. The variance of *part* is dependent on the variance of *disprev,* the variance of *partdis,* and the correlation between *disprev* and *partdis*. Our objective is to determine the relative contributions of *disprev* and *partdis* to the variance of *part*. To facilitate that determination, we use the natural log transformation of equation 4, which is additive (equation 6):

$$\ln(part) = \ln(disprev) + \ln(partdis). \tag{6}$$

The variance relationship is given in equation (7):

$$\begin{aligned} Var\left[\ln(part)\right] &= Var\left[\ln(disprev)\right] \\ &+Var\left[\ln(partdis)\right] \\ &+2Cov\left[\ln(disprev), \ln(partdis)\right]. \end{aligned} \tag{7}$$

We define three variance decomposition measures. The first is the percentage of variance in the natural log of the DI/SSI participation rate attributed to the natural log of disability prevalence; we call this measure *percentage variance in disability* or $PV_{disability}$ (equation 8):

$$PV_{disability} = \frac{Var\left[\ln(disprev)\right]}{Var\left[\ln(part)\right]} \times 100. \tag{8}$$

The second is the percentage of variance in the natural log of DI/SSI participation among persons with disabilities; we call this measure *percentage variance in participation* or $PV_{participation}$ (equation 9):

$$PV_{participation} = \frac{Var\left[\ln(partdis)\right]}{Var\left[\ln(part)\right]} \times 100. \tag{9}$$

The third is the percentage of variance in the natural log of DI/SSI participation among persons with disabilities that is due to the correlation between the prevalence of disability and the DI/SSI participation rate; this measure, the *percentage variance in correlation,* or $PV_{correlation}$, accounts—as its name suggests—for the variation that is due to correlation (equation 10):

$$PV_{correlation} = 100 - PV_{disability} - PV_{participation}. \tag{10}$$

If the prevalence of disability *disprev* and the DI/SSI participation rate among those with disabilities *partdis* are not correlated, the sum of $PV_{disability}$ and $PV_{participation}$ is approximately 100 percent. If *disprev* and *partdis* are positively correlated, the sum of $PV_{disability}$ and $PV_{participation}$ is less than 100 percent and the sum decreases as the positive correlation increases. Conversely, the sum is greater than 100 percent in the case of a negative correlation and the sum increases as the negative correlation increases.

Participation Among Persons with Disabilities Decomposition

To reiterate, $PV_{participation}$ and $PV_{disability}$ indicate how much of the variance in DI/SSI participation is attributed to variation in DI/SSI participation among persons with disabilities and how much is attributed to variation in disability prevalence. We use principal-components analysis to further decompose the variation in DI/SSI participation among persons with disabilities into socioeconomic subcomponents. This study does not further decompose the variation in disability prevalence, which we defer to future research.

As noted earlier, area-level patterns in numerous socioeconomic characteristics are expected to be associated with DI/SSI participation among persons with disabilities. These include the relative prevalence of certain demographic, income, and poverty characteristics; disability types; labor market conditions; and public assistance participation and health insurance coverage rates. We expect that some area-level socioeconomic characteristics will be endogenous if they are based on the population of persons with disabilities. For example, an area may have a low employment rate among persons with disabilities because of both the negative employment effects of DI/SSI participation and the area's unfavorable economic conditions. When we expect that a characteristic would be endogenous if it were calculated based on the population of persons with disabilities, we address that limitation by calculating variables based on the population of persons without disabilities. We do so because we expect that the area-level conditions reflected in characteristics based on persons without disabilities are also experienced by persons with disabilities. For example, a high labor-force participation rate likely indicates the area labor market conditions experienced by persons both with and without disabilities. In other words, we define variables based on the population of persons with disabilities when the characteristic (for example, percentage female) is not expected to be affected by DI/SSI participation. Box 1 shows which population subgroup (with or without disabilities) we used to calculate each variable. An ordinary least squares regression of DI/SSI participation among persons with disabilities versus socioeconomic characteristics would provide an indication of overall explained variation; however, because the variables are correlated, it would not support estimates of the variance contribution of separate subcomponents (for example, labor market conditions). To estimate the subcomponent contributions, we use principal-component analysis.

By using principal-component analysis, we transform the socioeconomic characteristics into a smaller set of subcomponents that are uncorrelated. The variance contribution of each subcomponent to the total variance in $partdis_g$ can be determined by the square of the correlation between $partdis_g$ and the subcomponent. Because the subcomponents are a transformation of the original socioeconomic variables, a given subcomponent's meaning is not obvious. To determine its meaning, we examine the correlation of a given subcomponent with the original variables. For example: Referring to the variables in Box 1, a subcomponent that had a strong

Box 1.
Population subgroup for which each socioeconomic variable was calculated

Population with disabilities

- Demographics
  - Average age
  - Percentage—
    - Female
    - Black
    - Hispanic
    - Not speaking English at home
    - Born in United States
    - U.S. citizen
    - Never married
    - High school diploma or less
- Disability
  - Percentage reporting difficulty with—
    - Hearing
    - Independent living
    - Self-care
    - Vision
  - Percentage reporting—
    - Ambulatory difficulty
    - Cognitive difficulty

Population without disabilities

- Income and poverty
  - Percentage in poverty [a]
  - Average dollar amount of annual—
    - Personal income
    - Household income
    - Earned income
  - Percentage with—
    - Public assistance
    - Health insurance coverage
- Labor market indicators
  - Labor force participation rate among—
    - Men
    - Women
  - Self-employment rate
  - Average hours usually worked per week
  - Percentage of workers with 26 or fewer weeks worked
  - Occupation type
    - Service
    - Production
    - Sales
    - Construction and maintenance
    - Management
  - Industry group
    - Manufacturing
    - Education and health services
    - Professional and business services
    - Wholesale and retail trade
    - Leisure and hospitality
    - Other industries

SOURCE: Authors' definitions.

a. Having income of less than 100 percent of the federal poverty level.

positive correlation with area average annual personal income, average annual household income, and average annual earned income and had a strong negative correlation with area poverty level was interpreted to represent area income and poverty. We will revisit the subcomponents and discuss their correlations in the Results section under "Participation Among Persons with Disabilities Decomposition Estimates."

Unexplained Between-State and Within-State Decomposition

Principal-component analysis decomposes the variance in DI/SSI participation among persons with disabilities into observed socioeconomic subcomponents. However, the principal components do not capture all of the variance of the original socioeconomic variables; unobserved factors also account for some of the variance. Further, the principal-component analysis was conducted using substate geographic areas and it is possible that some of the unaccounted variance may occur at the state level. For example, differing state welfare policies may result in state-level variation in DI/SSI participation among persons with disabilities. It is also possible that factors that vary between states but are not determined by state policy—for example, employment discrimination against persons with disabilities, as well as attitudes about employment among persons with disabilities—may contribute to state-level variation in DI/SSI participation. To determine the state-level variation, we first estimated a regression without state fixed effects (total unexplained) and then added state fixed effects to determine how much more of the variation those variables explained (unexplained between-state).

