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Panel 6: Retirement Finances

Moderator

Gary V. Engelhardt (Syracuse University)

"The Evolution of Late-Life Income and Assets: Measurement in IRS Tax Data and Three Household Surveys"

James Choi (Yale University and NBER), Lucas Goodman (U.S. Department of the Treasury), Justin Katz (Harvard University), David Laibson (Harvard University and NBER), and Shanthi Ramnath (Federal Reserve Bank of Chicago)

"How Much Taxes Will Retirees Owe on Their Retirement Income?"

Anqi Chen and Alicia H. Munnell (Boston College)

"Broad Framing in Retirement Income Decision Making"

Hal E. Hershfield (UCLA), **Suzanne B. Shu** (Cornell University and NBER) and Stephen A. Spiller and David Zimmerman (UCLA)

The Evolution of Late-Life Income and Assets:
Measurement in IRS Tax Data and Three Household Surveys

James Choi (Yale University and NBER),
Lucas Goodman (U.S. Department of the Treasury),
Justin Katz (Harvard University),
David Laibson (Harvard University and NBER), and
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Recent research has found that some U.S. household surveys underreport income from sources such as pensions and IRAs, calling into question assessments of retirement income adequacy based on survey data (Bee and Mitchell 2017; Chen, Munnell, and Sanzenbacher, 2018). In this paper, we examine how well three widely used U.S. household surveys – the *Health and Retirement Study* (HRS), the *Survey of Income and Program Participation* (SIPP), and the *Current Population Survey* (CPS) – capture levels of and trends in late-life financial well-being. To do so, we compare income estimates from these surveys to those from a 5-percent random sample of administrative IRS tax records covering the 1933-1952 birth cohorts. IRS data contain administrative records for most income sources in retirement, including distributions from pensions and IRAs. IRS data hence offer a unique benchmark to assess bias in survey estimates.

To ensure comparability across sources, we harmonize income definitions, household definitions, and the populations covered by each dataset. We adjust for household size by dividing household income by the square root of the number of members (either one or two, as we do not consider dependents). Our income measures exclude non-taxable government transfers such as SSI and SNAP benefits, which are important for the left-tail of the income distribution.

We first compare survey estimates of levels and trends in the distribution of pre-tax income as households age to equivalent tax data estimates. We focus on two groups: 1) households in the 1943-1949 birth cohorts observed from ages 58-68, during the initial transition to retirement; and 2) households in the 1933-1939 birth cohorts observed from ages 68-78, during later retirement. For each birth cohort in each source, we measure, at each age, the 10th,

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25th, 50th, 75th, and 90th income percentiles and the fraction of households receiving income greater than $500 – all in 2010 dollars. To compare income levels across datasets, we calculate the percentage difference between each survey estimate and the tax data estimate. To estimate trends as households age, we compute the proportional change at each point in the income distribution from age 58 to age 68 for each of the 1943-1949 birth cohorts, and from age 68 to age 78 for each of the 1933-1939 birth cohorts.

Table 1 reports across-cohort averages of percentile estimates and probabilities of receipt at ages 58, 68, and 78, proportional changes across ages, and percentage differences between survey data and tax data. Panel I averages across the 1943-1949 birth cohorts, and Panel II averages across the 1933-1939 birth cohorts. The results indicate that all survey sources underestimate median income for older households. For the 1943-1949 birth cohorts, average median income at age 68 is $37,972 in the tax data, exceeding estimates in the HRS, the SIPP, and the CPS by an average of 7.4 percent, 14.1 percent, and 14.7 percent, respectively. For the 1933-1939 birth cohorts, average median income at age 78 is $29,336 in the tax data, greater than estimates in the HRS, the SIPP, and the CPS by an average of 10.7 percent, 13.0 percent, and 21.6 percent, respectively. Additionally, the survey sources overestimate the proportional decline at and above the median from age 58 to age 68 during the initial transition to retirement. Median income in the tax data declines by an average of 11.7 percent from age 58 to age 68, compared to average declines of 24.4 percent in the HRS, 16.8 percent in the SIPP, and 29.0 percent in the CPS. The results suggest that relying on survey estimates to measure income levels or changes in income as households age may paint an overly pessimistic picture of financial well-being.

