Tail and Center Rounding of Probabilistic Expectations in the Health and Retirement Study[1]

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Abstract A large and growing number of surveys have been eliciting respondents' expectations for future events on a 0-100 scale of percent chance. The evidence from different surveys and populations reveals that these data display substantial heaping at multiples of 10 and 5 percent, suggesting that respondents round their reports. The extent of rounding, however, is unobserved and its impact on inference unknown. In this paper, we study the nature of rounding in numerical reports of expectations by analyzing response patterns across numerous expectations questions and waves of the Health and Retirement Study (HRS). We discover a systematic tendency by about half of the respondents to provide more refined responses in the tails of the 0-100 scale than in its center. In contrast, only about five percent of the respondents provide more refined responses in the center than the tails. We also find that rounding practice varies somewhat across question domains, which range in the HRS from personal health to personal finances to macroeconomic events. We develop a two-stage framework to characterize person-specific rounding in each question domain and scale segment. Our framework incorporates the evidence from the first part of the analysis in the form of assumptions that partially identify respondents' rounding. In particular, the first stage uses each respondent's response pattern across questions and waves to bound the extent to which the respondent rounds responses in each question domain and scale segment. The second stage replaces each original point response with an interval, representing the range of possible values of the respondent's true latent belief implied by the degree of rounding inferred in the first stage. Next we demonstrate how the interval data thus obtained can be employed as either an outcome variable or a covariate in prediction analyses of substantive interest. To assess the importance of rounding we compare empirical findings when rounding is ignored and when it is accounted for using our proposed approach.

Key words: Interval data; Partial identification; Probabilistic expectations; Rounding; Survey data.

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1. Introduction

Judgements about the likelihood of future events are an important input for predictions and decisions by citizens, policy makers, and researchers alike. From the early 1990s on, surveys have increasingly measured respondents' subjective expectations for future events using numerical scales of chance.[3] These measures have become widely employed in models, analyses, and predictions of individual and household decisions under uncertainty.[4]

The Health and Retirement Study (HRS), whose data we analyze in this paper, has measured probabilistic expectations since its start in 1992; Juster and Suzmann (1995) describe the initial design.[5] Section P of the HRS core questionnaire has been devoted to expectations measurement, each wave including approximately 25 to 35 questions spanning different domains of personal and macroeconomic uncertainty. From 2002 on, expectations have been consistently elicited on a 0-100 percent-chance scale, with many questions repeated across multiple waves.

Survey questions eliciting expectations on a 0-100 percent-chance scale in principle enable respondents to report their beliefs to the nearest 1 percent, thereby encouraging a common rounding convention with minimal data coarsening. But how do respondents use the scale in practice? The evidence accumulated across different surveys and populations reveals that respondents tend to use a subset of values in the 0-100 range. Responses that are not a multiple of 5 or 10 percent occur infrequently and, when observed, they tend to occur near the endpoints of the scale to convey very small or very large probabilities. This evidence suggests that respondents tend to round their expectations reports.[6]

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[3] This endeavor was prompted by earlier empirical evidence and/or theoretical arguments demonstrating the greater informativeness of elicited probabilities for binary events over "yes/no" intention measures with respect to actual population outcomes (Juster, 1966) as well as agents' expectations (Manski, 1990).
[4] Manski (2004, 2017), Attanasio (2009), Hurd (2009), van der Klaauw (2012), Armantier et al. (2013), Delavande (2014), Schotter and Trevino (2014), and Giustinelli and Manski (2016) review the literature from various perspectives.
[5] Additional information can be found at http://hrsonline.isr.umich.edu/.
[6] The early literature has devoted special attention to responses of 50, 0, and 100 percent. Fischhoff, Bruine de Bruin, and coauthors have hypothesized that a fraction of respondents use 50 percent to signal epistemic uncertainty (e.g., Fischhoff and Bruine de Bruin (1999), Bruine de Bruin et al. (2002)). Willis and coauthors have developed a model in which respondents first form full subjective distributions for the probability of an event and then report whichever of the three values (0, 50, 100) is closest to the mode of this subjective distribution (e.g., Lillard and Willis (2001), Hudomiet and Willis (2013)). They called these three values "focal responses." In this paper, we analyze each respondent's reports of 0, 50, and 100 percent jointly with that individual's responses to the entire set of expectations questions she is asked.