Advantages of Variance Decomposition Methods

The variance decomposition approach has advantages over the regression approach used in prior research such as Rupp (2012), Coe and others (2011), Soss and Keiser (2006), and Ruffing (2015). For illustrative purposes, we assume that the data-generating processes for *disprev* and *partdis* are represented by equations 11 and 12. We assume that these two processes differ. For example, we expect that age has an independent effect on both *disprev* and *partdis*:

$$disprev_g = \beta X_g; \tag{11}$$

$$partdis_g = \alpha Y_g. \tag{12}$$

In equation 11, X_g is a vector of variables affecting *disprev* and β is a vector of their effects. In equation 12, Y_g is a vector of variables affecting *partdis* and α is a vector of their effects. Some variables may independently affect both *disprev* and *partdis* and some variables may separately affect only *disprev* or *partdis*. For variables that affect both data-generating processes, the magnitudes and signs of the effects may differ. Using a research method that examines the variation in *part* directly, for example by using regression methods to estimate the parameters of equation 13,

$$part_g = \gamma Z_g, \tag{13}$$

will reveal associations and the total explained variation; however, the associations will not reveal the effects or explained variance of the separate data-generating processes (equations 11 and 12).

The estimates of equation 13 will not determine how much of the explained variation is because of *disprev* or *partdis* or the correlation between *disprev* and *partdis*. It will be difficult to interpret the estimated effects, for example the effect of age, because the estimate will not reveal the independent effects on *disprev* or *partdis*. Thus, studies based on models similar to equation 13 limit researchers' ability to explain the variation in DI/SSI participation, interpret the results, and assess policy implications. Separate analysis of the variation in *disprev* or *partdis* is preferred.

Data

We use data from the 2009–2011 American Community Survey (ACS) Public Use Microdata Sample to estimate the following substate statistics: the number of persons with disabilities, the number of working-age (18–64) persons, and socioeconomic characteristics. We choose the years 2009–2011 because substate geographic boundaries and ACS disability questions were consistent during that period. We do not include individuals living in institutional group quarters because DI/SSI participation is precluded for a large majority of the group-quarters population—those who are incarcerated—and the data do not allow us to differentiate that population from those living in other institutional group quarters, such as nursing homes.

We first determine the number of persons with disabilities. An ACS respondent who answers "yes" to any of the following questions is considered to have a disability:

- Is this person deaf or does he/she have serious difficulty hearing?
- Is this person blind or does he/she have serious difficulty seeing even when wearing glasses?

- Because of a physical, mental, or emotional condition, does this person have serious difficulty concentrating, remembering, or making decisions?
- Does this person have serious difficulty walking or climbing stairs?
- Does this person have difficulty dressing or bathing?
- Because of a physical, mental, or emotional condition, does this person have difficulty doing errands alone such as visiting a doctor's office or shopping?

We use publicly available data from SSA reports to determine the county-level numbers of DI and SSI participants (SSA 2012b, Table 4; 2012c, Table 2). For DI participants, we observe disabled workers but do not include disabled widow(er)s or disabled adult children because data for those groups were not available across geographic areas. In 2011, there were approximately 8.5 million disabled workers and 1.2 million disabled widow(er)s and disabled adult children (SSA 2015, Table 3). SSI payments include both federal and state supplementation payments. The available data do not distinguish federal SSI recipients from recipients of federally administered state supplementation payments across geographic areas. In December 2010, there were approximately 6.5 million federal payment recipients and 167,000 state supplementation–only recipients (SSA 2012a, Table 7.A1).

Our analysis assumes that people who meet the SSA standard for disability (with the exception of the requirement that the person's earnings are less than the amount that signifies substantial gainful activity) are a subgroup of the population of persons with disabilities.[5] However, if ACS survey data are used to identify persons with disabilities, that assumption is not necessarily valid. Using Current Population Survey (CPS) data matched with SSA administrative records, Burkhauser, Houtenville, and Tennant (2014) found that the CPS questions on disability only identified approximately 63 percent of DI and SSI beneficiaries. The CPS and the ACS ask the same disability questions, suggesting that disability is also underreported in the ACS. The underreporting of disability will not substantially bias the decomposition estimates, provided the underreporting is not associated with DI/SSI participation.[6]

However, it is possible that the underreporting of disability is associated with DI/SSI participation. For example, DI/SSI participants, wishing to justify their participation, may be more likely to report their disabilities than are nonparticipants with equivalent disabilities. This justification bias would result in a positive correlation between the bias in the estimates of disability prevalence (*disprev*) and of DI/SSI participation (*part*), which would in turn bias the variance decomposition estimates.[7] In such a case, the variance contribution of disability prevalence ($PV_{disability}$) would be overestimated and the variance contribution of DI/SSI participation among persons with disabilities ($PV_{participation}$) would be underestimated. The bias in the variance contribution of correlation ($PV_{correlation}$) depends on the relative dispersion of disability prevalence compared with that of DI/SSI participation among persons with disabilities. The coefficient of variation (CV) is a measure of the standardized dispersion of a distribution and is defined as the ratio of the standard deviation to the mean. If the CV of disability prevalence is greater than the CV of DI/SSI participation among persons with disabilities, the variance contribution of correlation will be underestimated. If the opposite is true, the variance contribution of correlation will be overestimated.[8] We assess the potential effect of justification bias on the variance decomposition estimates in the Results section under "Bias Assessment."

Geographic Regions

ACS data on disability prevalence are available at the Public Use Microdata Area (PUMA) level of geographic detail. PUMAs are defined by the Census Bureau and consist of intrastate regions of approximately 100,000 to 200,000 people. SSA data on DI/SSI participation are available at the county level for all but 104 counties.[9] To facilitate analysis of disability prevalence and DI/SSI participation, we define a common geography that combines PUMAs and counties and call the resulting units county-aligned Public Use Microdata Areas (CAPUMAs). We define CAPUMAs as the smallest areas that intersect one or more PUMAs and one or more counties. For example, for areas where the PUMA boundary matches the county boundary, the CAPUMA is equivalent to both the PUMA and the county. For areas where the PUMA contains multiple complete counties, the CAPUMA is equivalent to the PUMA. Conversely, for areas where the county contains multiple complete PUMAs, the CAPUMA is equivalent to the county.[10] We combined the 2,069 PUMAs and 3,142 counties into 937 CAPUMAs with estimated working-age (18–64) populations ranging widely, from about 50,000 to about 6.3 million people.

Results

DI participation varies widely across CAPUMAs. Overall, the average DI participation rate among working-age persons is 5.4 percent, with a standard deviation of 2.1 (Table 1), and the CAPUMA-level participation rates range from 1.0 percent to 16.6 percent, as indicated by the lower- and upper-bound values for the participation-rate quintiles shown in the legend to Chart 1.

Chart 1 is a choropleth map showing the variation in DI participation across the United States by CAPUMA. Because of varying population density across areas, some geographically large CAPUMAs represent very few people, and some small areas represent many. For example, the Coconino County, Arizona CAPUMA land area is 18,600 square miles, yet it includes only about 90,000 working-age people and approximately 2,000 DI beneficiaries. By contrast, the Kings County (Brooklyn), New York CAPUMA is small, approximately 71 square miles, yet it includes 1.6 million working-age people and about 51,000 DI beneficiaries.