Next, we compare how each source measures the evolution of the household income distribution across birth cohorts. In Table 2 (Panel I), we examine average proportional changes at fixed ages from the 1944 birth cohort to the 1950 birth cohort, averaging across ages 58 to 67. Median pre-tax income fell by an average of 0.2 percent in the tax data, compared to declines of 7.8 percent in the HRS, 0.7 percent in the SIPP, and 0.9 percent in the CPS. At other percentiles, the SIPP and CPS do a good job capturing trends, while the HRS overestimates growth at the 10th and 25th percentiles and overestimates declines at the 75th and 90th percentiles. Table 2 (Panel II) reports average changes from the 1933 birth cohort to the 1943 birth cohort, averaging across ages 68 to 74. The tax data show that income has grown across the distribution – by an average of 14.6 percent, 16.3 percent, and 19.9 percent at the 25th percentile, median, and 75th percentile, respectively. However, the survey data tend to exaggerate this trend at and above the median. The average growth at the median is 21.7 percent in the HRS, 23.5 percent in the SIPP, and 23.6 percent in the CPS; at the 75th percentile, average growth is 23.3 percent in the HRS, 28.9 percent in the SIPP, and 27.1 percent in the CPS. Overall, relying exclusively on survey data will produce an overly *optimistic* assessment of across-cohort trends in retirement income.

Lastly, we examine the extent to which the trend towards higher income at older ages is explained by increased income outside of the Social Security system. Table 3 measures changes in non-Social Security income from the 1933 to 1943 birth cohorts, averaging across estimates at ages 68-74 as before. In the tax data, for middle- and lower-income households, stripping out Social Security income results in considerably *less* income growth across cohorts. Non-Social Security income grew by only 9.4 percent on average at the median, and *fell* by 16.5 percent on average at the 25th percentile. The survey sources qualitatively capture this drop-off at the 25th percentile, although the HRS and the SIPP on average overestimate the proportional decline.

Table 1. *Levels and Changes in the Pre-Tax Income Distribution Across Various Ages*

Panel I. *Average Levels and Average Changes from 58-68 for Younger Birth Cohorts (1943-1949)*

	Tax data			HRS			SIPP			CPS		
	58	68	Avg. % change	58	68	Avg. % change	58	68	Avg. % change	58	68	Avg. % change
10th percentile	6,948	8,446	23.2%	8,988	10,592	16.7%	8,267	9,796	21.5%	8,872	10,087	15.4%
(% diff vs. tax)				37.9%	25.0%		21.3%	15.6%		31.1%	20.1%	
25th percentile	21,625	19,726	-8.8%	24,872	19,008	-24.1%	19,900	18,862	-5.1%	23,882	17,344	-27.1%
(% diff vs. tax)				16.3%	-4.7%		-7.7%	-5.0%		10.6%	-12.0%	
50th percentile	43,032	37,972	-11.7%	47,198	35,145	-24.4%	39,071	32,607	-16.8%	45,610	32,378	-29.0%
(% diff vs. tax)				9.9%	-7.4%		-9.1%	-14.1%		6.1%	-14.7%	
75th percentile	71,456	62,892	-12.0%	82,746	64,595	-20.5%	64,403	53,247	-17.4%	76,426	57,283	-25.0%
(% diff vs. tax)				15.9%	3.0%		-9.8%	-15.2%		7.0%	-8.9%	
90th percentile	112,544	99,635	-11.5%	132,162	110,751	-16.4%	96,875	85,548	-11.8%	117,815	92,560	-21.3%
(% diff vs. tax)				17.5%	11.3%		-13.9%	-14.1%		4.8%	-7.2%	
frac w/ income	0.94	0.96	2.0%	0.96	0.99	2.6%	0.96	0.97	2.2%	0.95	0.97	1.7%
(% diff vs. tax)				1.8%	2.5%		1.2%	1.2%		0.9%	0.5%	

