

DISCUSSION PAPER SERIES

IZA DP No. 12263

**Behavioral Impediments to Valuing  
Annuities: Complexity and Choice  
Bracketing**

Jeffrey R. Brown  
Arie Kapteyn  
Erzo F.P. Luttmer  
Olivia S. Mitchell  
Anya Samek

MARCH 2019

## DISCUSSION PAPER SERIES

IZA DP No. 12263

# Behavioral Impediments to Valuing Annuities: Complexity and Choice Bracketing

**Jeffrey R. Brown**

*University of Illinois and NBER*

**Arie Kapteyn**

*University of Southern California, NBER and  
IZA*

**Erzo F.P. Luttmer**

*Dartmouth College, NBER and IZA*

**Olivia S. Mitchell**

*The Wharton School of the University of  
Pennsylvania and NBER*

**Anya Samek**

*University of Southern California*

MARCH 2019

Any opinions expressed in this paper are those of the author(s) and not those of IZA. Research published in this series may include views on policy, but IZA takes no institutional policy positions. The IZA research network is committed to the IZA Guiding Principles of Research Integrity.

The IZA Institute of Labor Economics is an independent economic research institute that conducts research in labor economics and offers evidence-based policy advice on labor market issues. Supported by the Deutsche Post Foundation, IZA runs the world's largest network of economists, whose research aims to provide answers to the global labor market challenges of our time. Our key objective is to build bridges between academic research, policymakers and society.

IZA Discussion Papers often represent preliminary work and are circulated to encourage discussion. Citation of such a paper should account for its provisional character. A revised version may be available directly from the author.

ISSN: 2365-9793

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9  
53113 Bonn, Germany

Phone: +49-228-3894-0  
Email: [publications@iza.org](mailto:publications@iza.org)

[www.iza.org](http://www.iza.org)

## ABSTRACT

---

# Behavioral Impediments to Valuing Annuities: Complexity and Choice Bracketing\*

This paper examines two behavioral factors that diminish people's ability to value a life-time income stream or annuity, drawing on a survey of about 4,000 adults in a U.S. nationally representative sample. By experimentally varying the degree of complexity, we provide the first causal evidence that increasing the complexity of the annuity choice reduces respondents' ability to value the annuity, measured by the difference between the sell and buy values people assign to the annuity. We also find that people's ability to value an annuity increases when we experimentally induce them to think jointly about the annuitization decision as well as how quickly or slowly to spend down assets in retirement. Accordingly, we conclude that narrow choice bracketing is an impediment to annuitization, yet this impediment can be mitigated with a relatively straightforward intervention.

**JEL Classification:** D14, D91, G11, H55

**Keywords:** pension, annuity, retirement income, Social Security, cognition, behavioral

**Corresponding author:**

Erzo F.P. Luttmer  
Department of Economics  
Dartmouth College  
Hanover, NH 03755  
USA

E-mail: [Erzo.FP.Luttmer@Dartmouth.edu](mailto:Erzo.FP.Luttmer@Dartmouth.edu)

---

\* This paper was funded as a pilot project as part of a Roybal grant awarded to the University of Southern California, entitled "Roybal Center for Health Decision Making and Financial Independence in Old Age" (5P30AG024962-12). We are also grateful for support provided by the Pension Research Council/Boettner Center at the Wharton School of the University of Pennsylvania. The project described in this paper relies on data from survey(s) administered by the Understanding America Study (UAS) which is maintained by the Center for Economic and Social Research (CESR) at the University of Southern California. The authors thank Peter Choi for excellent research assistance. We are grateful for helpful comments from Alan Gustman and seminar audiences at the Federal Reserve Board, Tsinghua University, Uppsala University, the University of Virginia, and the George Washington University. Brown is a Trustee of TIAA and has served as a speaker, author, or consultant for a number of financial services organizations, some of which sell annuities and other retirement income products. Mitchell is a Trustee of the Wells Fargo Advantage Funds and has received research support from the TIAA Institute. The opinions and conclusions expressed herein are solely those of the authors and do not represent the opinions or policy of any institution with which the authors are affiliated nor of USC, CESR or the UAS. © Brown, Kapteyn, Luttmer, Mitchell, and Samek.

## 1. Introduction

The possibility of exhausting financial resources or having to severely curtail retirement consumption is a significant risk to older individuals' wellbeing, and annuities can be invaluable in helping people avoid outliving their assets. Nevertheless, there is relatively little demand for these insurance products (Mitchell, Piggott, and Takayama, 2011; Poterba, Venti, and Wise, 2011). A voluminous literature reviewed in Brown (2009) explores rational explanations for why observed levels of annuitization are much lower than predicted by standard optimizing models such as those by Yaari (1965) and Davidoff, Brown, and Diamond (2005). Recent contributions to this literature include several papers that combine multiple deviations from the standard optimizing framework. For instance, Ameriks, Caplin, Laufer, and Van Nieuwerburgh (2011), Ameriks, Briggs, Caplin, Shapiro, and Tonetti (2018), and Lockwood (2012, 2018) explain observed low annuity demand using structural models that combine a precautionary savings motive (for long-term care expenses when there is public care aversion) with a bequest motive; Reichling and Smetters (2015) do so as well by introducing stochastic mortality and correlated uninsured health care costs. Peijnenburg, Nijman, and Werker (2017) show that medical expenditure risk can rationalize low observed annuitization levels early in retirement, but not why many older people fail to buy annuities. Finally, Laitner, Silverman, and Stolyarov (2018) show analytically how the presence of implicit longevity insurance provided by Medicaid nursing home care can crowd out demand for annuities for the lower and middle classes.

A different strand of literature explores whether behavioral factors help explain low observed levels of annuitization. Several hypothetical choice experiments suggest that behavioral factors influence the demand for annuities, including studies showing that framing of the annuity choice affects the demand for annuities (Brown, Kling, Mullainathan, and Wrobel, 2008, 2013; Beshears, Choi, Laibson, Madrian, and Zeldes, 2014; Brown, Kapteyn, and Mitchell, 2016; Merkle, Schreiber, and Weber, 2017; and Bockweg, Ponds, Steenbeek and Vonken, 2018). Similar findings emerge in incentivized laboratory settings (Agnew, Anderson, Gerlach, and Szykman, 2008; Gazzale and Walker, 2011). Another source of evidence is research demonstrating that individuals in a hypothetical choice setting provide widely divergent valuations for small increases versus small decreases in annuitization (Brown, Kapteyn, Luttmer, and Mitchell, 2017). This latter result is consistent with people having trouble assessing the value of an annuity stream and therefore requiring a high selling price and offering a low buying price, as they are reluctant to trade what they do not understand. There is also suggestive evidence from non-hypothetical

choices that points to behavioral mechanisms. For instance, in 10 Swiss companies, Bütler and Teppa (2007) show that annuitization rates were much higher on average in the firms that offered an annuity as the default payout option, than in the one firm that paid out a lump sum as the default. This finding suggests that annuitization rates are influenced by the default, implying a deviation from a standard rational model. Similarly, Hagen, Hallberg, and Lindquist (2018) show that a nudge affected annuitization decisions of Swedish pensioners. Other papers finding patterns in observed annuitization choices suggestive of deviations from rational choice models include Hurd and Panis (2006), Chalmers and Reuter (2012), Previtro (2014), and Fitzpatrick (2015). Shepard (2011) and Bronshtein, Scott, Shoven, and Slavov (2016) use arbitrage arguments to show that, for many people, the annuitization decision implicit in when to claim Social Security benefits cannot be fully explained by a standard rational model.

While credible rational models can be constructed to match the low observed demand for annuities, our take from the literature on the annuity puzzle is that behavioral factors still remain operative. In short, we share Brown's (2009, p. 185) assessment that while "it is possible to generate more limited annuitization by extending the rational model in several directions, such an approach does not seem to provide the complete answer to the puzzle" of low observed levels of annuitization. Similarly, Benartzi, Previtro, and Thaler (2011, p.161) conclude that the "tiny market share of individual annuities should not be viewed as an indicator of underlying preferences but rather as a consequence of institutional factors about the availability and framing of annuity options."

Despite the fact that many studies find that behavioral factors influence annuitization decisions, relatively little is known about the mechanisms driving this behavior. Brown et al. (2008, 2013) report that presenting annuities in terms of the consumption streams they generate leads to higher annuity demand, versus presenting annuities as investment products. Brown et al. (2008) suggest that the adoption of a narrow decision frame, also referred to as choice bracketing (Thaler, 1985; Read, Loewenstein, and Rabin, 1999), may drive this finding: that is, people evaluate annuities based on the return and variance of the payouts in isolation, rather than focusing on the level and variance of the consumption stream flowing from the annuity (which is what matters for utility). It remains a leap of faith, however, to infer that the choice is more rational simply because demand is higher. Brown et al. (2017) establish that the deviation from rational choice, measured by the gap between peoples' sell versus buy prices for annuities, is lower for individuals with better cognition scores. The authors take this as suggestive evidence that valuing

annuities is cognitively challenging, because it is a complex task. Nevertheless, they do not claim that this is *causal* evidence of a mechanism, as they lack exogenous variation in the complexity of the annuitization decision.

In the present paper, we produce stronger evidence on behavioral mechanisms that may affect the annuitization decision. Rather than asking for a respondent's own hypothetical annuitization decision, we first describe a vignette where a hypothetical person faces an annuity decision, and we then ask our respondents to advise that vignette person. This alternative way of eliciting hypothetical annuitization choices allows us to experimentally vary characteristics of the vignette person that affect the complexity of the annuitization decision, but to hold the characteristics of the annuity itself constant. The annuitization decision faced by the vignette person is a choice between a lump sum amount and a change in Social Security benefits. We use the stream of Social Security benefits as the annuity in our experiment for two main reasons. First, most respondents are aware that Social Security payments last as long as they live (Greenwald, Kapteyn, Mitchell, and Schneider, 2010), which means they understand that Social Security provides an annuity even if they do not understand the term "annuity."<sup>1</sup> Second, because Social Security is a widely held annuity, it is natural to ask both about the value of decreases and increases in Social Security benefits, which allows us to measure the divergence between sell and buy valuations of the annuity. This divergence is our measure of deviations from rational decision-making.

Specifically, we present respondents regularly interviewed by the nationally representative Understanding America Study (UAS) with a vignette in which a hypothetical person faces a choice between receiving a \$100 per month *increase* in Social Security benefits, versus receiving a lump sum amount. We ask each respondent what the vignette person should choose and repeat the question for various values of the lump sums until we find the lump sum deemed equivalent in value to a \$100 per month increase in the Social Security annuity. We call this lump sum amount the "sell" valuation, because the respondent advises the vignette person to sell a \$100 a month annuity for this lump sum. At a different point in the experiment, we ask each respondent to advise the same vignette person on a choice between a \$100 per month *decrease* in Social Security benefits, versus paying a lump sum. The lump sum amount that is valued as much as the decrease in benefits is the "buy" valuation, as it represents the amount of money the respondent advises the

---

<sup>1</sup> While policy risk reduces people's valuation of the stream of Social Security benefits (Luttmer and Samwick, 2018), this should reduce both the buy and sell valuation, leaving their differential unaffected.

vignette person to pay to avoid forfeiting a \$100 per month annuity. We refer to the absolute difference between the log sell valuation and the log buy valuation as the “sell-buy spread,” and we use this to measure deviations from rational decision-making.

We introduce two experimental interventions to test for two types of behavioral impediments to valuing annuities.<sup>2</sup> First, we vary the complexity of the annuitization choice. Valuing an annuity stream is more difficult when there is greater uncertainty about longevity. We experimentally manipulate this uncertainty by telling the respondent what longevity information the vignette person received from a doctor. Valuing an annuity is also more difficult when the description of the annuity contains additional information that turns out to be irrelevant but nevertheless takes effort to process. This is an alternative means by which we vary complexity. Second, and independently, we randomize whether or not the respondent receives information about the benefits and drawbacks of spending down non-annuitized wealth during retirement more rapidly versus more slowly. This intervention occurs before the respondent advises the vignette person about annuitization. The purpose of the intervention is to induce people to think about the consumption consequences of holding an annuity during retirement. The “consequence message” intervention therefore has the potential to be a new instrument (besides framing) to reduce the narrow choice bracketing that Brown et al. (2008) identified as a behavioral mechanism.

Our experiment yields two main findings. First, we show that greater complexity causes the sell-buy spread to increase, indicating that complexity associated with annuities reduces people’s ability to assess the value of an annuity. This is the first causal evidence of complexity as a mechanism that impedes valuing annuities, and we consider this to be the first main contribution of our paper. This result supports the interpretation offered by Brown et al. (2017) that the cognitive challenge of assessing the value of an annuity makes people reluctant to either buy or sell an annuity, leading to a low buy price but a high sell price. Our finding is consistent with results from other contexts documenting that complexity reduces people’s responsiveness to incentives or the quality of their decision-making, including in work decisions (Abeler and Jäger, 2015), portfolio choice (Carlin, Kogan, and Lowery, 2013; Carvalho and Silverman, 2017), benefit claiming (Bhargava and Manoli, 2015), and the selection of health insurance plans (Schram and Sonnemans, 2011; Besedeš, Deck, Sarangi, and Shor, 2012a, b).

---

<sup>2</sup> As described below, we have included additional experimental interventions to test for anchoring and to test whether results are robust. All these experimental interventions are orthogonal to the two main interventions designed to test for behavioral impediments to valuing annuities.

Our second result is that the “consequence message” intervention reduces the sell-buy spread. In other words, people are better able to assess the value of an annuity if they think about the effect of the annuity on the distribution of their future consumption streams, versus when they do not make this connection. This finding supports Brown et al. (2008, 2013) on the role of choice bracketing in annuity decisions. Yet unlike that study, here we measure a deviation from rational decision-making by the discrepancy between the buy and sell price of a small change in annuitized wealth, which is a more objective indicator of lack of rational decision-making than simply the level of annuitization. We consider this additional evidence on choice bracketing the second main contribution of this paper, and our finding adds to the growing empirical evidence on choice bracketing based on experimental variation in the breadth of the decision frame. For example, Bertrand and Morse (2011) report that people take out smaller payday loans when they are experimentally induced to think more broadly about the consequences of taking out such loans, and Enke (2017) shows that people develop more accurate beliefs when they are experimentally induced to adopt broader mental frames.<sup>3</sup>

Evidence that behavioral mechanisms affect annuitization decisions has the important implication that one cannot infer how much people value annuities by simply observing their annuitization decisions. Specifically, the fact that observed voluntary annuitization levels are low does not necessarily imply that utility-maximizing levels of annuitization are also low. In light of behavioral mechanisms affecting annuitization decisions, the fact that Social Security pays out benefits exclusively as an annuity is particularly valuable to people that would otherwise underannuitize.

Evidence that complexity impedes annuitization decisions has the important implication that reducing complexity can improve individuals’ annuitization decisions. While it may be possible to make the decision less complex by presenting information about the annuity more clearly, we stress that much of the complexity is inherent in the annuitization decision itself: people need to jointly evaluate how much they will consume each future year with and without the annuity, how much they care about consumption fluctuations, and the probability that they will be alive in each future year. No matter how well the decision is presented, it remains a complex task. Similarly, evidence that inducing people to consider the consequences of annuitization decisions

---

<sup>3</sup> In addition, there is compelling empirical evidence that people do not treat money as fungible. Studies showing this include Kooreman (2000), Milkman and Beshears (2009), Feldman (2010), Hastings and Shapiro (2013), Beatty, Blow, Crossley, and O’Dea (2014), and Abeler and Marklein (2017). While these papers do not experimentally vary the breadth of the decision frame, a leading explanation of these findings is mental accounting, which is a form of choice bracketing.

for their consumption streams enables them to better assess the value of an annuity is important, because it provides clear guidance on how annuitization decisions should be presented. Still, while the consequence message limits the degree to which choice bracketing acts as an impediment to valuing an annuity, we emphasize that the sell-buy spread remains substantial even for those exposed to the consequences message.