Chart 1 shows both within-state and between-state variation. In Georgia, for example, DI participation is relatively low in the vicinity of Atlanta and higher in other areas of the state. The two CAPUMAs that include greater Atlanta, Fulton County and Dekalb County, have respective DI participation rates of 2.9 percent and 3.1 percent. By contrast, the DI participation rate is 7.9 percent in the southeast Georgia CAPUMA containing Atkinson, Bacon, Brantley, Charlton, Cinch, Coffee, Pierce, and Ware Counties.

Chart 1 indicates that many high-population urban areas have relatively low DI participation. The CAPUMAs in the northeast corridor from Washington, DC to New York City and those that include and surround Atlanta, Chicago, San Antonio, Dallas, Los Angeles, and San Francisco are generally in the lowest quintile for DI participation. For example, the CAPUMA of Cook County, Illinois, which includes Chicago, has a working-age population of 3.3 million and a DI participation rate of 3.2 percent. Similarly, the Harris County, Texas CAPUMA includes Houston and has a working-age population of 2.6 million and a DI participation rate of 2.6 percent. Participation is generally low in CAPUMAs in the midwestern and western states of North Dakota, South Dakota, Nebraska, Montana, Wyoming, and Utah. Chart 1 also indicates high DI participation in CAPUMAs across southeastern states including Arkansas, Mississippi, Alabama, Tennessee, Kentucky, and West Virginia. For example, two adjacent CAPUMAs—one in eastern Kentucky (Boyd, Carter, Elliot, and Lawrence Counties) and one in western West Virginia (Lincoln, Logan, Mingo, and Wayne Counties)—have DI participation rates of 11.1 percent and 12.9 percent, respectively.

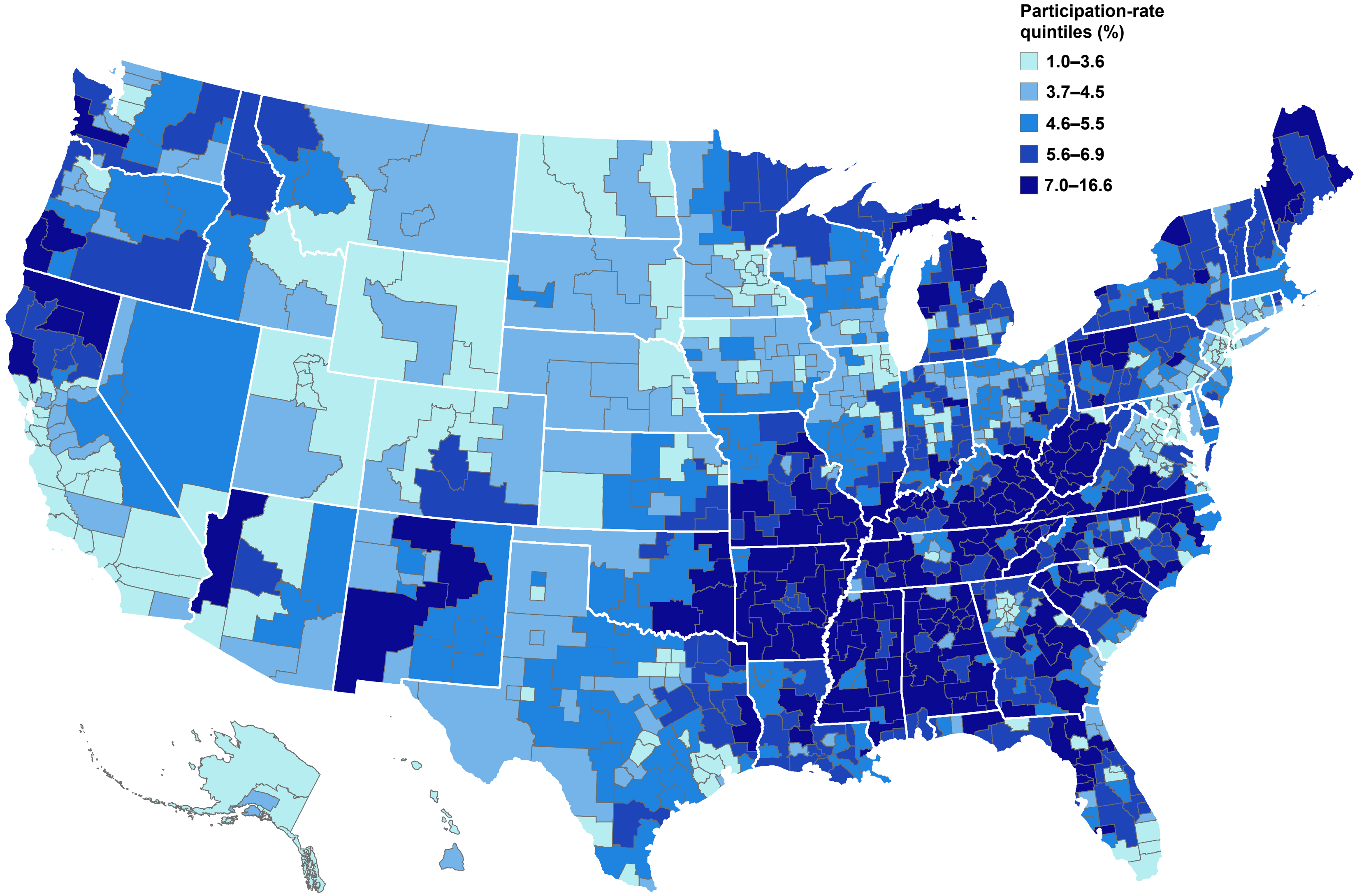
Chart 2 shows the same data for SSI participation that Chart 1 shows for DI. The national average SSI participation rate of 2.8 percent (standard deviation = 1.6) is lower than that for DI (Table 1); however, the CAPUMA-level range of SSI participation rates, from 0.2 percent to 13.7 percent (indicated in the legend to Chart 2), is roughly similar to that for DI. SSI participation varies both within and between states, as does DI participation. Also similar to DI is that many CAPUMAs in the northeast corridor, and in or surrounding other major U.S. cities, have relatively low SSI participation. However, there are exceptions; for instance, the Bronx County, New York CAPUMA and the city of Baltimore, Maryland CAPUMA have high SSI participation (6.6 percent and 6.2 percent, respectively). Chart 2 shows many high SSI participation CAPUMAs in southeastern states including Arkansas, Louisiana, Mississippi, Alabama, Georgia, Kentucky, and West Virginia. The four CAPUMAs with the highest SSI participation, all exceeding 10 percent, are in southeastern Kentucky.[11]

Table 1.
Disability prevalence and DI and SSI participation rates among working-age persons (in percent)

Statistic	Disability prevalence	DI participation rate: Persons with disabilities	DI participation rate: Overall	SSI participation rate: Persons with disabilities	SSI participation rate: Overall
Mean	12.0	45.1	5.4	22.7	2.8
Standard deviation	3.9	7.9	2.1	7.9	1.6
75th percentile	14.2	50.2	6.5	26.3	3.5
Median	11.4	45.1	5.1	21.2	2.5
25th percentile	9.1	39.8	1.7	17.4	1.8