Panel II. *Average Levels and Average Changes from 68-78 for Older Birth Cohorts (1933-1939)*

	Tax data			HRS			SIPP			CPS		
	68	78	Avg. % change	68	78	Avg. % change	68	78	Avg. % change	68	78	Avg. % change
10th percentile	7,632	6,251	-17.8%	10,502	10,092	-3.0%	9,555	8,351	-10.3%	9,257	8,522	-7.8%
(% diff vs. tax)				38.7%	62.0%		25.7%	33.3%		21.9%	37.2%	
25th percentile	18,139	15,468	-14.6%	18,385	15,517	-14.3%	16,959	15,185	-10.0%	15,696	14,618	-6.7%
(% diff vs. tax)				-6.3%	-1.8%		-6.3%	-1.8%		-13.4%	-5.4%	
50th percentile	33,667	29,336	-12.8%	32,415	25,951	-18.1%	28,351	25,397	-10.2%	27,461	23,013	-16.1%
(% diff vs. tax)				-3.8%	-10.7%		-15.7%	-13.0%		-18.4%	-21.6%	
75th percentile	53,767	48,534	-9.6%	55,972	42,173	-23.7%	47,183	41,257	-11.6%	48,020	40,181	-16.5%
(% diff vs. tax)				4.2%	-11.7%		-12.3%	-14.5%		-10.5%	-17.2%	
90th percentile	85,220	78,862	-7.3%	95,833	71,741	-22.5%	71,300	67,435	-5.6%	84,706	65,406	-22.9%
(% diff vs. tax)				12.2%	-7.5%		-16.3%	-13.8%		-0.4%	-17.2%	
frac w/ income	0.96	0.94	-1.9%	0.99	0.99	0.2%	0.98	0.97	-1.5%	0.97	0.96	-1.0%
(% diff vs. tax)				3.0%	5.2%		1.9%	2.4%		1.0%	1.9%	

Sources: Authors' calculations using Internal Revenue Service tax data, the *Health and Retirement Study*, the *Survey of Income and Program Participation*, and the *Current Population Survey*.

Table 2. *Trends in the Pre-Tax Income Distribution Across Birth Cohorts*

Panel I. *Average Changes from 1944-1950 Birth Cohorts at Younger Fixed Ages (58-67)*

	Tax data			HRS			SIPP			CPS		
	1944	1950	Avg. % change	1944	1950	Avg. % change	1944	1950	Avg. % change	1944	1950	Avg. % change
10th percentile	6,589	7,481	15.5%	8,353	10,076	22.7%	7,294	8,408	15.9%	7,559	8,544	13.4%
25th percentile	19,302	20,481	6.2%	19,954	21,400	10.8%	17,791	19,216	8.1%	18,500	19,276	4.1%
50th percentile	39,946	39,837	-0.2%	46,002	40,916	-7.8%	35,715	35,422	-0.7%	38,185	37,825	-0.9%
75th percentile	68,051	65,955	-3.1%	76,495	68,936	-5.1%	60,241	59,933	1.2%	67,084	65,312	-2.7%
90th percentile	108,492	104,554	-3.6%	131,028	113,511	-10.8%	97,437	87,757	-8.5%	107,386	103,450	-3.5%
frac w/ income	0.94	0.95	0.7%	0.97	0.98	0.6%	0.95	0.97	1.6%	0.94	0.96	1.2%

Panel II. *Average Changes from 1933-1943 Birth Cohorts at Older Fixed Ages (68-74)*