The rest of the paper proceeds as follows. Section 2 describes our methodology and explains our experimental design. In Section 3, we present our empirical findings, and Section 4 concludes.

## **2. Methodology and Experimental Design**

### ***2.1 Understanding America Study***

Our experiment is conducted using the Understanding America Study (UAS), a probability-based Internet panel of about 6,000 adults (age 18+) representative of the U.S. population. Panel members are recruited exclusively through address-based sampling, in which invitation letters are sent to randomly-selected households using address lists obtained from the U.S. postal service. This provides a broadly representative sample, since individuals lacking prior access to the Internet were provided with a tablet and broadband Internet.<sup>4</sup> In addition, the UAS contains small oversamples (about 5% each) of Native Americans and of residents of Los Angeles County. Our experimental module was fielded between June and October of 2016, and all UAS panel members at the time were invited to participate. Panel members received \$10 for completing the survey, which took an average of 14 minutes, and they could also receive additional earnings depending on their answers to quiz questions. Of the 5,521 invited panel members, 83.2% opened the link to the survey.<sup>5</sup> Of those who opened the link, 99.1% completed both annuity valuation questions for an overall response rate of 82.4% (4,549 respondents).

The UAS gathers information on demographic characteristics for all respondents as well as detailed measures of cognitive capabilities and financial literacy (the latter for about 90% of respondents). Given that cognitive ability and financial literacy are important predictors of responses to annuity questions, we limit our analysis sample to those observations with nonmissing

---

<sup>4</sup> An extensive discussion of the UAS is provided in Alattar, Messer, and Rogofsky (2018).

<sup>5</sup> This response rate is typical in UAS surveys. The invitation read “In the following survey we want you to play the role of financial advisor. We will show you some examples of persons who have to make a decision about money and we will ask you to help them make the decision.”

measures of cognitive ability and financial literacy. In addition, we exclude 0.5% of observations with missing values for any demographic characteristics. The final analysis sample was therefore of 4,060 observations (89.2% of the total respondents who completed both questions and 73.5% of the panel members).

We recognize that a drawback of hypothetical choice data is that people may not put as much effort in making decisions as they might in real-life situations. As a result, their answers may contain more measurement error than would be true in the real world. Nevertheless, it seems unlikely that people can fully overcome cognitive biases simply by exerting more effort. Moreover, concerns about the reliability of willingness-to-pay responses in the UAS are allayed by Mas and Pallais (2017) who show that the distribution of willingness-to-pay for flexible work arrangements obtained in the UAS closely matched the willingness-to-pay distribution provided from a similar field experiment. In our case, using hypothetical choice data has the important advantage that we can elicit *both* a willingness-to-pay and a willingness-to-accept for the same person, permitting us to measure deviations from rational decision-making. We know of no field setting that allows for the simultaneous measurements of willingness-to-pay and a willingness-to-accept for an annuity for the same person. Moreover, in our setting, we observe the valuations of all respondents, in contrast to most revealed preference approaches where only the valuations of marginal individuals can be observed and the valuations of inframarginal persons can only be bounded, absent functional form assumptions.

Table 1 provides summary statistics for our baseline sample and compares it to the Current Population Survey (CPS) of the same year. Compared to the CPS, our sample overrepresents respondents between the ages of 35 and 65 by 11 percentage points, females by 6 percentage points, married respondents by 7 percentage points, Nonhispanic whites by 11 percentage points, individuals with more than a high school education by 16 percentage points, households with annual incomes above \$75,000 by 3 percentage points, households with two or fewer members by 10 percentage points, and households with no children by 5 percentage points. While these differences are generally statistically significant, the two samples are reasonably similar in terms of economic magnitudes, with the absolute difference in the fraction of respondents in a category being 5 percentage points on average across the 25 demographic categories listed in Table 1. As such, we consider our sample to be broadly representative of the U.S. adult population.

## ***2.2 Experimental Context***

Rather than describing an unfamiliar hypothetical annuity product, we use Social Security benefits as the context for the analysis of payout annuities. Specifically, we asked respondents to make trade-offs between receiving higher or lower Social Security benefits (a change in a real annuity stream), and paying or receiving different one-time payments (lump sums). Our setting is policy relevant because past discussions of pension reforms around the world, including in the U.S., have included proposals to offer workers lump sum payments in exchange for a reduction in their annuitized pension benefits (Maurer, Mitchell, Rogalla and Tschimetschek, 2018). Several U.S. corporations have also recently offered to buy back defined benefit pension annuities from retirees in exchange for lump sums (Wayland, 2012).

## ***2.3 Elicitation of the Valuation of an Annuity Stream***

Throughout the experiment, we use vignettes to describe trade-offs and ask respondents to give the hypothetical “vignette person” advice about annuitization decisions. This approach has several attractive features. First, we can directly manipulate the complexity of the annuitization decision by using different experimental treatments. Second, we control for the respondent’s own characteristics: unlike making a decision for one’s own situation (as in Brown et al. 2017), we need not worry about factors such as liquidity constraints or private knowledge that the respondent may have about his or her situation.

The vignette person in the control condition was described as follows:

*Mr. Jones is a single, 60-year old man with no children. He will retire and claim his Social Security benefits at 65. When he retires, he will have \$100,000 saved for his retirement, and he will receive \$[SSB] in monthly Social Security benefits. Based on his current health and family history, doctors have told Mr. Jones that he will almost certainly be alive at age 75 but almost certainly will not live beyond age 85.*

The gender and name of the vignette person was experimentally varied between respondents. The variable \$[SSB] represents the vignette person’s monthly Social Security benefits, and it was randomized with equal probability across respondents to \$800, \$1,200, \$1,600 and \$2,000.

Our main outcome of interest is the respondent’s advice for how the hypothetical “vignette person” should trade off annuitized wealth and lump sum amounts at retirement. All respondents answer a series of questions that elicit either the equivalent variation (EV) of a \$100 increase in

monthly Social Security benefits, or the EV of a \$100 decrease in monthly Social Security benefits. Each respondent was asked both questions, and the order in which they were asked was randomized.

The valuation of a \$100 increment in the annuity stream was elicited by asking a series of questions of the form:

*What should Mr. Jones do?*

*(1) Receive a Social Security benefit of  $[\$SSB+100]$  per month starting at age 65.*

*or*

*(2) Receive his expected Social Security benefit of  $[\$SSB]$  per month and receive a one-time payment of  $[\$LS]$  from Social Security at age 65.*

The \$100 increment in benefits of  $[\$SSB+100]$  was displayed as a single number on the screen. The variable  $LS$  represents the lump sum amount that is traded off, which was randomized across respondents to start at \$10,000, \$20,000 or \$30,000. The question was subsequently asked four more times for different values of  $LS$ . For example, if the person declined a \$20,000 lump sum, we inferred that that the valuation must exceed \$20,000, so for the next question we used a higher value of  $LS$ , namely \$60,000. Had the person accepted the \$20,000 lump sum, we would have used a lower value of  $LS$ . Next, if the person accepted the \$60,000 lump sum, we inferred that the valuation must lie below \$60,000, and we asked the question three more times to further reduce the difference between the lower and upper bound of the person's valuation of the \$100 increment in the annuity stream. The exact sequence of values for  $LS$  is shown in the survey instrument in the Online Appendix. We refer to this question as the "sell" version, because the person receives a payment in exchange for a smaller annuity stream.

The valuation of a \$100 decrease in the annuity stream was elicited by asking a series of questions of the form:

*What should Mr. Jones do?*

*(1) Receive a Social Security benefit of  $[\$SSB-100]$  per month starting at age 65.*

*or*

*(2) Receive his expected Social Security benefit of  $[\$SSB]$  per month and make a one-time payment of  $[\$LS]$  to Social Security at age 65.*

As before, the question was asked five times for different values of  $LS$  until we could place the respondent's valuation of the annuity into one of 32 bins. We refer to this question as the “buy” version, because the person is making a payment in exchange for a larger annuity stream.

Given that a \$100 change in the annuity stream is small relative to the average monthly benefit of \$1400, a rational respondent should value this change approximately the same whether it is an increase or a decrease. We therefore take the absolute difference of the sell and buy valuations to measure the deviation from rational decision-making.

## **2.4 Experimental Design**

Our experiment consisted of a 3x2 between-subjects design, summarized in Table 2. First, we experimentally varied the complexity of the vignette in one of two ways, either by increasing the uncertainty associated with length of life (*Complexity: Wide age range* treatment), or by adding extraneous information to the vignette that was not relevant to the decision (*Complexity: Added information* treatment). For example, control group respondents were told that the vignette person will “*almost certainly be alive at age 75 but almost certainly will not live beyond age 85.*” By contrast, respondents in the *Complexity: Wide age range* treatment were told that the vignette person “*has an 80% chance of being alive at age 70, a 50% chance of being alive at age 80, a 20% chance of being alive at age 90, and a 10% chance of being alive at age 95.*” Determining the value of an annuity is a more complex task when the variation in possible ages of death is more dispersed, as is the case in this second vignette. The extraneous information added to the *Complexity: Added information* treatment included information about Social Security qualification rules and described why the vignette person qualified. Here the increased complexity required the respondent to think about the additional information and determine whether it was relevant.

Second, prior to the advice decision, in half of the treatments we additionally provided a message about the consequences of spending down retirement savings (*Consequence message*). This message described an interaction between a different vignette person and his or her financial advisor. In this interaction, the advisor described the benefits and drawbacks of spending down savings relatively quickly (more likely to be able to use money in one's lifetime, but running a larger risk of running out of money while alive), versus relatively slowly (less likely to run out of money, but running a larger risk of not getting to enjoy one's money in one's lifetime). This message was framed as neutrally as possible and designed to encourage the respondent to avoid

narrow choice bracketing: by inducing respondents to think about the problem of how to spend down wealth in retirement, we intended that respondents consider the annuitization decision and the asset decumulation decisions jointly, rather than as disjoint decisions. To ensure that respondents paid attention to the message, respondents were further told that, at the end of the message, they would be asked two questions about the facts in the story and would receive an additional \$1 for each question they answered correctly. These factual questions were two multiple choice questions about the financial advisor’s explanation about the benefits and drawbacks under each scenario (spending down slowly or quickly). Of the respondents who were asked the two questions, 63% answered both correctly, 27% answered one correctly, and 10% answered neither correctly.

In summary, all respondents were asked to give advice to a primary vignette person about buying and selling a small fraction of that vignette person’s Social Security benefit stream. Between respondents, we had two main treatments: (1) the information about the vignette person, which was randomized between “*No added complexity*”, “*Complexity: Wide age range*”, and “*Complexity: Added information*”, and (2) whether we discouraged narrow choice bracketing, where we randomized between “*No consequence message*” and “*Consequence message.*” In addition, we had six secondary randomizations. We also performed two randomizations to test for anchoring, which is another indication of lack of rational decision-making: (3) the starting value for the lump sum amount (\$LS=\$10,000, \$20,000, \$30,000); and (4) the order of the two annuity valuation questions. Finally, we randomized (5) the name and gender of the primary vignette person (*Mr. Jones, Mrs. Jones, Mr. Smith, Mrs. Smith*) and the secondary vignette person, featured in the consequence message, had the opposite name and gender of the primary vignette person;<sup>6</sup> (6) the Social Security benefit (\$SSB=\$800, \$1,200, \$1,600 or \$2,000); (7) the order of the options shown (option with lump sum always shown first, option with lump sum always shown last); and (8) whether the consequence message first discussed the consequences of spending wealth down quickly or slowly. The latter four manipulations were intended to verify that choices in the vignette

---

<sup>6</sup> In short, the secondary vignette person was female if and only if the primary vignette person was male, and vice versa. Similarly, the secondary vignette person was named Jones if and only if the primary vignette person was named Smith, and vice versa. We did this to eliminate the possibility that the consequence message affected advice on annuity choices for the primary vignette person by respondents inferring the primary vignette person’s preferences or circumstances from information provided in the consequence message. Because the consequence message used a different person, it can only have altered the advice by the respondent through the respondent thinking differently about annuitization decisions rather than the respondent knowing more about the annuitant him- or herself.

that we assumed would be innocuous indeed did not matter for our results. All randomizations occurred across subjects and were mutually orthogonal. The options within each randomization had equal probability of being selected.

## ***2.5 Data on Cognition***

To investigate how the ability to value annuities varies by cognitive ability, we merged the data from our survey with existing data in the UAS, including a financial literacy survey (Lusardi and Mitchell, 2014). We also included four subtests of the Woodcock-Johnson Test of Cognitive Ability, a nationally normed test. The sub-tests included numeracy, number series, verbal analogies, and picture vocabulary. Whereas the first two sub-tests measure numerical ability, the second two tests measure lexical ability. We standardize the financial literacy measure and each of the four test scores. For the main analysis, we create a “cognition index” from these four tests and the financial literacy measure by taking their first principal component. In the robustness section, we demonstrate the robustness of the main results to using alternative measures of cognition.

## **3. Results**

### ***3.1 Baseline Sample and Randomization Check***

As noted in Section 2.1, our baseline sample consists of respondents who answered both annuity valuation questions and who have nonmissing values for the cognition and demographic variables. We investigate whether the exclusion from the baseline sample due to missing data is balanced across the two key treatment conditions (see Appendix Table A1), and we find that neither the complexity treatment nor the consequence message treatment affect the likelihood that the respondent failed to answer the annuity questions ( $p$ -values: 0.322 and 0.491, respectively). The fraction of observations with missing demographic data is marginally significantly higher in the complexity treatment than in the control condition, and the fraction with missing cognition data is significantly higher in the complexity treatment than in the control condition. Since both demographic and cognition data were collected prior to randomization, these findings cannot logically be a consequence of the treatment, and we conclude they were a fluke of the randomization. There are no significant differences in the fractions with missing demographics or cognition data between the consequence treatment and the control condition. In Section 3.5 below,

we explore the robustness of the main results to including observations with missing demographic or cognition information.

We also test for balance on the control variables in the baseline sample by the two main treatments (Panel B, Appendix Table A1). Of the four dozen tests of differences in means across treatments for individual control variables, four are significant at the 10-percent level and one at the 5-percent level. This is roughly what one would expect by chance. Jointly, the control variables do not significantly predict the complexity treatment ( $p$ -value: 0.107) or the consequence message treatment ( $p$ -value: 0.788).

### ***3.2 Annuity Valuation Distributions and Summary Statistics***

Figure 1 shows the distribution of buy valuations for the subsample in which the buy valuation was asked first, and the distribution of sell valuations for the subsample in which the sell valuation was asked first. By focusing on valuations when the question was asked first, we avoid any influence of anchoring on a previously-asked valuation question. The figure clearly shows that the buy valuation is lower than the sell valuation throughout the distribution. Respondents advised our hypothetical vignette individuals to *buy* an annuity that pays \$100 per month for a median price of \$4,750 (s.e.: \$180) but advised them to *sell* this annuity for a median price of \$16,250 (s.e.: \$543). This represents a statistically significant difference (two-sample Wilcoxon-Mann-Whitney rank-sum test  $z$ -statistic=25.8,  $p$ -value<0.001).<sup>7</sup> The actuarially fair value of this annuity is roughly \$15,000 at a 3% real discount rate.