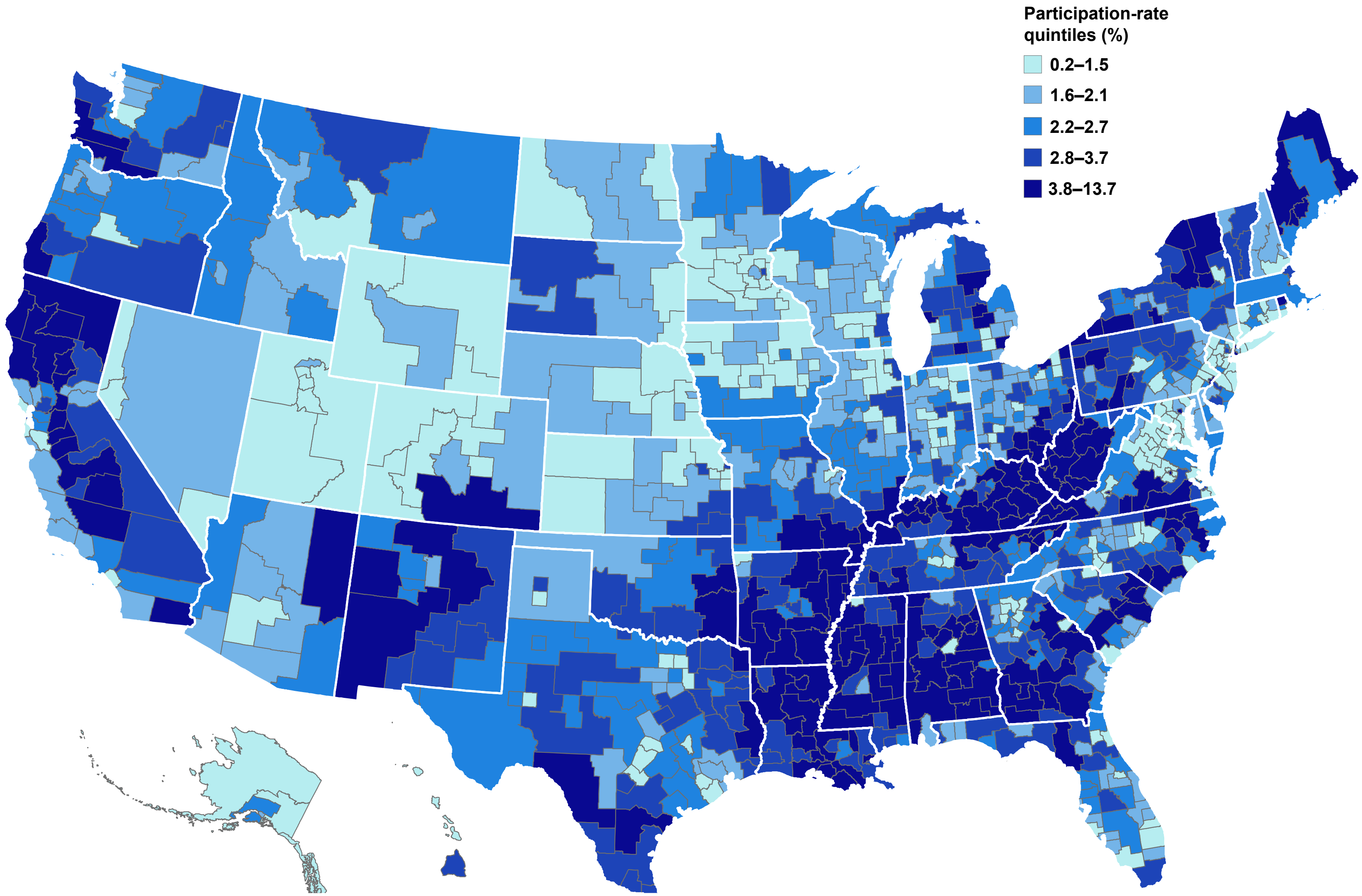
SOURCE: Authors' calculations based on ACS data and SSA reports.

Chart 1.
Geographic distribution of DI participation: CAPUMAs, by working-age participation-rate quintile. 2009–2011



SOURCE: Authors' calculations based on ACS data and SSA reports.

Chart 2.
Geographic distribution of SSI participation: CAPUMAs, by working-age participation-rate quintile. 2009–2011



SOURCE: Authors' calculations based on ACS data and SSA reports.

There is also wide geographic variation in disability prevalence and DI/SSI participation among persons with disabilities. Table 1 provides summary nationwide statistics. The average disability prevalence is 12.0 percent (standard deviation = 3.9). The average DI participation rate among working-age persons with disabilities is 45.1 percent (standard deviation = 7.9) and the average SSI participation rate among working-age persons with disabilities is 22.7 percent (standard deviation = 7.9).

Disability Prevalence and Program Participation Decomposition Estimates

To determine how much of the variance in DI/SSI participation across CAPUMAs is because of the variation in disability prevalence and how much is because of variation in DI/SSI participation among persons with disabilities, we estimated the variance decomposition measures $PV_{disability}$ and $PV_{participation}$, as described in the Methods section.

Approximately two-thirds (67.9 percent) of the variance in DI participation is attributable to the variation in disability prevalence and approximately one-fifth (21.2 percent) is attributable to the variation in DI participation among persons with disabilities (Table 2). The correlation between area disability prevalence and area DI participation among persons with disabilities is relatively low (0.12; not shown) and it accounts for approximately one-tenth (10.9 percent) of the variation in DI participation.

For SSI participation, the variance attributable to variation in disability prevalence (37.5 percent) and the variance attributable to variation in SSI participation among persons with disabilities (36.7 percent) are approximately equal. There is weak correlation between area disability prevalence and area SSI participation among persons with disabilities (0.31; not shown) and the correlation accounts for 25.8 percent of the variation.

Table 2.
Geographic variation in DI/SSI participation: Variance decomposition summary estimates (percentage distributions, by factor)

Statistic	DI	SSI
Disability prevalence	67.9	37.5
Participation among persons with disabilities	21.2	36.7
Correlation	10.9	25.8

SOURCE: Authors' calculations based on ACS data and SSA reports.

The results provide an indication of the hypothetical variation in DI/SSI participation that would exist if there were variation in only one component, either disability prevalence or DI/SSI participation among persons with disabilities. For example, if disability prevalence were geographically constant, the cross-CAPUMA variation in DI participation would be approximately 21 percent of the current variation and the cross-CAPUMA variation in SSI participation would be approximately 37 percent of the current variation. Correspondingly, if program participation among persons with disabilities were geographically constant, the cross-CAPUMA variation in DI participation would be approximately 68 percent of the current variation and the cross-CAPUMA variation in SSI participation would be approximately 38 percent of the current variation.