	Tax data			HRS			SIPP			CPS		
	1933	1943	Avg. % change	1933	1943	Avg. % change	1933	1943	Avg. % change	1933	1943	Avg. % change
10th percentile	7,227	8,486	17.5%	9,678	10,725	13.6%	9,190	10,135	12.2%	9,114	9,825	7.9%
25th percentile	16,862	19,325	14.6%	16,985	18,055	5.0%	15,435	18,416	20.8%	14,614	16,928	15.9%
50th percentile	31,227	36,303	16.3%	28,608	34,649	21.7%	25,073	31,069	23.5%	23,981	29,570	23.6%
75th percentile	49,938	59,867	19.9%	48,445	51,651	23.3%	39,536	51,651	28.9%	40,695	51,532	27.1%
90th percentile	79,757	96,291	20.9%	80,183	82,515	37.7%	56,384	82,515	44.2%	72,894	82,945	14.4%
frac w/ income	0.96	0.97	0.6%	0.99	0.98	0.3%	0.98	0.98	0.2%	0.97	0.97	0.3%

Sources: Authors' calculations using Internal Revenue Service tax data, the *Health and Retirement Study*, the *Survey of Income and Program Participation*, and the *Current Population Survey*.

Table 3. *Trends in the Non-Social Security Income Distribution from 1933-1943 Birth Cohorts: Averages Across Ages 68-74*

	Tax data			HRS			SIPP			CPS		
	1933	1943	Avg. % change	1933	1943	Avg. % change	1933	1943	Avg. % change	1933	1943	Avg. % change
10th percentile	2,916	2,399	-16.5%	3,569	2,571	-26.9%	2,525	1,388	-45.5%	452	400	-11.1%
25th percentile	15,916	17,395	9.4%	14,361	16,802	15.7%	11,452	13,209	12.0%	9,322	12,484	37.4%
50th percentile	34,449	40,077	16.5%	32,407	42,632	29.0%	25,398	32,864	27.8%	26,630	35,214	33.4%
75th percentile	65,315	76,585	17.6%	63,369	95,479	54.1%	43,404	62,394	41.2%	57,840	67,263	17.3%
90th percentile	0.81	0.79	-1.9%	0.83	0.81	-2.2%	0.81	0.77	-5.1%	0.73	0.73	0.2%

Sources: Authors' calculations using Internal Revenue Service tax data, the *Health and Retirement Study*, the *Survey of Income and Program Participation*, and the *Current Population Survey*.

Figure 1. *Fraction with No Income or IRA by Age and Cohort*

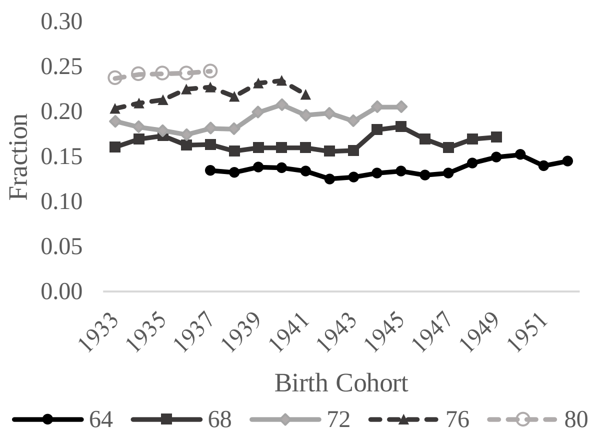
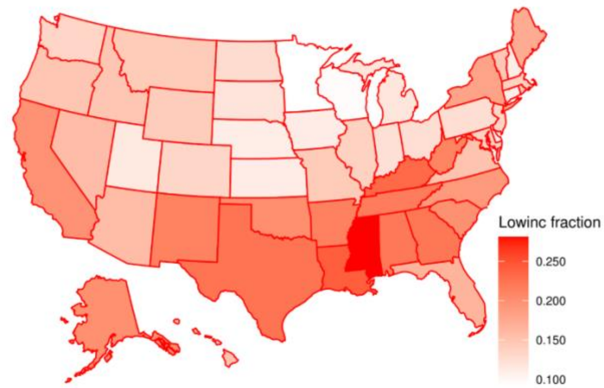


Figure 2. *Fraction with No Income or IRA Born 1933 at Age 72, By State*



Source: Authors' calculations using Internal Revenue Service tax data.