Rational individuals should value a marginal increase in the Social Security annuity the same as a marginal decrease. To examine the extent to which this holds in our data, where we ask about a \$100 change in the Social Security annuity, we calculate for each respondent the difference between the log sell price and the log buy price. Figure 2 shows the distribution of this log difference for our baseline sample. The figure highlights two facts. First, there are large differences between buy and sell values at the individual level. Only about 10 percent of respondents have a buy value that is equal to their sell value, and only 40 percent have a buy and sell value that are within one log unit (i.e., within a factor of 2.72) of each other. In short, deviations from the

---

<sup>7</sup> Appendix Figure A1 shows the distributions of the buy and sell valuations in the entire baseline sample which, unlike Figure 1, includes responses to valuation questions that followed an earlier valuation question. The distributions are similar to those in Figure 1.

predictions of the rational model for buy and sell valuations of marginal changes in Social Security benefits are substantial.<sup>8</sup> Second, the distribution is not symmetric around zero: 63% have sell valuations that strictly exceed their buy valuations, whereas buy valuations strictly exceed sell valuations for about 27% of respondents. As Brown et al. (2017) explain, people may worry that they might be taken advantage of when they trade a good that they cannot value accurately. Accordingly, it can be a useful heuristic to be reluctant to trade such goods, and only to sell them at a very high price (or buy them at very low price). Such a heuristic predicts that sell prices exceed buy prices whenever it is difficult to accurately determine the value of a good, as is the case with an annuity. We note that status-quo bias (or an endowment effect) in the level of Social Security benefits cannot explain why sell prices generally exceed buy prices. We elicited the sell price as the price for which people would be willing to sell \$100 of Social Security benefits that would be received on top of the expected benefits. Someone with status-quo bias would put a low price on this \$100 of benefits because this amount is in addition to the status-quo level of benefits. Conversely, we elicited the buy price as the price for which people would be willing to buy \$100 of Social Security benefits that would bring the total benefit level back to the expected level. Thus, someone with status-quo bias would place a high price on these benefits because they would return the benefit level to the status quo.

Any difference between the sell and buy price is a deviation from the prediction of the rational model for marginal changes in Social Security benefits, whether the sell price differs from the buy price due to the reluctance-to-trade heuristic offered by Brown et al. (2017) or for other reasons. Accordingly, our measure of the deviation from rational decision-making is the absolute value of the difference between the log buy price and the log sell price. We refer to this variable as the *spread* and use it as our main outcome variable. Figure 3 shows the distribution of the spread and Table 3 presents summary statistics. Results show that 90 percent of respondents have a strictly positive spread, the median spread is 1.55, and the mean spread is 2.21. The table also shows the components of the spread, namely the log buy price and the log sell price. Anchoring mainly affects the buy price, which is significantly higher when asked after the (generally higher) sell price is elicited. The spread is slightly higher when the sell question was asked first (2.27 versus 2.16), but this difference is only marginally significant ( $p$ -value: 0.079). Because the spread is measured as

---

<sup>8</sup> In Section 3.5, we show that these deviations cannot be explained by the fact that the \$100 change in Social Security benefits is not strictly speaking a marginal change.

an absolute log difference, an increase in the spread of 0.11 (from 2.16 to 2.27) can be interpreted as the difference between the higher valued annuity and the lower valued annuity increasing by 12 ( $=\exp(0.11)$ ) percentage points.

Our findings on the discrepancy between buy and sell valuations are in line with the results of Brown et al. (2017), who asked respondents for how much they *themselves* would buy or sell an annuity that paid them \$100 per month. This similarity is reassuring, as it suggests that our elicitation of valuation advice to a vignette person (rather than asking about respondents' own valuations) does not meaningfully alter the responses. A further similarity is that we also find that the log buy and the log sell valuations are negatively correlated (correlation coefficient: -0.11,  $p$ -value < 0.001).<sup>9</sup> Our use of vignettes allows us to vary the complexity of the annuity by experimentally altering the dispersion of ages of death, which would not be ethically feasible when asking about an annuity tied to the respondent's own life.

### **3.3 Treatment Effects**

In Table 4, we investigate our two main research questions. The first asks whether complexity inhibits respondents' ability to value an annuity stream. The second asks whether narrow choice bracketing contributes to respondents' difficulty in valuing the annuity. We measure respondents' inability to value an annuity by the spread between their sell and buy valuations, because the spread should be approximately zero for fully rational respondents. In all regressions, we control for the experimental manipulations,<sup>10</sup> the cognition index, and a common set of control variables (see Panel B, Appendix Table A1). In Table 4, we report only the coefficients of interest (the full set of coefficient estimates is provided in Appendix Table A2).

The estimate in the first row of Column 1 shows that the complexity treatment increases the sell-buy spread by 0.131, implying a 14 percent ( $=\exp(0.131)$ ) increase in the ratio of the higher-valued to the lower-valued annuity. To our knowledge, this is the first causal evidence that the complexity of an annuity choice affects peoples' reported annuity valuations. The fact that complexity increases the spread between the buy and sell price indicates that complexity reduces

---

<sup>9</sup> The negative correlation and the discrepancy between buy and sell prices are also consistent with the results of Chapman, Dean, Ortoleva, Snowberg, and Camerer (2017), who elicit buy and sell prices for a monetary lottery in an incentivized way and show that these prices are persistent within person over time and that the discrepancy between buy and sell prices is not due to measurement error.

<sup>10</sup> We do not control for the order in which the two blocks of consequence message treatment were shown because this variable is available for only half the sample. Within the half of the sample for which this order was randomized, the order has no significant effect on the spread ( $p$ -value: 0.758).

individuals' ability to accurately value an annuity. The next two columns show the effect of the complexity treatment on the buy and sell price, separately. While the estimates seem to indicate that the complexity treatment primarily operates on the buy price, and hence it reduces the average of the log sell and buy price, this is not a valid interpretation as we cannot reject that increase in the sell price and the decrease in the buy price are the same in absolute value ( $p$ -value 0.302). We also evaluate whether the two types of complexity treatments (*wide age range* vs. *added information*) have different effects on the spread. As reported in Appendix Table A3, this is not the case ( $p$ -value: 0.646), so we therefore pool the two complexity treatments.

The second row shows the treatment effects of the consequence message. The consequence message decreases the sell-buy spread by 0.141. This means that inducing respondents to think about how to spend down savings during retirement causes them to report an annuity sell price and a buy price that are closer together, which is consistent with being more able to value annuities rationally. Apparently, the consequence message reduces the degree to which respondents consider annuitization and the spending down of assets during retirement as two separate decisions, a form of narrow choice bracketing. The consequence message does move the buy and sell value closer by 15 percentage points, but this still leaves a substantial spread of  $2.21 - 0.14 = 2.07$  log units among respondents who received the consequence message. In short, decision-making among those who receive the consequence message is still far from rational, given that their spread remains well above 0. The next two columns show that the consequence message has virtually no effect on the sell price but significantly increases the buy price. In fact, it marginally significantly *increases* the average of the log buy and sell price ( $p$ -value 0.073), suggesting that the consequence message not only increases the rationality of the annuity valuations but also raises the levels. The latter finding is what one would expect when people jointly consider the asset decumulation decision and how to value the lifetime income stream. In particular, annuities remove uncertainty in consumption associated with asset decumulation in the face of uncertain life spans.

The third row shows that the cognition index is a very strong predictor of the sell-buy spread, with a standard deviation increase in the cognition index narrowing the sell-buy spread by 0.788. This underscores the conclusion that cognitive limitations play an important role in people's inability to value an annuity. This limitation had been previously established in a different setting by Brown et al. (2017), but we now have causal evidence on two mechanisms by which cognition affects people's ability to value annuities: narrow choice bracketing, and the complexity of the annuity choice. The effect of cognition also allows us to put the magnitudes of the treatment effects

in perspective. Each of our two treatments, which by coincidence have the same absolute magnitude of around 0.14, has the same effect on the spread as roughly a 17% ( $=0.14/0.79$ ) of a standard deviation change in cognitive ability.

The remaining rows examine the effects of our secondary randomizations. Consistent with earlier findings in the literature, and indicative of less-than-fully rational decision-making, we find significant effects of anchoring. When we ask the sell valuation first (which typically has a higher valuation than the buy valuation), the respondent's buy valuation is significantly higher, consistent with the buy valuation being anchored on the sell valuation. We find no significant anchoring of the sell price on the buy price when the latter is asked first. The starting values (\$10,000, \$20,000, or \$30,000) of the lump sum amount used in the annuity value elicitation procedure also have a strong effect on the valuation reported: in fact, we can reject at the 1-percent level that the starting value has no effect on the sell price or the buy price. The starting value has a similar effect on the sell and buy price, resulting in no significant net effect on the spread. The remaining randomizations cover the various choices we made in the design of the experiment (whether the lump sum amount was the first or second choice, the monthly Social Security benefit amount, and the name of the vignette person). We anticipated that these choices would be innocuous, but the randomizations allow us to test whether outcomes indeed are insensitive to them. The last three rows show that these choices had no significant effects on our main outcome variable, the sell-buy spread. With the exceptions of the effect of vignette name and the benefit amount on the buy price, these choices also do not affect the sell or buy price.<sup>11</sup>

What would annuity valuations be if we had an intervention sufficiently powerful to cause the mean log sell price and the mean log buy price to be equal (so no deviation from rationality at the mean)? We can get a rough answer to this question by extrapolating the effects of each of our two main experimental interventions. The mean log difference between the sell and buy price is 1.01 (see Figure 2), and the consequence message moves log sell and buy price closer by 0.122 ( $=0.133-0.011$ , see columns 2 and 3 of Table 4). Thus, a treatment about  $8 \approx 1.01/0.122$  times more powerful than our current consequence message would close the gap between the mean log sell and buy price. At that level of treatment, the median sell and buy price would be predicted to be

---

<sup>11</sup> One might expect that people with a higher Social Security benefit amount to begin with put a lower value on a \$100 change in Social Security benefits. After all, they are already more highly annuitized. To test this, we ran an alternative specification in which the baseline Social Security benefit amount was included as a linear control instead of as a set of dummy variables. Both the buy and sell value decline in the baseline amount of Social Security benefits. The effect is not significant for the sell value ( $p$ -value 0.145) but there is a significant 2.5% decline in the buy value for each additional \$100 in baseline Social Security benefits.

about \$17,000. Similarly, we can extrapolate the complexity treatment, but in the direction of making the problem less complex, such that the sell and buy price coincide. This would require reducing complexity by about 5 times the amount of complexity added by our complexity treatment. The resulting sell and buy prices would then be predicted to be about \$12,000. These point estimates obviously rely on a substantial extrapolation, and therefore they should be taken as only suggestive. Nevertheless, it is noteworthy that a simple average of these two predicted valuations at treatments sufficiently powerful to eliminate the discrepancy between the buy and sell prices is quite close to the actuarially fair value (of about \$15,000).

### ***3.4 Heterogeneous Treatment Effects***

In Table 5, we explore whether the impact of our two main treatments varies across respondent subgroups. The first column examines heterogeneity in the effect of the complexity treatment, and the second column investigates whether the consequence message has different effects across subgroups. For each specification, we create two subgroups that are as close as possible in size to each other in order to maximize statistical power.

The first two specifications examine interaction effects between our treatments. One might expect that the complexity treatment has a greater impact on the spread when people engage in narrow choice bracketing, because they do not recognize how annuities help in the asset drawdown process. In line with this prediction, the point estimate of the complexity treatment is larger for respondents who receive no consequence message than for those who do; nevertheless, this difference is not statistically significant ( $p$ -value: 0.408). The second specification is the flipside of the first, asking whether the consequence message has a greater impact on persons exposed to the complexity treatment. While the point estimates do go in this direction, this effect is not significant either (and the  $p$ -value is the same as in the first specification by construction).

The remaining specifications examine heterogeneity by cognition, gender, education, age, income, and level of Social Security benefits, respectively. In none of the 10 specifications do we find a difference in the treatment effect by demographic characteristic significant at the 5-percent level or better. Respondents age 50 or older are marginally significantly more affected by the complexity treatment than younger respondents, but we are reluctant to make much of this single marginally significant result given issues surrounding multiple hypothesis testing when running more than a dozen specifications.

The last specification splits the estimates by the randomly assigned level of Social Security benefits. The \$100 change in Social Security benefits is closer to a marginal change for someone with monthly benefits of \$2000 than for someone with monthly benefits of \$800. The stability of treatment effects by level of benefits helps alleviate concerns that the estimates are affected by the fact that the \$100 change is not literally a marginal change.

### ***3.5 Robustness***

Table 6 examines the robustness of the two primary treatments to different measures of cognition, to different ways of selecting the sample, to different sets of controls, and to transformations of the outcome variable. The first row reproduces our baseline specification from Column 1 of Table 4. Subsequent rows provide estimates on the two main treatments in specifications identical to the baseline specification, except for the change noted in the row heading.

In Panel A, we examine the robustness to using different measures of cognition because cognition is a very strong predictor of the spread and because we saw in Appendix Table A1 that the cognition index is marginally significantly higher for those who received the complexity treatment than for those who did not. Rows (2) and (3) show that the point estimates and standard errors are not at all sensitive to the details of the construction of the cognition index: it does not matter whether we control for cognition by using the first principal component of the five available cognition measures, by taking a simple average of these five measures, or by entering all five measures separately. However, it is important for the significance of complexity treatment that we exploit information from all the cognition tests. If we control only for financial literacy, the point estimate on the complexity treatment declines moderately (by about a fifth) but loses statistical significance. If we control only for the two numeracy measures or only for the two verbal measures, the point estimate on the complexity treatment declines somewhat (by less than a fifth) but becomes only marginally statistically significant. In contrast, the point estimate on the consequence message is very stable, retaining statistical significance in all three specifications that use a subset of the cognition measures.

Panel B examines robustness to different sample definitions. Row (7) includes observations with missing demographic information, row (8) includes observations with missing cognition data, row (9) includes observations with any missing information (demographic or cognition), and row

(10) excludes the oversamples of Native Americans and Los Angeles county residents. We include observations with missing values in the regression by dummifying out the missing values. While the coefficient estimate of the complexity treatment is reasonably stable, it becomes only marginally significant once observations with missing cognition data are included or the oversample is excluded. The estimate of the treatment effect of the consequence message remains significant in all specifications of Panel B. Next, Panel C investigates robustness to excluding various controls. Given the earlier finding that cognition is not quite balanced across complexity treatments, it is not surprising that the complexity treatment is sensitive to having cognition controls included. Excluding the controls for the secondary experimental manipulations makes the complexity treatment only marginally significant. The four remaining estimates of panel C are not sensitive in magnitude or significance to the exclusion of controls.

Our module tells the respondent that the vignette person will have saved \$100,000 for retirement when making the annuity decision. Hence, unless there are other sources of savings, the vignette person cannot logically pay more than \$100,000 for an annuity. This implies that there is an implicit topcode of \$100,000 on the buy valuations, though respondents are permitted to give a buy recommendation at a price in excess of \$100,000, and 9% of them do so. Nevertheless, we want to be sure that this implicit topcode does not drive key results. More generally, it is useful to know that the results do not hinge on a few respondents with very high buy or sell valuations. In the final specification check, therefore, we topcode all buy and all sell valuations at \$100,000. Row 14 of Panel D shows that the main results are not sensitive in terms of economic magnitude or statistical significance to such topcoding. Similarly, Row 15 shows that the results are not sensitive to topcoding the spread itself at the 90<sup>th</sup> percentile, rather than topcoding the underlying sell or buy valuations. Row 16 shows that bottomcoding the buy and sell valuations at \$1000 each results in somewhat smaller estimates that are significant at the 10% level. Apparently, the low valuations given by some respondents do contribute to the significance of our treatment effects.

Our finding in Table 5 that the treatment effects do not meaningfully vary by the level of Social Security benefits already alleviated the concern that our estimates might be due to the fact that a \$100 change in monthly Social Security benefits is not literally a marginal change. Another way to address this concern is to not count small spreads, which could arise when a \$100 change is insufficiently marginal, as deviations from rational behavior. In row 17, we do this by setting

any spreads less than 0.50 log units equal to zero, and we find that the estimated treatment effects are essentially unaffected.

We defined the spread as strictly positive both when the sell price is larger than the buy price and vice versa. We did this because any difference is a deviation from rationality for a marginal change in Social Security benefits. However, if our treatment effects operate by reducing individuals' reluctance to trade when their understanding increases (due to the consequence message) or decreases (due to increased complexity), then they should operate predominantly on people who are reluctant to trade, i.e., whose sell price exceeds their buy price. We test this prediction in row 18 by having a positive spread only for those who are reluctant to trade, and setting the spread to zero for everyone else. Row 18 confirms that the treatment effects operate entirely on those who had sell prices exceeding buy prices, which is consistent with people's reluctance to trade being affected by the degree of their understanding.