Participation Among Persons with Disabilities Decomposition Estimates

To further decompose the variance of DI/SSI participation among persons with disabilities, we used principal-components analysis to define uncorrelated socioeconomic subcomponents. That analysis reduced the 37 socioeconomic variables shown in Box 1 to 12 subcomponents in 4 broad categories (Table 3). Those 12 subcomponents account for 84.1 percent of the total variation in the original variables. For each subcomponent, Table 3 also shows the variables that have strong or moderate correlations (positive or negative coefficients with an absolute value of at least 0.50). The subcomponent names were chosen to represent the general meanings of the correlated variables.[12]

Because the subcomponents are uncorrelated, we can calculate the percentage of the total variance in DI/SSI participation among persons with disabilities that is attributable to each subcomponent. For DI, the largest contributions to the variance are those of the Hispanic/non-English subcomponent (10.4 percent), the personal assistance needs subcomponent (7.4 percent), the education/health services subcomponent (7.0 percent), and the age/few cognitive difficulties subcomponent (6.1 percent). The Hispanic/non-English subcomponent is associated with lower levels of DI participation and the personal assistance needs, education/health services, and age/few cognitive difficulties subcomponents are associated with higher levels of DI participation (not shown).[13]

Table 3.
Principal uncorrelated sociodemographic subcomponents, with estimated percentage of attributable variance in DI and SSI participation and correlated variables

Subcomponent	Percentage variance in participation attributable to the subcomponent: DI	SSI	Correlated variables (with correlation coefficients): Positive correlations		Negative correlations	
Demographics and disability						
Hispanic/non-English	10.4	1.6	Hispanic origin	0.93	U.S.-born	−0.90
			English not spoken in home	0.95	U.S. citizen	−0.93
Black/low self-employment	0.5	18.3	Black	0.89	Self-employment	−0.60
			Never married	0.53	Hearing difficulty	−0.56
Age/few cognitive difficulties	6.1	0.1	Average age	0.77	Cognitive difficulty	−0.70
			Ambulatory difficulty	0.54		
Female	0.1	0.2	Female	0.93	. . .	. . .
Personal assistance needs	7.4	5.7	Self-care difficulty	0.85	. . .	. . .
			Independent living difficulty	0.83		
Income and poverty						
Income	1.0	8.1	Average annual personal income	0.93	Poverty status	−0.65
			Average annual household income	0.93		
			Average annual earned income	0.95		
			Professional and business services	0.77		
			Health insurance coverage	0.50		
Labor market						
Manufacturing	3.6	0.1	Production occupation	0.77	Service occupation	−0.60
			Manufacturing industry	0.83		
			Education: high school or less	0.53		
Labor force participation	0.6	3.7	Among men	0.68	≤26 weeks worked	−0.62
			Among women	0.83		
Construction	3.1	0.9	Hours worked per week	0.74	. . .	. . .
			Construction/maintenance occupation	0.67		
			Other industries	0.80		
Sales	0.5	0.1	Sales occupation	0.84	. . .	. . .
			Wholesale/retail trade industries	0.86		
Education/health services	7.0	4.2	Education/health services industries	0.77	. . .	. . .
Public assistance						
Program participation	2.4	10.3	Public assistance	0.82	. . .	. . .

SOURCE: Authors' calculations based on ACS data and SSA reports.

NOTE: . . . = not applicable.

For SSI, the largest contributions to the area variance are those of the black/low self-employment subcomponent (18.3 percent), the public assistance program participation subcomponent (10.3 percent), and the income subcomponent (8.1 percent). The black/low self-employment subcomponent and the public assistance participation subcomponent are associated with higher levels of SSI participation and the income subcomponent is associated with lower levels of SSI participation (not shown). Taken together, these subcomponents likely indicate the economic conditions in an area. Areas with high levels of the black/low self-employment and public assistance subcomponents and low levels of the income subcomponent are likely to be economically disadvantaged.

Unexplained Between-State and Within-State Decomposition Estimates

Although the principal-components analysis decomposes the variance in DI/SSI participation among persons with disabilities into observed socioeconomic subcomponents, unobserved CAPUMA-level and state-level factors account for further variance. Regression analysis decomposes the additional variance into two factors: variance of unobserved CAPUMA-level factors and variance of unobserved state-level factors.

Ordinary least squares regression estimates of equation 12 indicate that CAPUMA-level factors accounted for 50 percent of the variation in DI participation among persons with disabilities and for 63 percent of the variation for SSI. Estimates of the fixed-effects model indicate that in combination, variation in observed CAPUMA-level characteristics and variation between states account for 66 percent of the variation in DI participation (an increase of 16 percentage points) and for 80 percent of the variation in SSI participation (an increase of 17 percentage points). As described in the Methods section, the increase may be attributed to unobserved variation in state policy (involving matters such as health insurance regulation or access to welfare programs) or in other state-level factors (such as employment discrimination against persons with disabilities or attitudes about employment among persons with disabilities). We are not able to determine how much of the increase is attributed to state policy and how much is attributed to other factors. As an approximation, the increase represents the upper limit of the variance attributable to unobserved state policy.[14]

Variance Decomposition Summary

We combine the CAPUMA-level disability/participation variance decomposition, the principal-components variance decomposition, and the regression analysis to obtain an overall decomposition summary (Table 4). For the principal-components variance decomposition, we use five subcomponent categories: demographics and disability, income and poverty, labor market, public assistance, and other.

For DI, the variation in disability prevalence accounts for 67.9 percent of the geographic variation in total participation among working-age persons, variation in DI participation among persons with disabilities accounts for 21.2 percent, and correlation accounts for 10.9 percent. The contribution of participation among persons with disabilities is further decomposed into its components; 10.6 percentage points are attributed to variation in the observed CAPUMA-level characteristics combined, 3.4 percentage points are attributed to variation in unobserved CAPUMA-level characteristics, and 7.2 percentage points are attributed to unobserved state-level characteristics.

For SSI, the variations in disability prevalence and in SSI participation among persons with disabilities contribute approximately equally to the total variance (37.5 percent and 36.7 percent, respectively). Because disability prevalence and SSI participation among persons with disabilities are weakly correlated, correlation contributes approximately 25.8 percent to the

Table 4.
Geographic variation in DI/SSI participation: Variance decomposition estimates (percentage distributions, by factor and subcomponent)

Statistic	DI	SSI
Disability prevalence	67.9	37.5
Participation among persons with disabilities	21.2	36.7
Observed CAPUMA-level characteristics		
Demographics and disability	5.2	9.5
Income and poverty	0.2	3.0
Labor market	3.1	3.3
Public assistance	0.5	3.8
Other	1.6	3.6
Unobserved characteristics		
CAPUMA-level	3.4	6.2
State-level	7.2	7.3
Correlation	10.9	25.8

SOURCE: Authors' calculations based on ACS data and SSA reports.

total variance. The contribution of participation among persons with disabilities is further decomposed: 23.2 percentage points are attributed to variation in the observed CAPUMA-level characteristics combined, 6.2 percentage points are attributed to variation in unobserved CAPUMA-level characteristics, and 7.3 percentage points are attributed to variation in unobserved state-level characteristics.