To further investigate changes in the left tail over time, we track the fraction of households with less than $500 (in 2010 dollars) in non-Social Security income and no IRA balances at fixed ages. These households likely lack substantial savings, and so presumably rely completely on Social Security to finance their consumption. Figure 1 shows that in the tax data, the fraction of households completely reliant on Social Security is flat to increasing over time. For example, for age-72 households, this fraction rose from 18.9 percent in the 1933 birth cohort to 20.5 percent in the 1945 birth cohort. The survey data qualitatively capture these trends, although the CPS substantially overestimates levels of Social Security reliance. The tax data additionally grant visibility into substantial geographic variability in Social Security reliance across states. Figure 2 shows that Social Security reliance at age 72 in the 1933 birth cohort tends to be highest in the Deep South and lowest in the Northeast and Upper Midwest, ranging from 11.1 percent at the 10th percentile state (Kansas) to 22.1 percent at the 90th percentile state (Georgia).

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How Much Taxes Will Retirees Owe on Their Retirement Income?

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To evaluate their retirement resources, households approaching retirement will examine their Social Security statements, defined benefit pensions (DBs), defined contribution balances (DC), and other financial assets. However, many households may forget that not all of these resources belong to them; they will need to pay some portion to federal and state government in taxes. This project aims to shed light on the tax burden retirees face by estimating lifetime taxes for a group of recently retired households. However, due to delays in authorizing TAXSIM for use on restricted data, the results presented in this version of the paper are based on self-reported data and do not include state tax liabilities.

Data and Methodology

The analysis is based on the *Health and Retirement Study* (*HRS*) and focuses on recently retired households – specifically, households where at least one earner has claimed Social Security benefits from 2010-2018. This construct – excluding disability conversions – produces a sample of 3,419 individuals and 1,907 households. Table 1 shows the marital status and financial resources of the sample households at the time of retirement.

Table 1. *Marital Status and Average Retirement Resources in Year of Retirement in 2018 Dollars, by AIME Quintile*

AIME quintile	Percentage married	Social Security	DB pensions	DC balances	Financial wealth
Lowest	35%	$10,610	$2,730	$3,180	$125
Second	62	19,950	5,240	4,690	2,250
Middle	79	27,010	5,810	8,670	7,000
Fourth	80	32,290	9,130	27,760	23,000
Highest	81	33,130	21,550	180,790	87,500
Top 5%	83	36,610	29,360	466,380	167,500
Top 1%	92	38,040	32,440	739,420	445,000

Source: Authors' calculations from University of Michigan, *Health and Retirement Study* (2010-2018).

* The research reported herein was pursuant to a grant from the U.S. Social Security Administration (SSA), funded as part of the Retirement and Disability Research Consortium. The findings and conclusions expressed are solely those of the authors and do not represent the views of SSA, any agency of the federal government, or the Center for Retirement Research at Boston College.

The first step is to identify the income streams that the households will have available in retirement. Social Security benefits depend on earnings history and claiming age. At this point, we used self-reported earnings and claiming ages. For households with defined benefit plans, annual pension income is also based on self-reported estimates.

For households with assets in defined contribution retirement plans, the tax burden depends on whether the contributions were made pre-tax (traditional) or post-tax (Roth) and on the pattern of withdrawal. We use data from the *Survey of Consumer Finances*, IRS, and Vanguard to estimate the proportion of assets in Roth accounts. In terms of drawdown, our base case assumes that households withdraw nothing from their 401(k)s and IRAs until age 70½ (or 72) and follow the Required Minimum Distribution (RMD) rules. We also consider two alternatives. Under one option, households before the applicable RMD age withdraw at a rate implied by the RMD rules and then follow the RMD rules once they become binding.[1] Under the other option, households use their 401k)/IRA balances at the Social Security claiming age to purchase an immediate annuity, with joint and survivor benefits for married couples.

For financial assets outside of these retirement arrangements, our baseline assumption is that households use only the interest and dividends to support their consumption in retirement. Under an alternative option, households use half of their financial assets (paying taxes on accrued capital gains) to buy a joint-and-survivor annuity at the time they claim their Social Security benefits.