Overall, Table 6 shows that the results on the complexity treatment are reasonably stable in magnitude but somewhat sensitive in terms of statistical significance, which falls to marginal in 7 of the 17 specification checks and disappears in 2 of them. This sensitivity can be traced largely to the fact that the cognition control, a very strong predictor of the spread, was not balanced across the complexity treatment and control conditions. Hence, having good controls for cognition is important for the results of the complexity treatment. By contrast, the consequence message treatment is extremely robust and remains significant at the 5% level everywhere, except for one specification where it is significant at the 10% level.

#### **4. Conclusion**

Annuities allow people to smooth consumption in retirement when facing an uncertain age of death, yet annuity holdings are relatively low and only about 3 percent of individuals maximize their annual Social Security annuity payouts by delaying claiming benefits until age 70 (Social Security Administration, 2017). While these decisions may be rational for some people, this paper investigates whether behavioral factors impede people's annuitization choices. We do so in the context of a hypothetical choice experiment on a broadly representative sample of about 4,000 adults in the U.S. Such a setting confers two important advantages for our purposes. First, we can measure deviations from rational decision-making by observing for each respondent both his willingness to pay to forgo a small decrease in annuitization and his willingness to accept to forgo

a small increase in annuitization. Second, we can experimentally vary the complexity of the annuitization decision. We also experimentally vary whether respondents are encouraged to jointly consider the annuitization decision and the asset decumulation decision during retirement (thus discouraging narrow choice bracketing), though this treatment could in principle also be applied in non-hypothetical choice settings.

Our first main finding is that increasing the complexity of the annuity decision reduces people's ability to value the annuity. This decreased ability manifests itself as an increase in the divergence of people's sell and buy prices for a marginal change in annuitization. When the annuity decision becomes more complex, people tend to become more reluctant to buy or sell annuities, meaning they need greater inducements (lower buy or higher sell prices) to do so. Brown et al. (2017) document that a reluctance to trade annuities, as measured by the sell-buy price spread, is strongly negatively associated with cognitive ability, but of course, cognitive ability is not randomly assigned. In our setting, we experimentally vary the complexity of the annuitization decision to obtain the first causal evidence that more complex annuitization decisions reduce people's ability to place a value on an annuity, as measured by the sell-buy spread. Hence the observed low level of annuity holdings, at least in part, can be traced to the cognitive challenges of the complex task of valuing an annuity.

The second finding is that inducing people to jointly think about annuitization and how to draw down assets during retirement increases their ability to place a value on an annuity. We experimentally induce respondents to think about these decisions jointly by exposing them to a "consequence message" which explains the result of spending down assets more slowly or more rapidly during retirement. Respondents who think about this asset decumulation decision have a smaller sell-buy spread for annuities than do respondents not exposed to the consequence message. This finding suggests that narrow choice bracketing, which the consequence message counteracts, is one behavioral mechanism impeding people from placing a rational value on annuities.

Our results on the roles of complexity and cognitive ability offer relatively little scope for interventions to improve the quality of people's annuitization decisions. Cognitive ability is relatively immutable as is the complexity of the annuitization decision for any given person. While this complexity can be somewhat diminished by presenting the annuity information more transparently, most of the complexity stems from having to consider how the annuity would alter consumption streams in different states of the world, which is an inherently complex task. In contrast, our finding on the role of narrow choice bracketing does offer scope for interventions to

improve people's decision-making about annuities. In particular, people provide more rational annuity valuations if they first consider the question of how to spend down non-annuitized wealth during retirement. We therefore conclude that annuitization decisions can be improved by inducing people to jointly consider annuitization and spending down non-annuitized wealth.

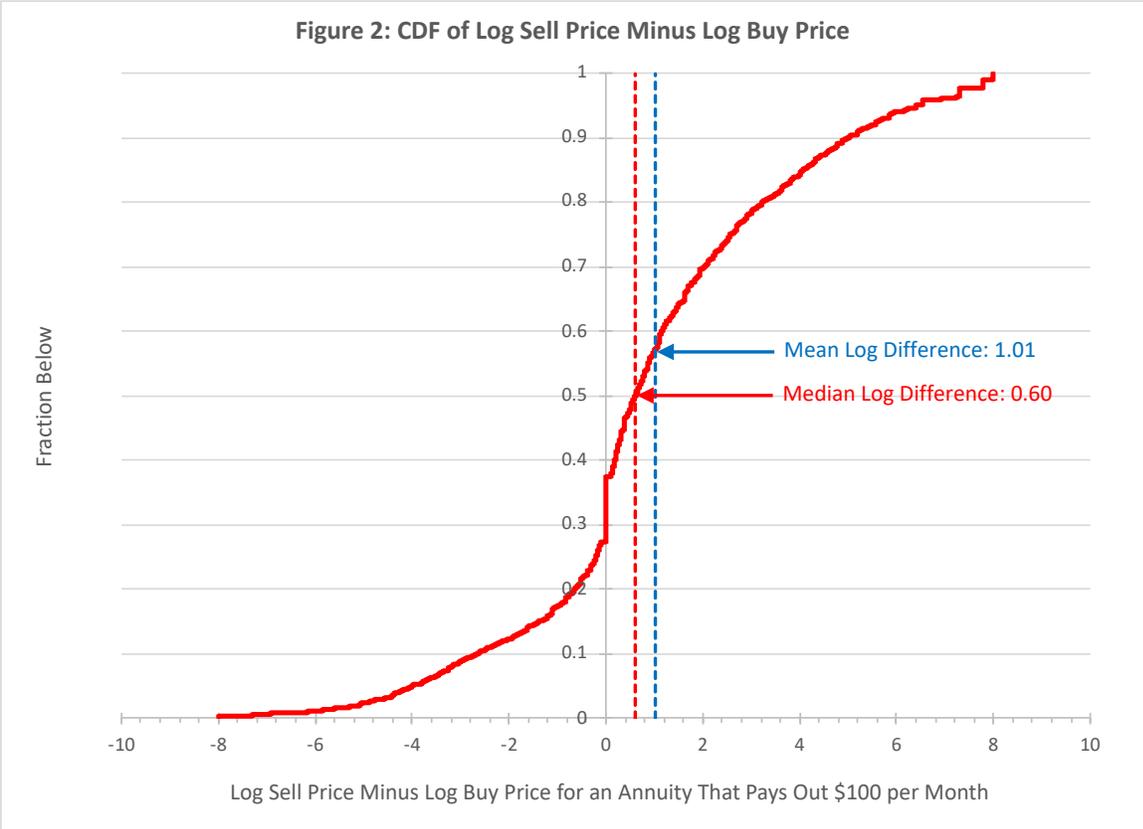
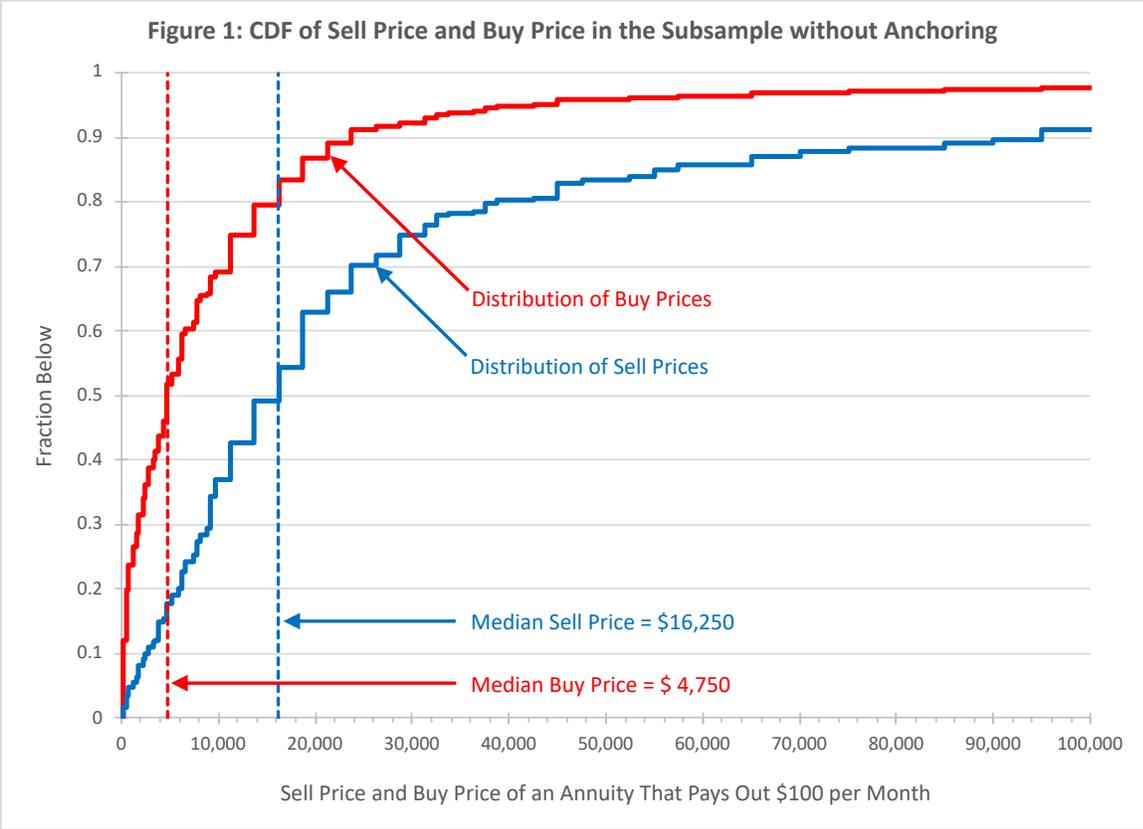
Our paper adds to the evidence that behavioral factors influence annuitization decisions, and it also provides causal evidence on two specific mechanisms: narrow choice bracketing and cognitive limitations to dealing with complex decisions. Naturally, our evidence on these two behavioral impediments to valuing annuities does not preclude other mechanisms (c.f., Brown 2009). An avenue for future investigation could quantify the welfare effects of behavioral deviations from rational decision-making in the context of annuitization decisions.

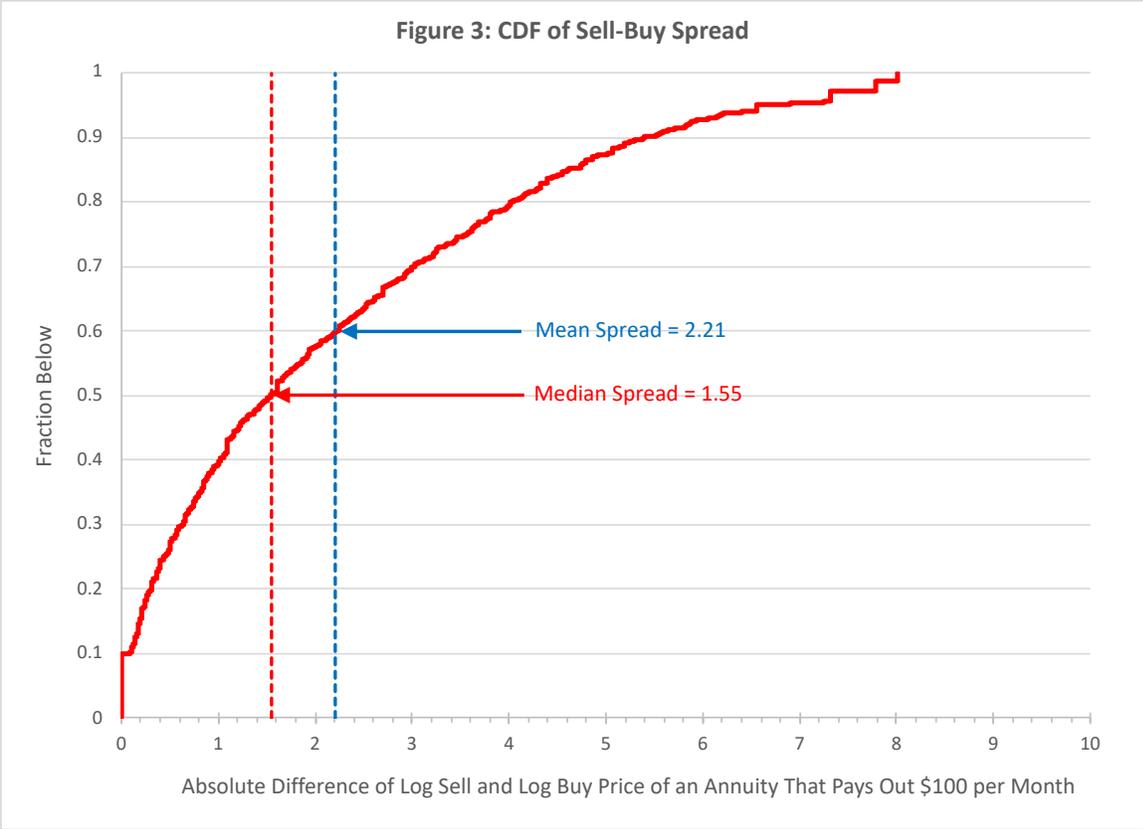
## References

- Abeler, Johannes, and Simon Jäger. 2015. "Complex Tax Incentives." *American Economic Journal: Economic Policy* 7(3): 1–28.
- Abeler, Johannes, and Felix Marklein. 2017. "Fungibility, Labels, and Consumption." *Journal of the European Economic Association* 15(1): 99–127.
- Agnew, Julie R., Lisa R. Anderson, Jeffrey R. Gerlach, and Lisa R. Szykman. 2008. "Who Chooses Annuities? An Experimental Investigation of the Role of Gender, Framing, and Defaults." *American Economic Review: Papers and Proceedings* 98(2): 418–422.
- Alattar, Laith, Matt Messel, and David Rogofsky. 2018. "An Introduction to the Understanding America Study Internet Panel." *Social Security Bulletin* 78(2): 13–28.
- Ameriks, John, Joseph Briggs, Andrew Caplin, Matthew D. Shapiro, and Christopher Tonetti. 2018. "Long-Term-Care Utility and Late-in-Life Saving." Vanguard Research Initiative Working Paper.
- Ameriks, John, Andrew Caplin, Steven Laufer, and Stijn Van Nieuwerburgh. 2011. "The Joy of Giving or Assisted Living? Using Strategic Surveys to Separate Public Care Aversion from Bequest Motives." *The Journal of Finance* 66(2): 519–561.
- Beatty, Timothy K.M., Laura Blow, Thomas F. Crossley, and Cormac O’Dea. 2014. "Cash by Any Other Name? Evidence on Labeling from the UK Winter Fuel Payment." *Journal of Public Economics* 118: 86–96.
- Benartzi, Shlomo, Alessandro Previtero, and Richard H. Thaler. 2011. "Annuitization Puzzles." *Journal of Economic Perspectives* 25(4): 143–64.
- Bertrand, Marianne, and Adair Morse. 2011. "Information Disclosure, Cognitive Biases, and Payday Borrowing." *The Journal of Finance* 66(6): 1865–1893.
- Besedeš, Tibor, Cary Deck, Sudipta Sarangi, and Mikhael Shor. 2012a. "Age Effects and Heuristics in Decision Making." *Review of Economics and Statistics* 2: 580–595.
- Besedeš, Tibor, Cary Deck, Sudipta Sarangi, and Mikhael Shor. 2012b. "Decision-Making Strategies and Performance among Seniors." *Journal of Economic Behavior and Organization* 81: 524–533.
- Beshears, John, James J. Choi, David Laibson, Brigitte C. Madrian, and Stephen P. Zeldes. 2014. "What Makes Annuitization More Appealing?" *Journal of Public Economic* 116: 2–16.
- Bhargava, Saurabh, and Dayanand Manoli. 2015. "Psychological Frictions and the Incomplete Take-Up of Social Benefits: Evidence from an IRS Field Experiment." *American Economic Review* 105(11): 3489–3529.
- Bockweg, Christian, Eduard Ponds, Onno Steenbeek, and Joyce Vonken. 2018. "Framing and the Annuitization Decision: Experimental Evidence from a Dutch Pension Fund." *Journal of Pension Economics and Finance* 17(3): 385–417.
- Bronshtein, Gila, Jason Scott, John B. Shoven, and Sita N. Slavov. 2016. "Leaving Big Money on the Table: Arbitrage Opportunities in Delaying Social Security." NBER Working Paper No. 22853.
- Brown, Jeffrey R. 2009. "Understanding the Role of Annuities in Retirement Planning." In *Overcoming the Savings Slump: How to Increase the Effectiveness of Financial Education and Saving Programs*, edited by Annamaria Lusardi. Chicago: University of Chicago Press: 178–206.
- Brown, Jeffrey R., Arie Kapteyn, Erzo F.P. Luttmer, and Olivia S. Mitchell. 2017. "Cognitive Constraints on Valuing Annuities." *Journal of the European Economic Association* 15(2): 429–462.