Bias Assessment

As discussed earlier, the variance decomposition estimates may be biased if self-reports of disability are associated with DI/SSI participation. Justification bias is the most likely reason for an association between self-reports of disability and DI/SSI participation. If justification bias exists, some of the geographic variation in estimated disability prevalence would be attributed to that bias and some would be attributed to the true variation. To assess the possible magnitude of such bias, we estimate the correlation between area disability prevalence and area factors that we expect to be correlated with disability prevalence but are less vulnerable to justification bias. These include mortality, the proportion of persons with diabetes, the proportion of persons with fair or poor health, and the proportion of smokers. If justification bias accounts for a substantial portion of the variation in disability prevalence, we would expect a weak correlation. However, we find strong correlations between disability prevalence and the area factors, ranging from 0.8 to 0.9. This suggests that justification bias, if present, is small. It also suggests that any biases in the variance decomposition estimates associated with justification bias would be small.[15]

Discussion

There has long been concern about possible inconsistencies in DI and SSI program administration across geographic areas. Some observers might assume that inconsistencies in program administration are a major reason for the wide geographic variation in program participation. Our results strongly suggest otherwise. We find that nearly all of the geographic variation in program participation is attributable to variation in disability prevalence and socioeconomic factors and that very little of it could be associated with inconsistencies in program administration.

If geographic inconsistencies in program administration exist, then some people with disabilities may have an incentive to migrate. For example, areas with lenient DI/SSI approval processes might attract migration from areas with more restrictive processes, resulting in geographic variation in program participation. The decomposition results do not indicate such an occurrence. The analysis uses an ACS-based definition of disability that does not distinguish between DI/SSI participants and nonparticipants. If migration based on administrative inconsistency exists, we expect that it affects disability prevalence and DI/SSI participation among people with disabilities similarly. People migrating to a given area to improve their chances of receiving DI/SSI benefits would increase both that area's disability prevalence and its DI/SSI participation among persons with disabilities. If the migration were substantial, the correlation between disability prevalence and DI/SSI participation among persons with disabilities would be high. However, because our results indicate that the correlation is weak, such migration is not implied by the geographic variation in disability prevalence.[16]

Geographic inconsistencies in program administration could conceivably be reflected in variation in socioeconomic characteristics as well. For example, areas with poor economic conditions might be expected to have a higher demand for benefits and more lenient approval processes. In such cases, variation that is due to inconsistencies in program administration would be correlated with one or more principal subcomponents such as area income or poverty. Even if the correlations exist, the decomposition results indicate that inconsistent program administration would not be a major reason for the variation in overall DI/SSI participation. The contribution of each subcomponent of variation is small relative to the total variation. Also, the subcomponents are uncorrelated with one another and thus we do not expect that inconsistencies in program administration would be correlated with more than one subcomponent.

We find that geographic variation in disability prevalence is a major reason for the wide variation in DI/SSI participation. If there were no variation in disability prevalence across CAPUMAs, the variation in DI participation would be reduced by approximately 80 percent and the variation in SSI participation would be reduced by approximately 63 percent. What accounts for the wide geographic variation in disability prevalence across CAPUMAs is not well understood. Future research is needed. The correlations between disability prevalence and DI/SSI participation among persons with disabilities are weak, suggesting that the factors associated with the former differ from the factors associated with the latter. The variation in disability prevalence may exist because of variation in the incidence of disability or in net migration of persons with disabilities relative to persons without disabilities across geographic areas. The incidence of disability could vary across areas because of geographic variation in demographics, health care access or quality, health or disability risk behaviors, risk of injury, or disease prevalence. Net migration could vary because of labor market, cost-of-living, or other area differences. For instance, if individuals without disabilities are more likely than those with disabilities to migrate from areas that are economically weak to areas that are strong, the prevalence of persons with disabilities would increase in economically weak areas relative to that of strong areas. There are strong regional differences in disability prevalence. Analysis of these patterns might help to identify the reasons for the variation.

There are differences between the decomposition of SSI participation among persons with disabilities and that for DI. SSI is a means-tested program and, for the most part, only individuals living in very low-income households are eligible. Thus, we expect that area variation in SSI participation would be associated with variation in area economic conditions, resulting in higher participation in economically disadvantaged areas. Our findings support that expectation. We find that variations in area socioeconomic characteristics associated with economic disadvantage account for the largest contributions to variance in SSI participation among persons with disabilities.

In contrast with SSI, little of the variance in DI participation is associated with area characteristics indicating economic disadvantage. Instead, certain demographic factors contribute most to the DI variance. Areas with higher proportions of people who are Hispanic, speak a language other than English in the home, were not born in the United States, or are noncitizens have lower DI participation. This could reflect access limitations, ineligibility (not enough quarters of coverage), language barriers, discrimination, or other possible factors. It is also possible that the demand for DI varies by ethnicity or country of origin.[17] Further research is needed to determine the causes.

Decomposition analysis also provides insight into how much unobserved state policy factors may contribute to geographic variation in DI/SSI participation. Although we find that unobserved state policies may contribute, their effect appears to be relatively small. Our fixed-effects estimates suggest that the upper limit of the contribution of unobserved state policies is approximately 7 percent.

The decomposition reveals the sources of approximately 90 percent of the variation in DI/SSI participation that Charts 1 and 2 illustrate. Why does some of the variation remain unexplained? There are a number of possible reasons. For example: Our methods rely on cross-sectional data that provide a current snapshot of area characteristics. However, DI/SSI participation depends on both current and past characteristics, such as long-term labor market trends. We are unable to account for characteristics in prior time periods that are uncorrelated with current characteristics. We are also not able to account for migration. DI/SSI participation may be affected by characteristics of a migrant's prior area of residence, for which we are not able to account. Also, area characteristics that we were unable to observe (such as employment discrimination and population density) may vary in ways that affect DI/SSI participation. Lastly, part of the unexplained variation is likely due to estimation errors that affect the survey data with which disability prevalence and area characteristics are calculated.

Publicly available ACS and SSA data for substate areas made this analysis possible. We merged ACS PUMA-level statistics with SSA county-level data to generate CAPUMA-level data. One shortcoming of this approach is that some of the CAPUMAs represent large populations, generally because some counties have large populations. Merging PUMAs and counties obscures some of the local-area variations, particularly in urban areas with dense populations. A PUMA-level analysis could offer improved results because it would more than double the number of observations, reveal urban-area variations, and provide study areas with consistent population sizes. Currently, however, DI/SSI participant counts are not available at the PUMA level. In addition, comparing subgroups that vary in DI/SSI participation rates, such as by age and sex, would improve the analysis. At present, substate DI/SSI participation counts by age and sex are not publicly available.

This study decomposes geographic variation in DI/SSI participation; however, the findings have implications beyond accounting for area variation. We discuss three. First, the decomposition analysis suggests that changes in disability prevalence, if they occur over time, will be reflected in DI participation changes. Disability prevalence is the predominant source of geographic variation in DI participation even though area labor markets and economic conditions can also vary widely. Changes in disability prevalence over time and in DI participation would likely have similar associations, suggesting that future changes in disability prevalence will proportionally change DI participation. Disability prevalence varies widely across areas, and accounting for this variation may provide insight into long-term trends in disability.