Once these income streams are identified, the next step is to calculate the annual tax burden for each household using the NBER's TAXSIM 27. Tax calculations are performed each year for each household between age 62 and its quintile-related life expectancy. The final step is to calculate taxes as a percentage of pre-tax income, discounted back to the Social Security claiming age.

Results

Table 2 shows the results for the base case, which involves taking only RMDs and living off the interest and dividends on financial assets. Households in the aggregate will have to pay roughly 6 percent of their income in federal income taxes. The rate varies sharply by AIME

[1] Implied RMDs for ages before 70½ (72 after 2020) are calculated by taking the inverse of the average life expectancy provided by the Internal Revenue Service (2019).

quintile. Those in the bottom three quintiles pay close to zero, but the rate rises to 1.5 percent for the fourth quintile and to more than 10.5 percent for the top quintile, 15.4 percent for the top 5 percent, and 20.9 percent for the top 1 percent. The rates also vary by household type.

Table 2. *Retirement Taxes as a Percentage of Retirement Income, Households Follow RMD and Consume Only Interest and Dividends from Financial Assets, by AMIE Quintile and Marital Status*

AIME quintile	All	Single	Married
Lowest	0.0%	0.0%	0.0%
Second	0.0	0.1	0.0
Middle	0.3	1.1	0.1
Fourth	1.5	5.0	0.8
Highest	10.5	13.6	9.8
Top 5%	15.4	18.8	15.0
Top 1%	20.9	20.7	21.0
All	5.7%	6.5%	5.4%

Source: Authors' calculations.

Table 3 shows the results for the final scenario, which assumes full annuitization of 401(k) balances as well as 50-percent annuitization of other financial wealth. Comparing the final scenario with the base case shows that, in a system with progressive rates, the retirement taxes are higher when more of retirement assets are withdrawn for consumption. The rate difference would be even greater except that the capital gains on financial assets, used to purchase an annuity, are taxed at much lower rates than ordinary income, and then only a small portion of the annuity purchased with after-tax income is subjected to taxation.[2]

[2] Under the Tax Cuts and Jobs Act of 2017, short-term capital gains are taxed as ordinary income at rates up to 37 percent, while long-term gains (assets held for more than one year) are taxed at lower rates, up to 20 percent. Taxpayers with modified adjusted gross income above certain amounts are subject to an additional 3.8-percent net investment income tax on long- and short-term capital gains.

Table 3. *Retirement Taxes as a Percentage of Retirement Income, Households Annuitize All DC Assets and 50 Percent of Financial Assets, by AMIE Quintile and Marital Status*

Quintile	All	Single	Married
Lowest	0.0%	0.0%	0.0%
Second	0.1	0.2	0.0
Middle	0.4	1.3	0.2
Fourth	1.9	6.1	0.8
Highest	11.5	15.7	10.6
Top 5%	16.2	19.9	15.5
Top 1%	19.5	23.6	19.1
All	6.5%	8.0%	6.0%

Source: Authors' calculations.

Regardless of the drawdown strategy, households in the bottom three AIME quintiles most likely pay zero taxes in retirement, and even those in the fourth quintile will pay only about 2 percent. In terms of financial security in retirement, this finding is good news – most households are not dramatically underestimating the resources available in retirement by not considering taxes.

Taxes, however, are meaningful for the top quintile, so it is important to consider the economic circumstances of these households. They are mostly married couples with average combined Social Security benefits of $33,130, 401(k)/IRA balances of $180,790, and financial wealth of $87,500. These households as a group are not what many would consider wealthy. The fact that they constitute the highest quintile highlights the fact that most households do not have a lot of money in retirement. Yet, they will pay about 12 percent of their retirement income in taxes. Given that, without considering taxes, about 40 percent of households in the top third of the income distribution are at risk of not being able to maintain their standard of living, taxes will make the goal even more difficult to attain.[3]

Those in the top 5 percent and 1 percent of the AIME distribution hold more wealth both inside and outside of retirement plans. But even here, the reported average 401(k)/IRA holdings of $466,380 and $739,410, respectively, must look quite similar to what many academics hold in their TIAA accounts. For these groups, taxes amount to 16 percent and 20 percent of retirement

[3] Munnell, Hou, and Sanzenbacher (2018).

income, respectively. Thus, taxes are an important consideration for those who hold meaningful balances and should be considered in their financial planning.