- Brown, Jeffrey R., Arie Kapteyn, and Olivia S. Mitchell. 2016. "Framing and Claiming: How Information Framing Affects Expected Social Security Claiming Behavior." *Journal of Risk and Insurance* 83(1): 139–162.
- Brown, Jeffrey R., Jeffrey R. Kling, Sendhil Mullainathan, and Marian V. Wrobel. 2008. "Why Don't People Insure Late Life Consumption? A Framing Explanation of the Under-Annuitization Puzzle." *American Economic Review* 98(2): 304–309.
- Brown, Jeffrey R., Jeffrey R. Kling, Sendhil Mullainathan, and Marian V. Wrobel. 2013. "Framing Lifetime Income." *The Journal of Retirement* 1(1): 27–37.
- Bütler, Monika, and Federica Teppa. 2007. "The Choice between an Annuity and a Lump Sum: Results from Swiss Pension Funds." *Journal of Public Economics* 91(10): 1944–1966.
- Carlin, Bruce Ian, Shimon Kogan, and Richard Lowery. 2013. "Trading Complex Assets." *The Journal of Finance* 68(5): 1937–1960.
- Carvalho, Leandro and Dan Silverman. 2017. "Complexity and Sophistication." Working Paper, The University of Southern California.
- Chalmers, John, and Jonathan Reuter. 2012. "How Do Retirees Value Life Annuities? Evidence from Public Employees." *Review of Financial Studies* 25(8): 2601–2634.
- Chapman, Jonathan, Mark Dean, Pietro Ortoleva, Erik Snowberg, and Colin Camerer. 2017. "Willingness to Pay and Willingness to Accept are Probably Less Correlated than You Think." National Bureau of Economic Research Working Paper No. 23954.
- Davidoff, Thomas, Jeffrey R. Brown, and Peter A. Diamond. 2005. "Annuities and Individual Welfare." *American Economic Review* 95(5): 1573–1590.
- Enke, Benjamin. 2017. "What You See Is All There Is." Working Paper, Harvard University.
- Feldman, Naomi E. 2011. "Mental Accounting Effects of Income Tax Shifting." *The Review of Economics and Statistics* 92(1): 70–86.
- Fitzpatrick, Maria Donovan. 2015. "How Much Are Public School Teachers Willing to Pay for Their Retirement Benefits?" *American Economic Journal: Economic Policy* 7(4): 165–188.
- Gazzale, Robert S., and Lina Walker. 2011. "I'll Cross That Bridge If I Get to It: Focusing on the Near (Certain) Future." Unpublished Manuscript. University of Toronto.
- Greenwald, Mathew, Arie Kapteyn, Olivia S. Mitchell, and Lisa Schneider. 2010. "What Do People Know about Social Security?" RAND Working Paper WR-792-SSA.
- Hagen, Johannes, Daniel Hallberg, and Gabriella Sjögren Lindquist. 2018. "A Nudge to Quit? The Effect of a Change in Pension Information on Annuitization, Labor Supply and Retirement Choices among Older Workers." GLO Discussion Paper Series 209, Global Labor Organization.
- Hastings, Justine S., and Jesse M. Shapiro. 2013. "Fungibility and Consumer Choice: Evidence from Commodity Price Shocks." *The Quarterly Journal of Economics* 128(4): 1449–1498.
- Hurd, Michael, and Stan Panis. 2006. "The Choice to Cash out Pension Rights at Job Change or Retirement." *Journal of Public Economics* 90(12): 2213–2227.
- Kooreman, Peter. 2000. "The Labeling Effect of a Child Benefit System." *American Economic Review* 90(3): 571–583.
- Laitner, John, Dan Silverman, and Dmitriy Stolyarov. 2018. "The Role of Annuitized Wealth in Post-Retirement Behavior." *American Economic Journal: Macroeconomics* 10(3): 71–117.
- Lockwood, Lee. 2012. "Bequest Motives and the Annuity Puzzle." *Review of Economic Dynamics* 15(2): 226–243.
- Lockwood, Lee. 2018. "Incidental Bequests and the Choice to Self-Insure Late-Life Risks." *American Economic Review* 108(9): 2513–2550.

- Lusardi, Annamaria, and Olivia S. Mitchell. 2014. "The Economic Importance of Financial Literacy: Theory and Evidence." *Journal of Economic Literature* 52(1): 5–44.
- Luttmer, Erzo F.P., and Andrew A. Samwick. 2018. "The Welfare Cost of Perceived Policy Uncertainty: Evidence from Social Security." *American Economic Review* 108(2): 275–307.
- Mas, Alexandre, and Amanda Pallais. 2017. "Valuing Alternative Work Arrangements." *American Economic Review* 107(12): 3722–3759.
- Maurer, Raymond, Olivia S. Mitchell, Ralph Rogalla, and Tatjana Schimetschek. 2018. "Will They Take the Money and Work? People's Willingness to Delay Claiming Social Security Benefits for a Lump Sum" *Journal of Risk and Insurance* 85(4): 877–909.
- Merkle, Christoph, Philipp Schreiber, and Martin Weber. 2017. "Framing and Retirement Age: The Gap between Willingness-To-Accept and Willingness-To-Pay." *Economic Policy* 32(92): 757–809.
- Milkman, Katherine L., and John Beshears. 2009. "Mental Accounting and Small Windfalls: Evidence from an Online Grocer." *Journal of Economic Behavior & Organization* 71(2): 384–394.
- Mitchell, Olivia S., John Piggott, and Noriyuke Takayama, eds. 2011. *Revisiting Retirement Payouts: Market Developments and Policy Issues*. Oxford: Oxford University Press.
- Peijnenburg, Kim, Theo Nijman, and Bas J.M. Werker. 2017. "Health Cost Risk: A Potential Solution to the Annuity Puzzle." *Economic Journal* 127: 1598–1625.
- Poterba, James, Steven Venti, and David Wise. 2011. "The Composition and Drawdown of Wealth in Retirement." *Journal of Economic Perspectives* 25(4): 95–118.
- Previtero, Alessandro. 2014. "Stock Market Returns and Annuitization." *Journal of Financial Economics* 113: 202–214.
- Read, Daniel, George Loewenstein, and Matthew Rabin. 1999. "Choice Bracketing." *Journal of Risk and Uncertainty* 19(1–3): 171–97.
- Reichling, Felix, and Kent Smetters. 2015. "Optimal Annuitization with Stochastic Mortality and Correlated Medical Costs." *American Economic Review* 105(11): 3273–3320.
- Schram, Arthur, and Joep Sonnemans. 2011. "How Individuals Choose Health Insurance: An Experimental Analysis." *European Economic Review* 55: 799–819.
- Shepard, Mark. 2011. "Social Security Claiming and the Life-Cycle Model." Working Paper, Harvard University.
- Social Security Administration. 2017. *Annual Statistical Supplement to the Social Security Bulletin, 2016*. Washington, DC.  
<https://www.ssa.gov/policy/docs/statcomps/supplement/2016/supplement16.pdf>
- Thaler, Richard. 1985. "Mental Accounting and Consumer Choice." *Marketing Science* 4(3): 199–214.
- Wayland, Michael. 2012. "GM Pensions: 13, 200 White Collar Retirees Taking Buyouts Makes Sense, Analysts Say." *MLive*, November 1.  
[http://www.mlive.com/auto/index.ssf/2012/11/gm\\_pensions\\_12600\\_white-collar.html](http://www.mlive.com/auto/index.ssf/2012/11/gm_pensions_12600_white-collar.html).
- Yaari, Menahem. 1965. "Uncertain Lifetime, Life Insurance, and the Theory of the Consumer." *Review of Economic Studies* 32(2): 137–150.





**Table 1: Summary Statistics and Comparison to the CPS**

| Variable:                       | (1)                                      | (2)                                    | (3)        |
|---------------------------------|--|--|------------|
|                                 | Understanding America<br>Study: Ages 18+ | Current Population<br>Survey: Ages 18+ | Difference |
|                                 | Mean                                     | Mean                                   |            |
| Age: 18-34                      | 0.223                                    | 0.300                                  | -0.077     |
| Age: 35-49                      | 0.296                                    | 0.248                                  | 0.048      |
| Age: 50-64                      | 0.317                                    | 0.258                                  | 0.060      |
| Age: 65+                        | 0.164                                    | 0.194                                  | -0.030     |
| Female                          | 0.574                                    | 0.516                                  | 0.058      |
| Married                         | 0.597                                    | 0.527                                  | 0.070      |
| Nonhispanic white               | 0.755                                    | 0.644                                  | 0.112      |
| Nonhispanic black               | 0.081                                    | 0.118                                  | -0.037     |
| Nonhispanic other               | 0.078                                    | 0.080                                  | -0.002     |
| Hispanic                        | 0.085                                    | 0.158                                  | -0.072     |
| High school dropout             | 0.053                                    | 0.117                                  | -0.064     |
| High school education           | 0.193                                    | 0.290                                  | -0.096     |
| Some college                    | 0.388                                    | 0.286                                  | 0.102      |
| Bachelor's degree               | 0.218                                    | 0.195                                  | 0.023      |
| Graduate degree                 | 0.148                                    | 0.112                                  | 0.036      |
| Household Income: Less than 25k | 0.166                                    | 0.161                                  | 0.005      |
| Household Income: 25k-50k       | 0.176                                    | 0.205                                  | -0.029     |
| Household Income: 50k-75k       | 0.165                                    | 0.173                                  | -0.008     |
| Household Income: 75k-100k      | 0.130                                    | 0.138                                  | -0.008     |
| Household Income: Above 100k    | 0.364                                    | 0.324                                  | 0.040      |
| Household size of one           | 0.201                                    | 0.145                                  | 0.057      |
| Household size of two           | 0.390                                    | 0.342                                  | 0.048      |
| Household size of three         | 0.174                                    | 0.191                                  | -0.017     |
| Household size of four or more  | 0.235                                    | 0.322                                  | -0.087     |
| Any kids                        | 0.328                                    | 0.378                                  | -0.050     |
| Observations                    | 4,060                                    | 134,420                                |            |

Notes: Column 1 shows the demographic characteristics of respondents in our baseline sample from the Understanding America Study. The UAS data throughout the paper are unweighted. The Current Population Survey data tabulated in the second column come from the 2016 Annual Social and Economic Supplement and are weighted. The sample is limited to non-institutionalized respondents age 18 and older. With four exceptions, each demographic characteristic's mean is statistically significantly different at the 1 percent level between the two samples. The exceptions are for the means of the fractions "Nonhispanic other," "Household Income: Less than 25k," "Household Income: 50k-75k," and "Household Income: 75k-100k," which are not even marginally statistically significantly different.

**Table 2: Experimental Design**

|                                      | No consequences message  | Consequences message  |
|--------------------------------------|--|---|
| <b>No added complexity</b>           | <b>Vignette 1:</b> Mr. Jones is a single, 60-year old man with no children. He will retire and claim his Social Security benefits at 65. When he retires, he will have \$100,000 saved for his retirement, and he will receive \$[SSB] in monthly Social Security benefits. Based on his current health and family history, doctors have told Mr. Jones that he will almost certainly be alive at age 75 but almost certainly will not live beyond age 85.   | <b>One of the vignettes 1-3 is offered with a consequence message preceding it, which is always the following. The order of the last two paragraphs was randomized.</b><br><br>First, we will show you a story about Mrs. Smith. Please pay close attention to the story, because at the end we will ask you two questions about the story. You will receive an additional \$1 for each question you answer correctly.<br><br>Mrs. Smith is a single, 65-year old woman with no children, and she is as healthy as the typical 65-year old woman. She just retired and receives her monthly Social Security check. She is talking with her financial adviser on how to spend her substantial savings in retirement.<br><br>Her advisor explains that she could decide to spend down her savings relatively quickly. In this case, she will be more likely to be able to enjoy her money during her lifetime. But she also runs a risk of running out of money while alive and having to cut back on her spending as a result.<br><br>Her advisor explains that she could also decide to spend down her savings relatively slowly. In this case, she will be less likely to run out of money. But now she runs a risk of not getting to enjoy all her money during her lifetime. |
| <b>Complexity: Wide age range</b>    | <b>Vignette 2:</b> Mr. Jones is a single, 60-year old man with no children. He will retire and claim his Social Security benefits at 65. When he retires, he expects to have \$100,000 saved for his retirement, and expects to receive \$[SSB] in monthly Social Security benefits. Based on his current health and family history, doctors have told Mr. Jones that he has an 80% chance of being alive at age 70, a 50% chance of being alive at age 80, a 20% chance of being alive at age 90, and a 10% chance of being alive at age 95.  | <b>This story is followed by two 4-option multiple-choice questions to induce the respondent to pay attention to the story. One question asks about the benefits and drawbacks of spending down wealth quickly while the other asks about the benefits and drawbacks of spending down wealth slowly. See the online appendix for the exact wording of these questions.</b><br><br><b>The screen with the two test questions is followed by an advice question where the respondent is asked to advise the vignette person how quickly to spend down her wealth. This question was asked to induce the respondent to think about the problem of how to spend down wealth during retirement. See the online appendix for the exact wording of this question.</b>  |
| <b>Complexity: Added information</b> | <b>Vignette 3:</b> Mr. Jones is a single, 60-year old man with no children. Social Security rules state that you need at least 40 credits, or 10 years of work, to qualify for Social Security – and Mr. Jones qualifies since he has worked for 30 years. Since Mr. Jones was born in 1956, his full retirement age is 66 years and 4 months, but he is eligible to start claiming starting at 62. He will retire and claim his Social Security benefits at 65. When he retires, he will have \$100,000 saved for his retirement, and he will receive \$[SSB] in monthly Social Security benefits. Based on his current health and family history, doctors have told Mr. Jones that he will almost certainly be alive at age 75 but almost certainly will not live beyond age 85. |   |

Note: The experiment featured 6 main treatment cells: one of Vignettes 1-3 without the consequences message, or one of the same three vignettes with a consequence message preceding it, as described in the “Consequences message” column. Additionally, we include experimental variation in the name and gender of the vignette person: Mr./Mrs., Smith/Jones, and the order of the last two paragraphs of the consequence message (spending quickly first, versus spending slowly first) are independently randomized across respondents. A different name and gender was used in the consequence message from that in the vignette. Finally, there is experimental variation in the monthly Social Security benefit value (SSB = \$800, \$1,200, \$1,600, or \$2,000).