Second, the analysis suggests that demographics and labor market characteristics affect DI participation. Prior research has shown the importance of temporal changes in the age/sex composition of the labor force in explaining changes in DI participation (Daly, Lucking, and Schwabish 2013; Liebman 2015). In addition to these characteristics, decomposition analysis suggests that temporal changes in the population shares of people who are Hispanic, noncitizens, born outside of the United States, and speak a language other than English at home could also affect DI participation. Further research is needed to evaluate these trends. Prior research also indicates that changes in the industry composition of the labor market affect DI participation (Autor and Duggan 2003). This study reinforces those findings.

Lastly, the geographic analysis illustrates the wide between-state and within-state variation in socioeconomic conditions experienced by persons with disabilities. In some urban areas, conditions can vary substantially between geographic areas in close proximity. Because of this heterogeneity, the effects of DI/SSI reforms will likely vary across locations. The design of DI/SSI reforms, pilot programs, and evaluations will be strengthened by taking this heterogeneity into account.

Limitations

There are four limitations to this analysis. The first is possible bias. The decomposition estimates may be biased if an underreporting of disability prevalence is associated with DI/SSI participation. Our analysis suggests that if this bias exists, it is small and would not substantially change the findings.

The variance decomposition of DI/SSI participation is based on a simple mathematical relationship: The DI/SSI participation rate equals the disability prevalence rate multiplied by the DI/SSI participation rate among persons with disabilities. Thus, unlike the principal-components analysis and the regression-based decomposition of DI/SSI participation among persons with disabilities, the variance decomposition is a descriptive association rather than a causal one. Therefore, the second limitation is the descriptive rather than causal nature of the associations in the decomposition of DI/SSI participation among persons with disabilities.

Third, the DI participation rates used in this study include disabled workers but do not include disabled widow(er)s or disabled adult children because those data were not available in geographic detail. In 2011, there were approximately 8.5 million disabled-worker beneficiaries as well as 1.2 million disabled widow(er)s and disabled adult children (SSA 2015, Table 3). It is possible that the variance decomposition would change with the inclusion of disabled surviving spouses and disabled adult children. This limitation would be alleviated if PUMA-level counts of disabled widow(er)s and disabled adult children were publicly available.

Finally, the SSI participation rates used in this study include federal SSI and federally administered state supplementation recipients. The inclusion of the latter group introduces some interstate variation in SSI participation because federally administered state supplementation is available in some states and not others. The variance decomposition does not account for this variation. Because overall participation in federal SSI (6.5 million) is much higher than that for federally administered state supplementation (167,000; SSA 2012a, Table 7.A1), we do not expect this limitation to substantially affect our findings.

Conclusions

There is wide geographic variation in DI and SSI participation rates. Approximately 90 percent of the geographic variation can be attributed to geographic variation in disability prevalence, area socioeconomic characteristics, and the correlation between disability prevalence and DI/SSI participation among persons with disabilities.

Geographic variation in disability prevalence is a major reason for the wide variation in DI/SSI participation. If disability prevalence did not vary across areas, the geographic variation in DI participation would be reduced by approximately 80 percent and the variation in SSI participation would be reduced by approximately 63 percent. What accounts for the wide geographic variation in disability prevalence is not well understood. It may indicate cross-area disparities in public health, net migration of persons with and without disabilities, or other factors. Further research is needed to examine possible causes.

Notes

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[1] We exclude counties with fewer than 1,000 persons aged 18–64. See the Methods and Data sections for details on our sources and calculations.

[2] We use the term "DI/SSI" to refer to participation in either program. Thus, it may include but is not restricted to concurrent participation in both programs.

[3] For example, a 2011 *Wall Street Journal* article reported that "in 2010, 63% of [DI] applicants [in Puerto Rico] won approval, four percentage points higher than New Jersey and Wyoming, the most generous states" and that the program "is set to soon become the first big federal benefit program to run out of cash—and one of the main reasons is U.S. states and territories have a large say in who qualifies," resulting in an "uneven selection process" (Paletta 2011).

[4] Ben-Shalom and Stapleton (2014) estimate the ratios of DI and SSI participation to the working-age population with disabilities by state, but they do not analyze factors underlying the variances.

[5] SSA requires that a person's disability has lasted or is expected to last for at least 1 year or to result in death and that a person is unable to engage in substantial gainful activity.

[6] For additional details, see Gettens, Lei, and Henry (2016, 7–11).

[7] See note 6.

[8] If DI/SSI participants underreport their disability relative to nonparticipants, the biases will be the opposite of those described.

[9] In our calculations, we impute the state mean SSI participation rates for those 104 counties.

[10] In some instances, the smallest area of common PUMA and county boundaries contain multiple PUMAs and multiple counties.

[11] Those four CAPUMAs include the following Kentucky counties: Rockcastle, Laurel, Jackson, Clay, Bell, Harlan, Knox, Whitley, Breathhitt, Knott, Lee, Leslie, Letcher, Owsley, Perry, Wolfe, Magoffin, Johnson, Floyd, Martin, and Pike.

[12] We note that the names of the subcomponents are somewhat subjectively assigned. Brief and broadly descriptive terms, selected on the basis of the correlated variables, best suit our present purpose.

[13] The association was determined by ordinary least squares regression estimates of equation 12.

[14] Unobserved state policies are those that are not reflected in the variation of substate area characteristics. For example, substate variation in poverty, public assistance participation, and health insurance coverage rates may in part be due to variation in state policy.

[15] For a description of the variables, data sources, detailed results, and estimates of the magnitude of the bias, see Gettens, Lei, and Henry (2016, 29–35). To further assess justification bias, we also compared the age profiles of disability prevalence and the age profiles of mortality, diabetes prevalence, and poor health. If justification bias were large, we would expect the increase in disability prevalence with age to exceed the increases with age in mortality, diabetes prevalence, or poor health because the increase in disability prevalence would reflect the justification bias associated with increased DI participation. We found that the age profiles are comparable, further suggesting that if justification bias exists, it is small.

[16] We estimate the correlation between disability prevalence and program participation among persons with disabilities to be 0.13 for DI and 0.31 for SSI.

[17] Furtado and Theodoropoulos (2012) found that social norms and information-sharing play important roles in SSI and DI participation among working-age immigrants.

References

Autor, David H., and Mark G. Duggan. 2003. "The Rise in Disability Rolls and the Decline in Unemployment." *Quarterly Journal of Economics* 118(1): 157–206.

Ben-Shalom, Yonatan, and David Stapleton. 2014. *National and State Program Participation Ratios for Working-Age People with Disabilities.* Washington, DC: Mathematica Policy Research.

Black, Dan, Kermit Daniel, and Seth Sanders. 2002. "The Impact of Economic Conditions on Participation in Disability Programs: Evidence from the Coal Boom and Bust." *American Economic Review* 92(1): 27–50.

Burkhauser, Richard V., J. S. Butler, and Robert R. Weathers II. 2001/2002. "How Policy Variables Influence the Timing of Applications for Social Security Disability Insurance." *Social Security Bulletin* 64(1): 52–83.