The final observation is that the drawdown strategy does not appear to have much impact on tax liability. That outcome may reflect simplifying assumptions underlying the analysis. But it also raises questions about how much attention people need to devote to taxes as they consider different drawdown strategies.

Note, again, these results are preliminary and partial. They are based on self-reported Social Security benefits and do not include the impact of state taxes. Including state taxes will likely raise the burden by 25 percent. Thus, for many households reliant on 401(k)/IRA assets for security in retirement, taxes are an important consideration.

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Broad Framing in Retirement Income Decision Making

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Retirees often make retirement income decisions in narrow brackets, myopically considering OASI claiming age, pension or 401(k) payouts, annuity purchases, long-term care insurance, and use of home equity as independent and unrelated decisions. Thoughtfully combining these different income sources into a comprehensive decumulation strategy requires mentally combining the risks and benefits associated with different programs and assets, which may be quite challenging for retirees. For example, when thinking about decisions for OASI

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claiming, wealth decumulation, and guaranteed lifetime income products (e.g., annuities), the tradeoffs between longevity risk, stock market risks, and higher future income can make each decision a highly complex task. Thinking of each domain as a separate decision, rather than looking at how they operate in aggregate, may make it even more difficult to evaluate global tradeoffs and also make it difficult to appreciate how potential outcomes can be complementary in generating a smoother path of retirement income.

Research on narrow versus broad framing in financial decisions regularly finds that this type of narrow decision framing can cause individuals to accept lower risk and lower value outcomes, whereas a more broadly bracketed set of options can lead to more optimal aggregated choices (Read, Loewenstein, and Rabin 1999). Broadly bracketing outcomes has also been shown to increase risk tolerance, especially for individuals seeing investment outcomes aggregated over larger periods of time (Benartzi and Thaler 1995; Langer and Weber 2001). In this project, we test how aggregating outcomes across different sources of retirement income, a topic which has previously been unexplored, affects retirement decisions. We expect that, similar to broad bracketing of other financial outcomes, an aggregate view of sources of retirement income (OASI benefits, savings wealth, and annuities) may lead to different decisions (resulting in different outcomes) relative to when each decision is made independently. Our study employs a custom-built retirement decision aid to experimentally test whether people select systematically different risk allocations (stocks vs bonds), make different annuity decisions, and adjust their Social Security claiming intentions when they are shown the aggregated outcome of those decisions or each piece individually. We predict that by combining these risks into a single integrated retirement income metric (broad bracketing), individuals can more clearly evaluate the risks and understand the impacts that each decision has on their overall circumstances. For example, calculating the exact implications of withdrawing retirement savings more heavily in early retirement in order to delay OASI claiming is a decision that involves complex risk tradeoffs that may be hard to reason about. A decision aid that shows the aggregated impact of these decisions may make it easier for the individual to reason through the costs and benefits of using one income source to make different decisions regarding other income sources.

Study Method

People were asked to make a financial plan for decumulation using an online tool. In order to simplify the decision, we gave people a specific age, income, and savings scenario rather than letting them input information about themselves and then creating a plan using those inputs. Participants were asked to make a plan using three different financial products: Social Security, retirement savings, and annuities. They received immediate feedback in the form of graphs showing estimated income (and, for some conditions, wealth) over time, along with a probability that they would run out of retirement savings by age 85.

We recruited 605 participants from Amazon Mechanical Turk (AMT), using their panel feature to screen for people ages 40 to 63. After exclusions and attrition, we have 399 participants (median age = 48, 44.9 percent female). Participants completed a comprehension check and then walked through an in-depth explanation of the task they were about to complete. The directions started with a general overview of how to navigate and understand the decumulation tool and then stepped through each decision they would be asked to make. In the decumulation tool people saw three different financial products they could make decisions about: Social Security old age (OASI) benefits, savings, and guaranteed income (a single, deferred life annuity). Instructions specific to each element of the tool, and highlighting how the outcome feedback would change according to their decisions, was provided through a series of screenshots and detailed instructions.