Rounding of expectations poses a series of challenges for statistical inference. First, rounding generates greater data coarsening than intended by the measurement scale. Second, the extent of rounding is not directly observable and may vary across respondents and/or questions. Third, the reasons why respondents round their expectations reports are incompletely understood.

Manski and Molinari (2010) hypothesize that respondents may round their expectations reports to simplify communication and/or to convey partial knowledge. They study respondents' response patterns across all expectations questions asked in the 2006 HRS and find strong evidence of rounding, with the extent of rounding differing across respondents. They propose use of a person's response pattern across multiple questions to infer the person's rounding practice, the result being interpretation of reported numerical values as interval data.[7]

In this paper, we perform a much more extensive analysis of rounding in the HRS and learn important new features of respondent practices. In Section 2 we analyze the response patterns of HRS respondents across all expectations questions asked in the core questionnaire between 2002 and 2014. We start by studying the patterns of responses to individual questions and across all questions asked in individual waves. In both cases, we find that rounding patters are stable across waves. Next, we analyze the patterns of responses across questions and waves simultaneously. We discover a tendency by about half of the respondents to provide more refined responses in the tails of the 0-100 scale than in its center. In contrast, only about five percent of the respondents provide more refined responses in the center than the tails. We also find that rounding practice varies somewhat across question domains, which range in the HRS from personal health to personal finances to macroeconomic events.

Based on our exploratory examination of rounding practices in Section 2, in Section 3 we develop a partial-identification framework where the response pattern of each respondent across

[7] Bassett and Lumsdaine (2001) study the main patterns of expectations reports for specific questions and across all questions in wave 1 of the HRS, but their analysis does not address rounding. Clements (2011) uses a modified version of Manski and Molinari (2010)'s approach to study rounding in the probabilities of decline and output growth histograms reported by respondents of the Survey of Professional Forecasters (SPF). Hudomiet et al. (2011) model measurement error in the stock market expectations of HRS respondents by partitioning the 0-100 scale into 10 percentage-points wide bins and assuming that the true subjective probability plus a zero-mean survey noise lies in the same bin as the corresponding survey report. Wang (2014) uses a similar method to address measurement error in reports of longevity expectations within a dynamic discrete choice model of smoking behavior in the HRS.

questions and waves are used to bound the extent to which the respondent rounds responses to particular questions in each domain and scale segment.[8]

Specifically, our approach consists in a two-stage rounding algorithm. The first stage classifies each respondent into one of a set of mutually exclusive and exhaustive rounding categories, which either point identify or partially identify the respondent's rounding type. The second stage assigns an interval to each of the respondent's original point responses, which represents the range of values in which the respondent's underlying true belief is plausibly deemed to lie based on the respondent's inferred rounding class.

Our approach accommodates substantial rounding heterogeneity. In particular, within a specific question domain, a respondent's rounding type is a bivariate vector of the form (tail, center) rounding, partitioning the 0-100 scale into two symmetric tails (0-24 and 76-100) and a center (25-75). Thus, in addition to being person specific, the inferred degree of rounding is allowed to differ between the tails and the center of the measurement scale and may vary across question domains. In turn, the assigned intervals vary across respondents and across values of the observed point responses. In Section 3 we further investigate heterogeneity of rounding across respondents' characteristics by analyzing the predictors of respondents' inferred rounding types.

In Section 4 we demonstrate how interval data on subjective expectations can be employed as either an outcome variable or a covariate in prediction analyses of substantive interest. One application considers best linear prediction of the labor supply expectations of working HRS respondents conditional on specified covariates. A second application studies the predictive power of longevity expectations and other covariates on hours worked.

In both cases we compare the estimates of the predictors' coefficients obtained when addressing rounding using our proposed approach with those obtained when rounding is ignored and expectations reports are taken at face value. We find that once rounding has been accounted for, identification of the coefficients' sign is preserved for only a subset of the predictors.