**Table 3: Descriptive Statistics on the Sell Price, Buy Price, and Spread**

|                  | (1)<br>Sell Question First |                    | (2)<br>Buy Question First |                    | (3)                   | (4)<br>Entire Baseline Sample |                    |
|------------------|----------------------------|--------------------|---------------------------|--------------------|-----------------------|-------------------------------|--------------------|
|                  | Mean                       | Standard Deviation | Mean                      | Standard Deviation | p-value on difference | Mean                          | Standard Deviation |
| Sell value (log) | 9.65                       | 1.53               | 9.71                      | 1.96               | 0.257                 | 9.68                          | 1.76               |
| Buy value (log)  | 9.06                       | 2.43               | 8.28                      | 1.68               | 0.000                 | 8.67                          | 2.12               |
| Sell-Buy Spread  | 2.27                       | 2.04               | 2.16                      | 2.21               | 0.079                 | 2.21                          | 2.13               |
| N                | 2,009                      |                    | 2,051                     |                    |                       | 4,060                         |                    |

Notes: Whether the buy valuation or sell valuation was asked first was randomized for each respondent. The p-value corresponds to the test that the mean in column 1 is equal to the mean in column 2. The Sell-Buy Spread is defined as the absolute difference between the log sell price and the log buy price for an annuity stream of \$100 per month.

**Table 4: Treatment Effects on the Sell-Buy Spread and its Components**

|                                     | (1)               | (2)               | (3)              |
|-------------------------------------|-------------------|-------------------|------------------|
| Explanatory variables:              | Sell-Buy Spread   | Sell price (log)  | Buy price (log)  |
| Complexity treatment                | 0.131** (0.065)   | 0.050 (0.057)     | -0.137** (0.068) |
| Consequence message treatment       | -0.141** (0.062)  | 0.011 (0.055)     | 0.133** (0.065)  |
| Cognition index                     | -0.788*** (0.043) | -0.188*** (0.038) | 0.098** (0.046)  |
| Sell question first                 | 0.166*** (0.062)  | -0.043 (0.055)    | 0.777*** (0.065) |
| P-value on lump-sum starting values | 0.623             | 0.000             | 0.000            |
| P-value on lump-sum shown first     | 0.633             | 0.425             | 0.316            |
| P-value on SS benefit amounts       | 0.249             | 0.363             | 0.000            |
| P-value on vignette names           | 0.375             | 0.552             | 0.033            |
| Demographic controls                | Yes               | Yes               | Yes              |
| R <sup>2</sup>                      | 0.157             | 0.035             | 0.067            |
| N                                   | 4,060             | 4,060             | 4,060            |

Notes: The Sell-Buy Spread is defined as the absolute difference between the log sell price and the log buy price for an annuity stream of \$100 per month. Each column displays the results from a single OLS regression, with the dependent variable listed in the column heading. Coefficient estimates on the secondary experimental treatments and the control variables are reported in Appendix Table A2. Robust standard errors are in parentheses. \* significant at 10%, \*\* significant at 5%, \*\*\* significant at 1%.

**Table 5: Heterogeneity in Treatment Effects**

| Dependent Variable: Sell-Buy Spread      |                                |                     |   |                     |                |         |
|--|--------------------------------|---------------------|---|---------------------|----------------|---------|
| Specification:                           | (1)<br>Complexity<br>Treatment |                     | (2)<br>Consequence Message<br>Treatment |                     | R <sup>2</sup> | N       |
|  | Coeff.                         | (S.E.)<br>[p-value] | Coeff.                                  | (S.E.)<br>[p-value] |                |         |
| (1) By Consequence Message               |                                |                     |   |                     | 0.1569         | 4,060   |
| <i>No consequence message</i>            | 0.185**                        | (0.094)             |   |                     |                | [1,998] |
| <i>Consequence message</i>               | 0.078                          | (0.089)             |   |                     |                | [2,062] |
| P-value on test of equal coefficients    |                                | [0.408]             |   |                     |                |         |
| (2) By Complexity Treatment              |                                |                     |   |                     | 0.1569         | 4,060   |
| <i>No complexity treatment</i>           |                                |                     | -0.071                                  | (0.104)             |                | [1,409] |
| <i>Complexity treatment</i>              |                                |                     | -0.178**                                | (0.077)             |                | [2,651] |
| P-value on test of equal coefficients    |                                |                     |   | [0.408]             |                |         |
| (3) By Cognition                         |                                |                     |   |                     | 0.1574         | 4,060   |
| <i>Below median cognition index</i>      | 0.132                          | (0.103)             | -0.167*                                 | (0.099)             |                | [2,030] |
| <i>Above median cognition index</i>      | 0.133*                         | (0.077)             | -0.117                                  | (0.074)             |                | [2,030] |
| P-value on test of equal coefficients    |                                | [0.988]             |   | [0.682]             |                |         |
| (4) By Gender                            |                                |                     |   |                     | 0.1568         | 4,060   |
| <i>Female</i>                            | 0.126                          | (0.089)             | -0.152*                                 | (0.086)             |                | [1,729] |
| <i>Male</i>                              | 0.139                          | (0.093)             | -0.125                                  | (0.088)             |                | [2,331] |
| P-value on test of equal coefficients    |                                | [0.917]             |   | [0.826]             |                |         |
| (5) By Education                         |                                |                     |   |                     | 0.1569         | 4,060   |
| <i>Some college or less</i>              | 0.135                          | (0.085)             | -0.179**                                | (0.082)             |                | [2,577] |
| <i>Bachelor's degree or more</i>         | 0.122                          | (0.098)             | -0.074                                  | (0.092)             |                | [1,483] |
| P-value on test of equal coefficients    |                                | [0.923]             |   | [0.397]             |                |         |
| (6) By Age                               |                                |                     |   |                     | 0.1577         | 4,060   |
| <i>Below median (less than 50)</i>       | 0.022                          | (0.091)             | -0.191**                                | (0.086)             |                | [2,107] |
| <i>Above median (50 or more)</i>         | 0.252***                       | (0.092)             | -0.083                                  | (0.089)             |                | [1,953] |
| P-value on test of equal coefficients    |                                | [0.075]             |   | [0.383]             |                |         |
| (7) By Income                            |                                |                     |   |                     | 0.1573         | 4,060   |
| <i>Below median (less than \$75k)</i>    | 0.074                          | (0.097)             | -0.220**                                | (0.091)             |                | [2,054] |
| <i>Above median (\$75k or more)</i>      | 0.186**                        | (0.086)             | -0.060                                  | (0.083)             |                | [2,006] |
| P-value on test of equal coefficients    |                                | [0.387]             |   | [0.196]             |                |         |
| (8) By Level of Social Security Benefits |                                |                     |   |                     | 0.1568         | 4,060   |
| <i>Below median (\$800 or \$1200)</i>    | 0.123                          | (0.092)             | -0.142                                  | (0.087)             |                | [2,015] |
| <i>Above median (\$1200 or \$1600)</i>   | 0.139                          | (0.091)             | -0.140                                  | (0.088)             |                | [2,045] |
| P-value on test of equal coefficients    |                                | [0.903]             |   | [0.985]             |                |         |

Notes: The Sell-Buy Spread is defined as the absolute difference between the log sell price and the log buy price for an annuity stream of \$100 per month. Each row reports the results from a single OLS regression in which the two main experimental treatments are interacted with the characteristics listed in the row header. Robust standard errors are in parentheses. \* significant at 10%, \*\* significant at 5%, \*\*\* significant at 1%.

**Table 6: Robustness of the Main Treatment Effects**

| Dependent Variable: Sell-Buy Spread                                   | (1)                                 | (2)  | (3)            | (4)   |
|---|-------------------------------------|--|----------------|-------|
| Specification:  | Coefficient on Complexity Treatment | Coefficient on Consequence Message Treatment | R <sup>2</sup> | N     |
| (1) Baseline  | 0.131**<br>(0.065)                  | -0.141**<br>(0.062)                          | 0.1568         | 4,060 |
| <b>Panel A: Changing Cognition Measures</b>                           |                                     |  |                |       |
| (2) Cognition index is the simple average of the 5 cognition measures | 0.131**<br>(0.065)                  | -0.141**<br>(0.062)                          | 0.1554         | 4,060 |
| (3) All five components of cognitions score entered separately        | 0.131**<br>(0.065)                  | -0.137**<br>(0.062)                          | 0.1614         | 4,060 |
| (4) Financial literacy is the only cognition measure                  | 0.107<br>(0.066)                    | -0.128**<br>(0.063)                          | 0.1146         | 4,060 |
| (5) Numeracy measures are the only cognition measures                 | 0.121*<br>(0.065)                   | -0.153**<br>(0.062)                          | 0.1495         | 4,060 |
| (6) Verbal measures are the only cognition measures                   | 0.111*<br>(0.066)                   | -0.152**<br>(0.063)                          | 0.1174         | 4,060 |
| <b>Panel B: Sample Selection</b>                                      |                                     |  |                |       |
| (7) Include observations with missing demographics (dummied out)      | 0.130**<br>(0.065)                  | -0.139**<br>(0.062)                          | 0.1585         | 4,081 |
| (8) Include observations with missing cognition index (dummied out)   | 0.118*<br>(0.062)                   | -0.120**<br>(0.059)                          | 0.1422         | 4,528 |
| (9) Include observations with any missing values (dummied out)        | 0.117*<br>(0.062)                   | -0.118**<br>(0.059)                          | 0.1441         | 4,552 |
| (10) Exclude Native American and LA county oversamples                | 0.113*<br>(0.068)                   | -0.169***<br>(0.064)                         | 0.1632         | 3,704 |
| <b>Panel C: Different Controls</b>                                    |                                     |  |                |       |
| (11) No cognition controls  | 0.087<br>(0.068)                    | -0.159**<br>(0.064)                          | 0.0825         | 4,060 |
| (12) No demographic controls  | 0.137**<br>(0.065)                  | -0.140**<br>(0.062)                          | 0.1465         | 4,060 |
| (13) No secondary experimental controls                               | 0.125*<br>(0.065)                   | -0.138**<br>(0.062)                          | 0.1534         | 4,060 |
| <b>Panel D: Adjustments to Outcome Variable</b>                       |                                     |  |                |       |
| (14) Buy and sell valuations topcoded at \$100,000                    | 0.111**<br>(0.054)                  | -0.108**<br>(0.051)                          | 0.1427         | 4,060 |
| (15) Topcoding spread at the 90th percentile                          | 0.119**<br>(0.055)                  | -0.106**<br>(0.053)                          | 0.1641         | 4,060 |
| (16) Bottomcoding buy and sell valuations at \$1000                   | 0.104*<br>(0.057)                   | -0.098*<br>(0.054)                           | 0.1501         | 4,060 |
| (17) Spread set to zero if spread ≤ 0.50                              | 0.131**<br>(0.066)                  | -0.142**<br>(0.063)                          | 0.1592         | 4,060 |
| (18) Spread set to zero if buy valuation > sell valuation             | 0.159**<br>(0.067)                  | -0.132**<br>(0.064)                          | 0.0930         | 4,060 |

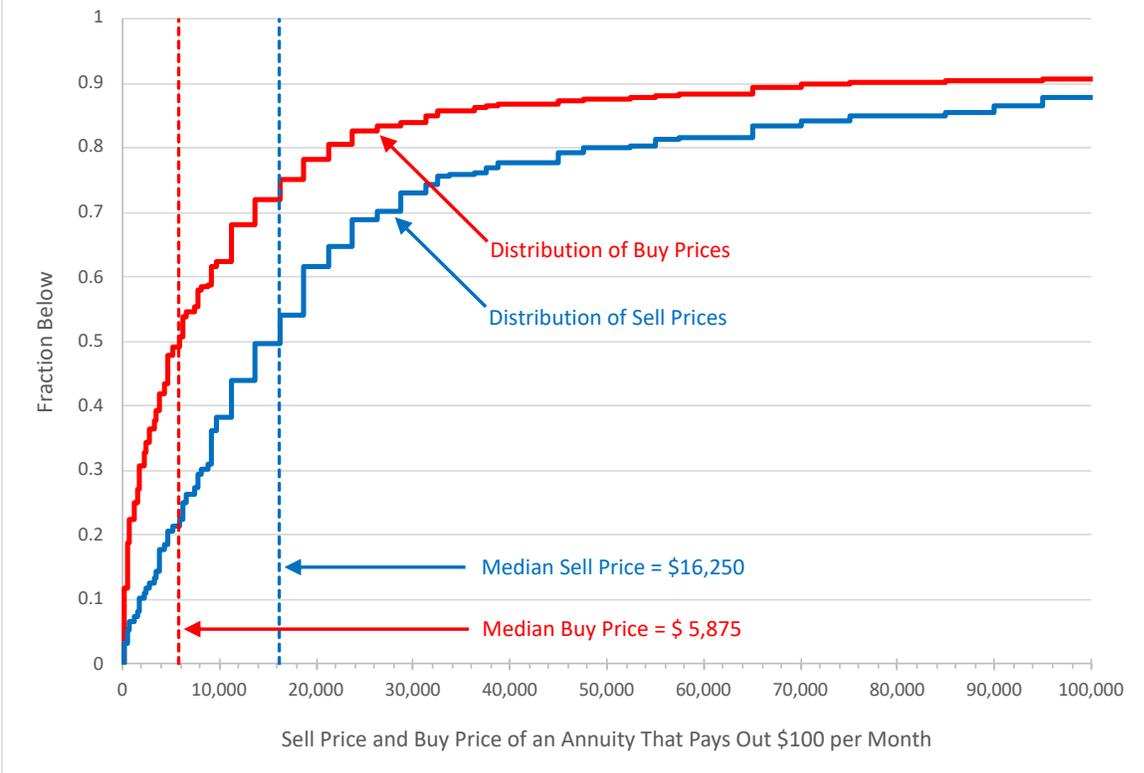
Notes: Each row displays the results of a single OLS regression that is identical to the baseline regression shown in Column 1 of Table 4 except for the difference described in the row header. In the baseline regression, the cognition index is the first principal component of five standardized cognition measures: financial literacy, a numeracy score, a number series score, a verbal analogies score, and a picture vocabulary score. Robust standard errors are in parentheses. \* significant at 10%, \*\* significant at 5%, \*\*\* significant at 1%.