Our main dependent variables are based on the retirement income decisions made within each financial product. For the Social Security product, people were able to select what age they would claim from ages 62 to 70. For retirement savings, participants were asked to select a general withdrawal progression from retirement savings: increasing, flat or decreasing withdrawals; were asked whether or not they would like to take extra withdrawals from retirement savings prior to claiming Social Security; and were asked to select one of three different investment allocation paths that varied the ratio of stocks to bonds. In the annuity product space, people were asked to select the percentage of their retirement savings to annuitize and the starting age for the annuity payments. Within each product decision space, individuals saw a graph of estimated income from ages 60 to 100. Within the retirement savings product decision screen, or for anyone in the aggregated outcome condition, a graph of estimated wealth over time from ages 60 to 100 was also provided. Additionally, people were provided with a calculated probability that they will still have positive (non-zero) retirement savings at age 85. Once they were satisfied with their choices, all participants responded to questions to measure individual levels of intertemporal discount rate, loss aversion, and confidence in their decisions and retirement planning, as well as basic demographics.

Study Results

We expected that individuals in the aggregate condition, who are able to have a more complete picture of their possible outcomes while making choices, would be more likely to take tradeoffs between the products into account. To test for differences in average retirement income per condition, we consider several different measures: average monthly income across ages 62 to 100, standard deviation of income from 62 to 100, and average year-by-year differences in income for those years. A regression with average retirement income as the dependent variable finds that the effect of condition is marginally significant when controls are included; average income is slightly lower for participants in the aggregate condition. Of more interest is what happens to the variability of income in the two conditions. There is a significant decrease in the average variability of income sequences selected by participants in the aggregate condition, both without and with controls ($b = -967.48$, $t(362) = -3.72$, $p < 0.001$). When using a measure of the absolute difference in expected income from each year to the previous year, averaged for each person, we find that participants in the aggregate condition had lower average lagged differences, again without and with controls for demographic and psychographic variables ($b = -118.61$, $t(362) = -4.07$, $p < 0.001$).

Looking at the outcomes for each of the three financial product domains, starting with the OASI benefits claiming decision, we find that on average people in the aggregate graph condition claimed nine months to one year earlier than those in the separate condition, without or with controls ($b = -1.06$, $t(365) = -3.69$, $p <0.001$). For the selection of retirement savings withdrawal strategies, we do not find evidence to suggest a difference between the selections in the aggregate and separate graph conditions. In both conditions, the majority of participants selected an increasing withdrawal strategy, with 51 percent of participants choosing it in the separate condition and 49% choosing it in the aggregate condition. We also do not see significant differences in the choice of whether or not to take extra withdrawals from savings in the years before claiming Social Security, or in the level of risk participants were willing to take with their retirement savings. Finally, for the guaranteed income decisions, we find that people in the aggregate condition on average had significantly lower annuitization rates of their retirement savings, both without and with controls ($b = -9.84$, $t(365) = -3.53$, $p < 0.001$).

Conclusion

As consumers approach retirement, they are faced with many difficult decisions regarding decumulation. Typically, these decisions are done in a siloed fashion. Although consumers may intuitively understand that all of these decisions are part of one overall decumulation strategy, it can be cognitively taxing to balance the effect of each independent decision on one's overall financial picture in retirement. In this preliminary examination of how broad bracketing affects retirement decisions, we found that making decisions in aggregate had several effects; the most robust and notable is that the participants who used the aggregate version of the tool had significantly smoother consumption patterns than participants who used the separate version of the tool. We hypothesize that the aggregate presentation permits consumers not just to maximize smoothness, but rather to choose the most-preferred consumption stream independent of the variability of its components. The finding that participants were more confident in their decisions in the aggregate condition rather than the separate condition lends credence to the notion that they were better able to choose the aggregate consumption pattern that more closely matched their preferences.

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