Our choice of assumptions used to (partially) identify respondents' rounding types and bound their unobserved true beliefs is informed by the respondents' response patterns across HRS

[8] Manski (1995, 2003, 2007) provide textbook treatments of the partial-identification approach. This approach has been used to bound causal effects of important economic variables, social programs, and market reforms (e.g., Manski et al. (1992), Manski and Pepper (2000), Siddique (2013), Klein and Tartari (2016)), and to analyze the roles of measurement error, missing data, and survey design features (e.g., Horowitz and Manski (2000), Kreider and Pepper (2007), Manski and Molinari (2008, 2010)).

questions and waves which we document in the first part of the analysis. Our proposed inferential framework, however, is substantially more general than the specific assumptions we make. In particular, a researcher entertaining a different set of assumptions about how survey respondents round their expectations reports could easily use our framework by simply replacing our assumptions with theirs. In general, stronger and/or more numerous assumptions will yield (weakly) tighter bounds on respondents' rounding types and latent beliefs as well as stronger inference on model parameters.[9]

There are only two papers systematically studying rounding in probabilistic expectations questions. One is Manski and Molinari (2010), on whose work we build. The other is Kleinjans and van Soest (2014), who develop and estimate a panel-data structural econometric model to analyze response patterns in each of six expectations questions in the HRS. Their analysis aims at investigating the extent to which probability reports are determined by genuine underlying probabilistic beliefs, rounding, a tendency to give "focal" responses, and selective item non-response. Despite the very different approaches taken, Kleinjans and van Soest's findings and ours reinforce each other in some important respects. For the six questions that they analyze, they find that rounding and the tendencies to give "focal" responses and non-responses tend to be persistent over time. They also find that probability reports are differentially affected by reporting behavior, the questions about receiving an inheritance and leaving a bequest (in personal finances) being the least affected and the questions about the future performance of the stock market (in general economic conditions) and own work limitations (in personal health) being the most affected.

Observed response patterns carry information about respondents' rounding practices, but they do not reveal why respondents give rounded expectations reports. Individuals may round to simplify communication, or they may round to convey partial knowledge.

If respondents round to simplify communication, one can think of rounding as a form of measurement error. However, the structure of the data errors produced by rounding is different

[9] For example, consider an intermediate assumption that would bound a respondent's rounding category and underlying belief uniquely based on the respondent's answer to the corresponding question, without using information from the respondent's pattern of responses across multiple responses or across waves. Hence, any response that is a multiple of 10 would be interpreted as consistent with any amount of rounding between no rounding and rounding to the nearest 10 percent, etc. This assumptions allows for complete heterogeneity across respondents and questions. A second version of this assumption would maintain stability across waves but not across questions belonging to the same domain.

from that occurring in the classical errors-in-variables model (Manski and Molinari (2010)). There is a rich literature studying nonclassical error-in-variable problems (e.g., see Schennach (2010, 2016)'s reviews). The proposed solutions typically require availability of an instrument that satisfies statistical independence restrictions. Moreover, additional technical restrictions required by these methods (called "completeness" conditions in the literature) have been shown to be untestable (see Canay et al. (2013)). The approach that we propose in this paper does not require availability of instruments, nor does it impose completeness conditions.

The structure of the data that we consider is also different from that analyzed in the literature on data coarsening (e.g., Heitjan and Rubin (1991), Heitjan (1994), Gill et al. (1997)). In that literature, it is assumed that the researcher observes a random set $\mathscr{X}$ (an interval, a group, a partial categorization, etc.) to which the (unobservable) random variable of interest x belongs with probability one. An assumption of "coarsening at random" is imposed, which requires that the probability of observing $\mathscr{X}$=A given $x = x_0$ is constant for all x_0 in A, where A denotes a subset of the support of x. In contrast, the HRS does not provide set-valued expectations data. The algorithm that we propose constructs sets $\mathscr{X}$ based on respondents' point responses and their tendencies for rounding across the entire set of questions eliciting subjective beliefs. Our approach does not assume ignorability of the coarsening mechanism and it allows for a coarsening mechanism that differs among respondents.