**Online Appendix for:**  
**Behavioral Impediments to Valuing Annuities:  
Complexity and Choice Bracketing**

Jeffrey R. Brown, Arie Kapteyn, Erzo F.P. Luttmer,  
Olivia S. Mitchell, and Anya Samek

Appendix Figure and Tables ..... pp. A2-A5  
Survey Instrument ..... pp. A6-A15

Figure A1: CDF of Sell Price and Buy Price in the Entire Baseline Sample



**Table A1: Balance Tests**

| Variable  | No<br>Complexity | Complexity | p-value<br>on test of<br>equal<br>means | No<br>Consequence<br>Message | Consequence<br>Message | p-value<br>on test of<br>equal<br>means |
|---|------------------|------------|---|------------------------------|------------------------|---|
| <b>Panel A: Excluded from Baseline Sample due to:</b>               |                  |            |   |                              |                        |   |
| Missing annuity valuation data                                      | 0.008            | 0.011      | 0.322                                   | 0.011                        | 0.009                  | 0.491                                   |
| Missing demographic data  | 0.003            | 0.007      | 0.099                                   | 0.006                        | 0.005                  | 0.507                                   |
| Missing cognition data  | 0.090            | 0.115      | 0.008                                   | 0.109                        | 0.104                  | 0.627                                   |
| <b>Panel B: Balance on Control Variables in the Baseline Sample</b> |                  |            |   |                              |                        |   |
| Age   | 48.43            | 48.51      | 0.876                                   | 48.50                        | 48.46                  | 0.925                                   |
| Age <sup>2</sup>  | 25.96            | 25.85      | 0.831                                   | 25.88                        | 25.90                  | 0.965                                   |
| Female  | 0.58             | 0.57       | 0.592                                   | 0.58                         | 0.57                   | 0.663                                   |
| Married   | 0.57             | 0.61       | 0.028                                   | 0.59                         | 0.60                   | 0.636                                   |
| Nonhispanic white   | 0.76             | 0.75       | 0.507                                   | 0.76                         | 0.75                   | 0.626                                   |
| Nonhispanic black   | 0.07             | 0.09       | 0.132                                   | 0.08                         | 0.08                   | 0.722                                   |
| Nonhispanic other   | 0.08             | 0.08       | 0.627                                   | 0.07                         | 0.08                   | 0.349                                   |
| Hispanic  | 0.09             | 0.09       | 0.960                                   | 0.08                         | 0.09                   | 0.843                                   |
| High School Dropout   | 0.05             | 0.05       | 0.805                                   | 0.05                         | 0.05                   | 0.697                                   |
| High School Education   | 0.19             | 0.20       | 0.381                                   | 0.20                         | 0.19                   | 0.651                                   |
| Some College  | 0.41             | 0.38       | 0.087                                   | 0.38                         | 0.40                   | 0.219                                   |
| Bachelor's Degree   | 0.21             | 0.22       | 0.151                                   | 0.22                         | 0.22                   | 0.998                                   |
| Graduate Degree   | 0.15             | 0.15       | 0.917                                   | 0.16                         | 0.14                   | 0.151                                   |
| Household Income: Less than 25k                                     | 0.17             | 0.17       | 0.944                                   | 0.16                         | 0.17                   | 0.114                                   |
| Household Income: 25k-50k   | 0.18             | 0.18       | 0.945                                   | 0.18                         | 0.17                   | 0.428                                   |
| Household Income: 50k-75k   | 0.15             | 0.17       | 0.060                                   | 0.17                         | 0.16                   | 0.915                                   |
| Household Income: 75k-100k  | 0.14             | 0.12       | 0.145                                   | 0.13                         | 0.13                   | 0.383                                   |
| Household Income: Above 100k  | 0.37             | 0.36       | 0.695                                   | 0.37                         | 0.36                   | 0.263                                   |
| Household size of one   | 0.22             | 0.19       | 0.114                                   | 0.20                         | 0.20                   | 0.818                                   |
| Household size of two   | 0.38             | 0.40       | 0.249                                   | 0.38                         | 0.39                   | 0.498                                   |
| Household size of three   | 0.18             | 0.17       | 0.730                                   | 0.18                         | 0.16                   | 0.074                                   |
| Household size of four or more                                      | 0.23             | 0.24       | 0.616                                   | 0.23                         | 0.24                   | 0.301                                   |
| Any Kids  | 0.32             | 0.33       | 0.711                                   | 0.33                         | 0.33                   | 0.764                                   |
| Cognition index   | -0.04            | 0.02       | 0.072                                   | -0.01                        | 0.01                   | 0.704                                   |
| P-value of joint test of equality of control variables              |                  | 0.107      |   |                              | 0.788                  |   |

Notes: Each cell contains the mean of the variable listed in the row header for observations subject to the experimental condition listed in the column header. The baseline sample consists of observations with nonmissing annuity valuation data, nonmissing demographic data, and nonmissing cognition data. The first panel (N=4,596) examines balance on inclusion into the baseline sample. The second panel (N=4,060) examines balance of control variables included into the baseline regression specifications.

**Table A2: Full Set of Coefficient Estimates from Table 4**

| Dependent Variable:            | (1)             |         | (2)              |         | (3)             |         |
|--------------------------------|-----------------|---------|------------------|---------|-----------------|---------|
| Sell-Buy Spread                |                 |         |                  |         |                 |         |
| Explanatory variables:         | Sell-Buy Spread |         | Sell price (log) |         | Buy price (log) |         |
| Complexity treatment           | 0.131**         | (0.065) | 0.050            | (0.057) | -0.137**        | (0.068) |
| Consequence message treatment  | -0.141**        | (0.062) | 0.011            | (0.055) | 0.133**         | (0.065) |
| Cognition index                | -0.788***       | (0.043) | -0.188***        | (0.038) | 0.098**         | (0.046) |
| Sell question first            | 0.166***        | (0.062) | -0.043           | (0.055) | 0.777***        | (0.065) |
| Lump-sum medium: 20k           | 0.063           | (0.076) | 0.239***         | (0.067) | 0.236***        | (0.079) |
| Lump-sum high: 30k             | -0.002          | (0.075) | 0.484***         | (0.068) | 0.476***        | (0.079) |
| Lump-sum shown first           | 0.029           | (0.062) | -0.044           | (0.055) | -0.065          | (0.065) |
| Social security benefit 1200   | 0.113           | (0.087) | 0.010            | (0.075) | -0.458***       | (0.093) |
| Social security benefit 1600   | 0.057           | (0.084) | -0.006           | (0.074) | -0.393***       | (0.091) |
| Social security benefit 2000   | 0.167*          | (0.087) | -0.118           | (0.080) | -0.353***       | (0.093) |
| Vignette name: Mr. Jones       | 0.114           | (0.086) | -0.028           | (0.076) | -0.098          | (0.089) |
| Vignette name: Mr. Smith       | 0.088           | (0.088) | -0.097           | (0.076) | 0.114           | (0.091) |
| Vignette name: Mrs. Smith      | -0.011          | (0.085) | -0.081           | (0.076) | 0.146           | (0.089) |
| Age                            | 0.025*          | (0.013) | 0.001            | (0.011) | -0.035***       | (0.013) |
| Age <sup>2</sup>               | -0.015          | (0.013) | 0.006            | (0.010) | 0.023*          | (0.013) |
| Female                         | 0.085           | (0.066) | -0.075           | (0.058) | -0.160**        | (0.069) |
| Married                        | 0.097           | (0.076) | -0.007           | (0.069) | -0.104          | (0.081) |
| Nonhispanic black              | 0.028           | (0.142) | -0.087           | (0.134) | -0.116          | (0.148) |
| Nonhispanic other              | 0.048           | (0.122) | -0.056           | (0.107) | -0.087          | (0.128) |
| Hispanic                       | 0.081           | (0.125) | -0.094           | (0.122) | -0.097          | (0.133) |
| High School Dropout            | -0.057          | (0.178) | 0.138            | (0.161) | 0.136           | (0.182) |
| High School Education          | 0.033           | (0.093) | 0.104            | (0.085) | 0.048           | (0.099) |
| Bachelor's Degree              | 0.008           | (0.084) | 0.019            | (0.073) | 0.100           | (0.086) |
| Graduate Degree                | 0.076           | (0.095) | 0.224***         | (0.077) | 0.233**         | (0.100) |
| Household Income: 25k-50k      | 0.102           | (0.117) | 0.046            | (0.108) | -0.136          | (0.123) |
| Household Income: 50k-75k      | -0.166          | (0.116) | -0.070           | (0.107) | -0.037          | (0.121) |
| Household Income: 75k-100k     | -0.055          | (0.130) | -0.104           | (0.119) | -0.010          | (0.132) |
| Household Income: Above 100k   | -0.257**        | (0.110) | -0.098           | (0.100) | -0.041          | (0.111) |
| Household size of two          | -0.025          | (0.095) | 0.042            | (0.084) | -0.007          | (0.100) |
| Household size of three        | 0.147           | (0.131) | 0.252**          | (0.113) | -0.025          | (0.134) |
| Household size of four or more | 0.182           | (0.145) | 0.178            | (0.135) | -0.207          | (0.151) |
| Any Kids                       | -0.177*         | (0.106) | -0.239**         | (0.101) | 0.117           | (0.114) |
| R <sup>2</sup>                 | 0.1568          |         | 0.035            |         | 0.0672          |         |
| N                              | 4,060           |         | 4,060            |         | 4,060           |         |

Notes: The regressions in Table A2 are identical to the regressions reported in Table 4, but here we also report the coefficients on all the secondary experimental manipulations as well as the coefficients on the demographic control variables. Robust standard errors are in parentheses. \* significant at 10%, \*\* significant at 5%, \*\*\* significant at 1%.

**Table A3: Complexity Treatment Split out by Type of Complexity Treatment**

| Dependent Variable: Sell-Buy Spread                               | (1)               | (2)               | (3)              |
|---|-------------------|-------------------|------------------|
| Explanatory variables:  | Sell-Buy Spread   | Sell price (log)  | Buy price (log)  |
| Complexity treatment: Wide Age Range                              | 0.149* (0.076)    | 0.066 (0.068)     | -0.117 (0.079)   |
| Complexity treatment: Added Information                           | 0.114 (0.075)     | 0.034 (0.066)     | -0.156** (0.079) |
| Consequence message treatment                                     | -0.140** (0.062)  | 0.011 (0.055)     | 0.134** (0.065)  |
| Cognition index   | -0.788*** (0.043) | -0.188*** (0.038) | 0.098** (0.046)  |
| Sell question first   | 0.165*** (0.062)  | -0.043 (0.054)    | 0.777*** (0.065) |
| P-value on lump-sum starting values                               | 0.624             | 0.000             | 0.000            |
| P-value on lump-sum shown first                                   | 0.623             | 0.434             | 0.323            |
| P-value on SS benefit amounts                                     | 0.248             | 0.368             | 0.000            |
| P-value on vignette names   | 0.374             | 0.566             | 0.032            |
| Demographic controls  | Yes               | Yes               | Yes              |
| P-value that coefficients on both complexity treatments are equal | 0.646             | 0.638             | 0.626            |
| R <sup>2</sup>  | 0.157             | 0.035             | 0.067            |
| N   | 4,060             | 4,060             | 4,060            |

Notes: This table is identical to Table 4, except that the two complexity treatments are estimated separately (rather than pooled). Robust standard errors are in parentheses. \* significant at 10%, \*\* significant at 5%, \*\*\* significant at 1%.

## Survey Instrument

### Notes on the Survey Instrument

- Everyone sees both EV-Sell and EV-Buy questions in the same survey
- Randomizations are all orthogonal and across subjects. All options within each randomization are selected with equal probability.
  - The main manipulations consist of a 3x2 design: three vignettes that vary the complexity, and whether or not the consequence message (see Table 2) is shown.
  - The secondary manipulations consist of a 4x3x4x2x2 design that is orthogonal to the main manipulations.
    - There are four different versions for name and gender of the vignette person to be advised on annuity decisions. This name and gender is randomized to one of the following: Mr. Jones, Mrs. Jones, Mr. Smith, or Mrs. Smith. The person featured in the consequence message has the opposite name and gender from the vignette person in the annuity valuation questions.
    - The starting value for lump-sum amounts is randomized at \$10,000, \$20,000, or \$30,000. For any given respondent, the same starting value is used for the EV-Sell and EV-Buy questions.
    - The baseline monthly Social Security Benefit,  $\$SSB$ , is randomized to \$800, \$1200, \$1600, or \$2000.
    - Whether the choice option with the lump-sum amount ( $\$LS$ ) is shown first or second is randomized. For each respondent, this is randomized once and the same order is used for EV-Buy and EV-Sell.
    - Whether EV-Buy is asked before or after EV-Sell is randomized.
    - For the consequence message, it is randomized whether the paragraph on the benefits and drawbacks of spending down retirement wealth quickly is shown before or after the paragraph on the benefits and drawbacks of spending down retirement slowly.
- Text in *Arial* are instructions to the programmers while text in Times New Roman is shown to respondents. Text in *italicized Arial* denote variables and the respondents see the value contained by that variable.
- Text between square brackets is replaced based on the randomization.
- Page breaks are shown by horizontal lines.

## Survey Instrument Text and Instructions for Understanding America Study #49

---

**Invitation to the survey.** When panelists logged on to their UAS account, they saw the following message. If they clicked on the link in this message, they entered into UAS49.

This survey asks you to make decisions as if you were giving someone financial advice. You will then play an insurance game. You will earn \$10 for completion, and have a chance to win more.

---

In the following survey we want you to play the role of financial advisor. We will show you some examples of persons who have to make a decision about money and we will ask you to help them make the decision.

---

**Consequence message treatment: Advisor explanations.** Only people in the consequence message treatment get this screen and the following two screens. Respondents are randomized to see one of four vignette person names: Mr. Jones, Mrs. Jones, Mr. Smith, or Mrs. Smith. The pronouns [he/she] and [his/her] should match the gender of the consequence-message vignette person. Similarly, the word [man/women] should match the gender of the vignette person.

First, we will show you a story about [Mr. Jones/Mrs. Jones/Mr. Smith/Mrs. Smith]. Please pay close attention to the story, because at the end we will ask you two questions about the story. You will receive an additional \$1 for each question you answer correctly.

[Mr. Jones/Mrs. Jones/Mr. Smith/Mrs. Smith] is a single, 65-year old [man/woman] with no children, and [he/she] is as healthy as the typical 65-year old [man/woman]. [He/She] just retired and receives [his/her] monthly Social Security check. [He/She] is talking with [his/her] financial adviser on how to spend [his/her] substantial savings in retirement.

Randomize whether either block 1 or block 2 is shown.

**Block 1:**

[His/Her] advisor explains that [he/she] could decide to spend down [his/her] savings relatively quickly. In this case, [he/she] will be more likely to be able to enjoy [his/her] money during [his/her] lifetime. But [he/she] also runs a risk of running out of money while alive and having to cut back on [his/her] spending as a result.

[His/Her] advisor explains that [he/she] could also decide to spend down [his/her] savings relatively slowly. In this case, [he/she] will be less likely to run out of money. But now [he/she] runs a risk of not getting to enjoy all [his/her] money during [his/her] lifetime.

**Block 2:**

[His/Her] advisor explains that [he/she] could decide to spend down [his/her] savings relatively slowly. In this case, [he/she] will be less likely to run out of money. But now [he/she] runs a risk of not getting to enjoy all [his/her] money during [his/her] lifetime.

[His/Her] advisor explains that [he/she] could also decide to spend down [his/her] savings relatively quickly. In this case, [he/she] will be more likely to be able to enjoy [his/her] money during [his/her] lifetime. But [he/she] also runs a risk of running out of money while alive and having to cut back on [his/her] spending as a result.

---

## Consequence message treatment: Test questions 1 and 2.

Remember, you will earn an extra \$1 for each question you answer correctly on this page.

The financial advisor tells [Mr. Jones/Mrs. Jones/Mr. Smith/Mrs. Smith] that spending down [his/her] savings more quickly:

- Increases the risk that [he/she] does not get to enjoy all of [his/her] money during [his/her] lifetime.
- Decreases the risk that [he/she] runs out of money during [his/her] lifetime.
- Increases the risk that [he/she] runs out of money during [his/her] lifetime.
- None of the above.

The financial advisor tells [Mr. Jones/Mrs. Jones/Mr. Smith/Mrs. Smith] that spending down [his/her] savings more slowly:

- Increases the risk that [he/she] runs out of money during [his/her] lifetime.
- Decreases the risk that [he/she] does not get to enjoy all of [his/her] money during [his/her] lifetime.
- Increases the risk that [he/she] does not get to enjoy all of [his/her] money during [his/her] lifetime.
- None of the above.

If a question is not answered, prompt once to answer the question, but move to next screen if respondent still leaves the question blank.

---

## Consequence message treatment: Question to induce respondent to think about how to draw down savings during retirement

Now we are going to switch to a different type of question. Instead of asking you about facts, we are going to ask your advice about what decisions [Mr. Jones/Mrs. Jones/Mr. Smith/Mrs. Smith] should make. Unlike the previous questions, there is no right or wrong answer; we just want to know what you think.

Recall [Mr. Jones/Mrs. Jones/Mr. Smith/Mrs. Smith], the retired, single, 65-year old [man/woman] with no children. [He/She] is as healthy as the typical 65-year old [man/woman].

How quickly should [he/she] spend [his/her] savings?

- Spend [his/her] savings by age 70. [he/she] can spend a large amount each year, but [he/she] will have to cut back if [he/she] lives beyond 70. If [he/she] dies before 70, [he/she] will not have enjoyed all of [his/her] savings.
- Spend [his/her] savings by age 80. [he/she] can spend a moderate amount each year, but [he/she] will have to cut back if [he/she] lives beyond 80. If [he/she] dies before 80, [he/she] will not have enjoyed all of [his/her] savings.
- Spend [his/her] savings by age 90. [he/she] can spend a modest amount each year, but [he/she] will have to cut back if [he/she] lives beyond 90. If [he/she] dies before 90, [he/she] will not have enjoyed all of [his/her] savings.
- Spend [his/her] savings by age 100. [he/she] can spend a small amount each year, and [he/she] will have to cut back if [he/she] lives beyond 100. If [he/she] dies before 100, [he/she] will not have enjoyed all of [his/her] savings.