Burkhauser, Richard V., Andrew J. Houtenville, and Jennifer R. Tennant. 2014. "Capturing the Elusive Working-Age Population with Disabilities: Reconciling Conflicting Social Success Estimates from the Current Population Survey and American Community Survey." *Journal of Disability Policy Studies*, 24(4): 195–205.

Coe, Norma B., Kelly Haverstick, Alicia H. Munnell, and Anthony Webb. 2011. "What Explains State Variation in SSDI Application Rates?" CRR Working Paper No. 2011-23. Chestnut Hill, MA: Center for Retirement Research at Boston College. http://crr.bc.edu/working-papers/what-explains-state-variation-in-ssdi-application-rates/.

Daly, Mary C., Brian Lucking, and Jonathan A. Schwabish. 2013. "The Future of Social Security Disability Insurance." FRBSF Economic Letter No. 2013-17. San Francisco, CA: Federal Reserve Bank of San Francisco. http://www.frbsf.org/economic-research/files/el2013-17.pdf.

Furtado, Delia, and Nikolaos Theodoropoulos. 2012. "Immigrant Networks and the Take-Up of Disability Programs: Evidence from U.S. Census Data." CRR Working Paper No. 2012-23. Chestnut Hill, MA: Center for Retirement Research at Boston College.

Gettens, Jack, Pei-Pei Lei, and Alexis Henry. 2016. "Accounting for Geographic Variation in DI and SSI Participation." DRC Working Paper 2016-03. Washington, DC: Mathematica Policy Research. https://www.mathematica-mpr.com/our-publications-and-findings/publications/accounting-for-geographic-variation-in-di-and-ssi-participation.

Guo, Xuguang (Steve), and John F. Burton, Jr. 2012. "The Growth in Applications for Social Security Disability Insurance: A Spillover Effect from Workers' Compensation." *Social Security Bulletin* 72(3): 69–88.

Iyengar, Radha, and Giovanni Mastrobuoni. 2014. "The Political Economy of the Disability Insurance: Theory and Evidence of Gubernatorial Learning." *IZA Journal of Labor Policy* 3(1): 1–31.

Keiser, Lael R. 2001. "Street-Level Bureaucrats, Administrative Power and the Manipulation of Federal Social Security Disability Programs." *State Politics and Policy Quarterly* 1(2): 144–164.

Liebman, Jeffrey B. 2015. "Understanding the Increase in Disability Insurance Benefit Receipt in the United States." *Journal of Economic Perspectives* 29(2): 123–150.

Maestas, Nicole, Kathleen J. Mullen, and Alexander Strand. 2013. "Disability Insurance and Healthcare Reform: Evidence from Massachusetts." MRRC Working Paper No. WP 2013-289. Ann Arbor, MI: University of Michigan Retirement Research Center. http://www.mrrc.isr.umich.edu/publications/papers/pdf/wp289.pdf.

McCoy, John L., Miles Davis, and Russell E. Hudson. 1994. "Geographic Patterns of Disability in the United States." *Social Security Bulletin* 57(1): 25–36.

McVicar, Duncan. 2006. "Why Do Disability Benefit Rolls Vary Between Regions? A Review of the Evidence from the USA and the UK." *Regional Studies* 40(5): 519–533.

Nelson, William J., Jr. 1994. "Disability Trends in the United States: A National and Regional Perspective." *Social Security Bulletin* 57(3): 27–41.

Paletta, Damian. 2011. "Insolvency Looms as States Drain U.S. Disability Fund." *Wall Street Journal*, March 22.

Pattison, David, and Hilary Waldron. 2013. "Growth in New Disabled-Worker Entitlements, 1970–2008." *Social Security Bulletin* 73(4): 25–48.

Ruffing, Kathy A. 2015. "Geographic Pattern of Disability Receipt Largely Reflects Economic and Demographic Factors." Washington, DC: Center on Budget and Policy Priorities. https://www.cbpp.org/sites/default/files/atoms/files/1-8-15ss.pdf.

Rupp, Kalman. 2012. "Factors Affecting Initial Disability Allowance Rates for the Disability Insurance and Supplemental Security Income Programs: The Role of the Demographic and Diagnostic Composition of Applicants and Local Labor Market Conditions." *Social Security Bulletin* 72(4): 11–35.

Rupp, Kalman, and David Stapleton. 1995. "Determinants of the Growth in the Social Security Administration's Disability Programs—An Overview." *Social Security Bulletin* 58(4): 43–70.

Rupp, Kalman, and David C. Stapleton, editors. 1998. *Growth in Disability Benefits: Explanations and Policy Implications*. Kalamazoo, MI: W. E. Upjohn Institute for Employment Research.

Rutledge, Matthew S. 2012. "The Impact of Unemployment Insurance Extensions on Disability Insurance Application and Allowance Rates." CRR Working Paper No. 2011-17. Chestnut Hill, MA: Center for Retirement Research at Boston College.

Rutledge, Matthew S., and April Yanyuan Wu. 2014. "Why Do SSI and SNAP Enrollments Rise in Good Economic Times and Bad?" CRR Working Paper No. 2014-10. Chestnut Hill, MA: Center for Retirement Research at Boston College.

Social Security Administration. 2012a. *Annual Statistical Supplement to the Social Security Bulletin, 2011.* Washington, DC: SSA. https://www.ssa.gov/policy/docs/statcomps/supplement/2011/index.html.

———. 2012b. *OASDI Beneficiaries by State and County, 2011.* Washington, DC: SSA. https://www.ssa.gov/policy/docs/statcomps/oasdi_sc/2011/index.html.

———. 2012c. *SSI Recipients by State and County, 2011.* Washington, DC: SSA. https://www.ssa.gov/policy/docs/statcomps/ssi_sc/2011/index.html.

———. 2015. *Annual Statistical Report on the Social Security Disability Insurance Program, 2014*. Washington, DC: SSA. https://www.ssa.gov/policy/docs/statcomps/di_asr/2014/index.html.

Social Security Advisory Board. 2001. *Charting the Future of Social Security's Disability Programs: The Need for Fundamental Change.* Washington, DC: Social Security Advisory Board.

———. 2012a. *Aspects of Disability Decision Making: Data and Materials*. Washington, DC: Social Security Advisory Board.

———. 2012b. *Filing for Social Security Disability Benefits: What Impact Does Professional Representation Have on the Process at the Initial Application Level?* Washington, DC: Social Security Advisory Board.

Soss, Joe, and Lael R. Keiser. 2006. "The Political Roots of Disability Claims: How State Environments and Policies Shape Citizen Demands." *Political Research Quarterly* 59(1): 133–148.

[SSA] *See* Social Security Administration.

Strand, Alexander. 2002. "Social Security Disability Programs: Assessing the Variation in Allowance Rates." ORES Working Paper Series No. 98. Washington, DC: SSA.

Woehl, Erica M. 2015 "Social Security Administration Disability Discrepancies: The Debate between Street-Level Bureaucrats and Administrative Law Judges." *North Dakota Law Review* 91: 353–373.

Zayatz, Tim. 2015. "Social Security Disability Insurance Program Worker Experience." Actuarial Study No. 123. Baltimore, MD: SSA, Office of the Chief Actuary.