This is the end of the screens shown for the consequence message.

**Complexity Treatment.** Respondents are randomized to one of the three vignettes shown below: Vignette 1 (corresponding to treatment “No added complexity”), Vignette 2 (corresponding to treatment “Complexity: Wide age range”) or Vignette 3 (corresponding to treatment “Complexity: Added information”). The name in the complexity vignette below is different than the name shown in the consequence-message vignette above. Similarly, the gender of the person in the complexity vignette is different from the gender of the person in the consequence-message vignette. The scalar variable *SSB* is randomized to 800, 1200, 1600, or 2000.

In the next few questions, we are going to ask you to give some advice to [Mrs. Smith/Mr. Smith/Mrs. Jones/Ms. Jones] for when [she/he] retires. You will be happy to know that whatever advice you give [Mrs. Smith/Mr. Smith/Mrs. Jones/Ms. Jones], [she/he] will not owe any taxes on the amounts shown and [her/his] benefits will keep up with inflation. There is no right or wrong answer; we just want to know what you think.

**Vignette 1 (“No added complexity”):**

[Mrs. Smith/Mr. Smith/Mrs. Jones/Ms. Jones] is a single, 60-year old [woman/man] with no children. [She/He] will retire and claim [her/his] Social Security benefits at 65. When [she/he] retires, [she/he] will have \$100,000 saved for [her/his] retirement, and [she/he] will receive \$[*SSB*] in monthly Social Security benefits. Based on [her/his] current health and family history, doctors have told Mr. Smith that [she/he] will almost certainly be alive at age 75 but almost certainly will not live beyond age 85.

**Vignette 2 (“Complexity: Wide age range”):**

[Mrs. Smith/Mr. Smith/Mrs. Jones/Ms. Jones] is a single, 60-year old [woman/man] with no children. [She/He] will retire and claim [her/his] Social Security benefits at 65. When [she/he] retires, [she/he] expects to have \$100,000 saved for [her/his] retirement, and expects to receive \$[*SSB*] in monthly Social Security benefits. Based on [her/his] current health and family history, doctors have told Mrs. Jones that [she/he] has an 80% chance of being alive at age 70, a 50% chance of being alive at age 80, a 20% chance of being alive at age 90, and a 10% chance of being alive at age 95.

**Vignette 3 (“Complexity: Added information”):**

[Mrs. Smith/Mr. Smith/Mrs. Jones/Ms. Jones] is a single, 60-year old [woman/man] with no children. Social Security rules state that you need at least 40 credits, or 10 years of work, to qualify for Social Security – and [Mrs. Smith/Mr. Smith/Mrs. Jones/Ms. Jones] qualifies since [she/he] has worked for 30 years. Since [Mrs. Smith/Mr. Smith/Mrs. Jones/Ms. Jones] was born in 1956, [her/his] full retirement age is 66 years and 4 months, but [she/he] is eligible to start claiming starting at 62. [She/He] will retire and claim [her/his] Social Security benefits at 65. When [she/he] retires, [she/he] will have \$100,000 saved for [her/his] retirement, and [she/he] will receive \$[*SSB*] in monthly Social Security benefits. Based on [her/his] current health and family history, doctors have told [Mrs. Smith/Mr. Smith/ Mrs. Jones/Ms. Jones] that [she/he] will almost certainly be alive at age 75 but almost certainly will not live beyond age 85.

**Initializations for EV-Sell and EV-Buy.** Whether the EV-Buy questions or the EV-Sell questions are shown first is randomized.

The scalar variable *LS\_STARTVALUE* is randomized to 1, 2, or 3.

The values in the matrices *LS\_LOW*, *LS\_MED*, and *LS\_HIGH* are listed at the very end of this document.

Initialization of the matrix *LS\_AMT*:

**If *LS\_STARTVALUE* == 1**

```
        Set the 16x5 matrix  $LS\_AMT=LS\_LOW$ 
Elseif  $LS\_STARTVALUE == 3$ 
        Set the 16x5 matrix  $LS\_AMT=LS\_HIGH$ 
Else
        Set the 16x5 matrix  $LS\_AMT=LS\_MED$ 
Endif
```

---

### EV-Sell Questions

Set the scalar  $j=1$

Set the scalar  $ROW=1$

For  $j=1$  to 5

This is the start of the loop for EV-Sell questions.

The text for each iteration of the loop is shown on a new screen.

**If**  $j = 1$ , Display:

**If** EV-Sell is asked before EV-Buy:

Suppose that the Social Security Administration is considering a new policy that gives people more choice in how they want to receive their benefits. As part of this policy, [Mrs. Smith/Mr. Smith/Mrs. Jones/Ms. Jones] is asked to make a choice between two money amounts.

What should [Mrs. Smith/Mr. Smith/Mrs. Jones/Ms. Jones] do?

**Else**

Now consider a different way of giving people more choice in how they want to receive their benefits. As part of this policy, [Mrs. Smith/Mr. Smith/Mrs. Jones/Ms. Jones] is asked to make a choice between two money amounts.

**Endif**

**Else**, Display:

Now we ask you the same question but with a different amount for the one-time payment.

What should [Mrs. Smith/Mr. Smith/Mrs. Jones/Ms. Jones] do?

**Endif**

The order of the two options shown is randomized once for each respondent.

The order remains the same for the EV-Sell and EV-Buy questions shown to a given respondent. The third appearance of the word “receive” (i.e., when it appears after the underlined word “and”) in the text below is shown in bold if and only if EV-Sell is asked after EV-Buy.

- Receive a Social Security benefit of  $\$[SSB+100]$  per month starting at age 65.
- Receive [her/his] expected Social Security benefit of  $\$[SSB]$  per month and receive a one-time payment of  $\$[LS\_AMT[ROW,j]]$  from Social Security at age 65.

If the respondent does not select any option, the respondent is prompted once to answer this question. If the respondent still doesn't give an answer, the variable  $j$  is set to 5, so that we get skipped out of this loop.

**If** Respondent selects the option that does **not** contain the one-time payment:

Set  $ROW=ROW+2^{(4-j)}$

Note: this will increase the size of one-time payment in the next iteration, so it makes the option that does not contain the one-time payment less attractive.

**Endif**

Set  $j=j+1$

This is the end of the loop for the EV-Buy questions.

---

**Vignette reminder.** The complexity vignette is shown again, but now preceded by the word “Remember, ”.

**Vignette 1 (“No added complexity”):**

Remember, [Mrs. Smith/Mr. Smith/Mrs. Jones/Ms. Jones] is a single, 60-year old [woman/man] with no children. [She/He] will retire and claim [her/his] Social Security benefits at 65. When [she/he] retires, [she/he] will have \$100,000 saved for [her/his] retirement, and [she/he] will receive \$[SSB] in monthly Social Security benefits. Based on [her/his] current health and family history, doctors have told Mr. Smith that [she/he] will almost certainly be alive at age 75 but almost certainly will not live beyond age 85.

**Vignette 2 (“Complexity: Wide age range”):**

Remember, [Mrs. Smith/Mr. Smith/Mrs. Jones/Ms. Jones] is a single, 60-year old [woman/man] with no children. [She/He] will retire and claim [her/his] Social Security benefits at 65. When [she/he] retires, [she/he] expects to have \$100,000 saved for [her/his] retirement, and expects to receive \$[SSB] in monthly Social Security benefits. Based on [her/his] current health and family history, doctors have told Mrs. Jones that [she/he] has an 80% chance of being alive at age 70, a 50% chance of being alive at age 80, a 20% chance of being alive at age 90, and a 10% chance of being alive at age 95.

**Vignette 3 (“Complexity: Added information”):**

Remember, [Mrs. Smith/Mr. Smith/Mrs. Jones/Ms. Jones] is a single, 60-year old [woman/man] with no children. Social Security rules state that you need at least 40 credits, or 10 years of work, to qualify for Social Security – and [Mrs. Smith/Mr. Smith/Mrs. Jones/Ms. Jones] qualifies since [she/he] has worked for 30 years. Since [Mrs. Smith/Mr. Smith/Mrs. Jones/Ms. Jones] was born in 1956, [her/his] full retirement age is 66 years and 4 months, but [she/he] is eligible to start claiming starting at 62. [She/He] will retire and claim [her/his] Social Security benefits at 65. When [she/he] retires, [she/he] will have \$100,000 saved for [her/his] retirement, and [she/he] will receive \$[SSB] in monthly Social Security benefits. Based on [her/his] current health and family history, doctors have told [Mrs. Smith/Mr. Smith/Mrs. Jones/Ms. Jones] that [she/he] will almost certainly be alive at age 75 but almost certainly will not live beyond age 85.

---

## **EV-Buy Questions**

Set the scalar  $j=1$

Set the scalar  $ROW=1$

For  $j=1$  to 5

This is the start of the loop for EV-Buy questions.

The text for each iteration of the loop is shown on a new screen.

**If  $j = 1$ , Display:**

**If EV-Buy is asked before EV-Sell:**

Suppose that the Social Security Administration is considering a new policy that gives people more choice in how they want to receive their benefits. As part of this policy, [Mrs. Smith/Mr. Smith/ Mrs. Jones/Ms. Jones] is asked to make a choice between two money amounts.

What should [Mrs. Smith/Mr. Smith/ Mrs. Jones/Ms. Jones] do?

**Else**

Now consider a different way of giving people more choice in how they want to receive their benefits. As part of this policy, [Mrs. Smith/Mr. Smith/ Mrs. Jones/Ms. Jones] is asked to make a choice between two money amounts.

**Endif**

**Else, Display:**

Now we ask you the same question but with a different amount for the one-time payment.

What should [Mrs. Smith/Mr. Smith/ Mrs. Jones/Ms. Jones] do?

**Endif**

The order of the two options shown is randomized once for each respondent. The order remains the same for the EV-Sell and EV-Buy questions shown to a given respondent. The word “payment” in the text below is shown bold if and only if EV-Buy is asked after EV-Sell.

- Receive a Social Security benefit of \$[SSB-100] per month starting at age 65.
- Receive [her/his] expected Social Security benefit of \$[SSB] per month and make a one-time payment of \$\$[LS\_AMT[ROW,j]] to Social Security at age 65.

If the respondent does not select any option, the respondent is prompted once to answer this question. If the respondent still doesn't give an answer, the variable *j* is set to 5 so that we get skipped out of this loop.

**If** Respondent selects the option that **does** contain the one-time payment:

Set  $ROW=ROW+2^{(4-j)}$

Note: this will increase the size of one-time payment in the next iteration, so it makes this option with the payment less attractive.

**Endif**

Set  $j=j+1$

This is the end of the loop for the EV-Buy questions

---

End of survey instrument for experiment on annuity valuations. The remainder of UAS49 consisted of approximately 24 screens with information and questions about insurance decisions that were collected for a different project.

## The Values of the Matrices for the Lump-Sum Amounts

The following tables show lump-sum amounts for three different starting values: low, medium and high, which are randomized as mentioned above.

|               |               |               |                |                |               |
|---------------|---------------|---------------|----------------|----------------|---------------|
| <b>10,000</b> | <b>4,000</b>  | <b>2,000</b>  | <b>1,000</b>   | <b>500</b>     | <b>Row 1</b>  |
|               |               |               |                | <b>1,500</b>   | <b>Row 2</b>  |
|               |               |               | <b>3,000</b>   | <b>2,500</b>   | <b>Row 3</b>  |
|               |               |               |                | <b>3,500</b>   | <b>Row 4</b>  |
|               |               | <b>7,000</b>  | <b>5,500</b>   | <b>4,750</b>   | <b>Row 5</b>  |
|               |               |               |                | <b>6,250</b>   | <b>Row 6</b>  |
|               |               |               | <b>8,500</b>   | <b>7,750</b>   | <b>Row 7</b>  |
|               |               |               |                | <b>9,250</b>   | <b>Row 8</b>  |
|               | <b>30,000</b> | <b>20,000</b> | <b>15,000</b>  | <b>12,500</b>  | <b>Row 9</b>  |
|               |               |               |                | <b>17,500</b>  | <b>Row 10</b> |
|               |               |               | <b>25,000</b>  | <b>22,500</b>  | <b>Row 11</b> |
|               |               |               |                | <b>27,500</b>  | <b>Row 12</b> |
|               |               | <b>60,000</b> | <b>40,000</b>  | <b>35,000</b>  | <b>Row 13</b> |
|               |               |               |                | <b>50,000</b>  | <b>Row 14</b> |
|               |               |               | <b>100,000</b> | <b>80,000</b>  | <b>Row 15</b> |
|               |               |               |                | <b>200,000</b> | <b>Row 16</b> |
| <b>Col. 1</b> | <b>Col. 2</b> | <b>Col. 3</b> | <b>Col. 4</b>  | <b>Col. 5</b>  |               |

We put the values of this in the 16x5 matrix  $LS\_LOW$ . The  $i^{\text{th}}$  row and  $j^{\text{th}}$  column of this matrix is denoted by  $LS\_LOW[i,j]$

|        |        |         |         |         |        |
|--------|--------|---------|---------|---------|--------|
| 20,000 | 4,000  | 2,000   | 1,000   | 500     | Row 1  |
|        |        |         |         | 1,500   | Row 2  |
|        |        |         | 3,000   | 2,500   | Row 3  |
|        |        |         |         | 3,500   | Row 4  |
|        |        | 10,000  | 7,000   | 5,500   | Row 5  |
|        |        |         |         | 8,500   | Row 6  |
|        |        |         | 15,000  | 12,500  | Row 7  |
|        |        |         |         | 17,500  | Row 8  |
|        | 60,000 | 30,000  | 25,000  | 22,500  | Row 9  |
|        |        |         |         | 27,500  | Row 10 |
|        |        |         | 40,000  | 35,000  | Row 11 |
|        |        |         |         | 50,000  | Row 12 |
|        |        | 100,000 | 80,000  | 70,000  | Row 13 |
|        |        |         |         | 90,000  | Row 14 |
|        |        |         | 200,000 | 150,000 | Row 15 |
|        |        |         |         | 500,000 | Row 16 |
| Col. 1 | Col. 2 | Col. 3  | Col. 4  | Col. 5  |        |

We put the values of this in the 16x5 matrix  $LS\_MED$ . The  $i^{\text{th}}$  row and  $j^{\text{th}}$  column of this matrix is denoted by  $LS\_MED[i,j]$

|        |        |         |         |         |        |
|--------|--------|---------|---------|---------|--------|
| 30,000 | 10,000 | 4,000   | 2,000   | 1,000   | Row 1  |
|        |        |         |         | 3,000   | Row 2  |
|        |        |         | 7,000   | 5,500   | Row 3  |
|        |        |         |         | 8,500   | Row 4  |
|        |        | 20,000  | 15,000  | 12,500  | Row 5  |
|        |        |         |         | 17,500  | Row 6  |
|        |        |         | 25,000  | 22,500  | Row 7  |
|        |        |         |         | 27,500  | Row 8  |
|        | 60,000 | 40,000  | 35,000  | 32,500  | Row 9  |
|        |        |         |         | 37,500  | Row 10 |
|        |        |         | 50,000  | 45,000  | Row 11 |
|        |        |         |         | 55,000  | Row 12 |
|        |        | 100,000 | 80,000  | 70,000  | Row 13 |
|        |        |         |         | 90,000  | Row 14 |
|        |        |         | 200,000 | 150,000 | Row 15 |
|        |        |         |         | 500,000 | Row 16 |
| Col. 1 | Col. 2 | Col. 3  | Col. 4  | Col. 5  |        |

We put the values of this in the 16x5 matrix  $LS\_HIGH$ . The  $i^{\text{th}}$  row and  $j^{\text{th}}$  column of this matrix is denoted by  $LS\_HIGH[i,j]$