If respondents round to convey partial knowledge about the likelihood of future events of the kind HRS expectations questions refer to, it would be better to allow them to express their ambiguity directly. This could be achieved by allowing respondents to give either a single percent-chance value or a range as they see fit. Then range measures of subjective expectations may be analyzed using existing econometric tools for interval data.[10] We conclude in Section 5.

2. Exploratory Analysis of Response Patterns across Questions and Waves in the HRS

[10] With the exceptions of Manski and Molinari (2010) and Giustinelli and Pavoni (2017), we are unaware of any empirical study in economics that has collected and analyzed measures of subjective belief ambiguity outside the laboratory. Wallsten et al. (1983) review earlier measurement attempts in psychology, where belief ambiguity is elicited in the form of numerical ranges. Drerup et al. (2017) develop an econometric model where heterogeneous responsiveness of stock market participation to changes in primitives of the economic model are interpreted in terms of heterogeneous precision of respondents' beliefs about future stock market performance (rather than as measurement error). However, the authors do not have direct measures of precision of respondents' stock market expectations.

Since 2002 the HRS has devoted an entire section of its core questionnaire to measurement of respondents' expectations in the domains of personal health, personal finances, and general economic conditions. Across seven biannual waves spanning 2002 to 2014, expectations have been consistently elicited on a 0-100 percent chance scale and many questions have been repeated across multiple waves. Figure 1 shows the list of expectations questions asked in Section P of the HRS core questionnaire between 2002 and 2014 organized by domain.[11]

The total number of questions per wave ranges between a minimum of 22 in 2002 and a maximum of 38 in 2006. The majority of questions are in the personal finances domain (between 11 and 23 per wave, 31 overall), followed by those in the personal health domain (between 3 and 9 per wave, 10 overall), and those in the general economic conditions domain (between 2 and 7 per wave, 12 overall). A subset of 12 questions across the three domains was asked in all waves.

Given that questions have been added and removed over time, the number of responses varies across questions, as shown in Table 1. An additional reason for the observed variation in the number of responses across questions is that the HRS makes extensive use of skip sequencing.[12] Finally, the total number of responses generated by a specific question across the seven waves may differ from the product of the number of waves in which the question was asked and the number of respondents to whom the question was asked due to changes in sample composition across waves.[13]

In Section 2.1 we study patterns of response to specific questions in each of the seven waves between 2002 and 2014. In Section 2.2 we investigate response patterns across questions in individual waves between 2002 and 2014, alternatively using all questions asked in each wave and the 12 questions asked in all waves. Focusing on the latter set of questions, we further

[11] Most expectations questions in the HRS and in other surveys of expectations refer to future realizations of discrete, usually binary, random variables. However, in some cases the questions ask respondents to report their subjective probabilities that the future realization of a continuous variable will be above or below a set of monotonic thresholds. Answers to these questions are typically interpreted as measuring the respondent's subjective cdf of the variable in question; see Dominitz and Manski (1997) for an early example of elicitation and validation of the latter format.

[12] Thus, whether a specific question is asked or not to a certain respondent depends on the previous answers given by the respondent and on whether the event specified by the question is relevant to the respondent. E.g., a respondent who responds 'Don't know' (DK) or 'Refuse' (RF) to three consecutive expectations questions is skipped to the next section. Moreover, respondents who are older than 62 are not asked their subjective probability of working full-time past 62. Similarly, respondents over 75 are not asked their subjective chances of living to be 75 or older, and so on.

[13] The HRS sample has been augmented with new cohorts of respondents who joined the study in specific waves. On the other hand, respondents may exit the study due to attrition or death.

analyze the stability of response tendencies across pairs of waves. In Section 2.3 we analyze the response patterns of individual respondents across questions and waves separately by question domain. We pay particular attention to the location of responses inside the 0-100 scale and learn important features of respondents' response patterns in specific domains.

2.1 Time Pattern of the Cross-Sectional Distributions of Responses to Specific Questions

We start by investigating the empirical distributions of responses to each of the questions listed in Table 1 separately for each wave between 2002 and 2014. To reduce length, in Table 2 we present the response patterns for a subset of 9 questions in different domains. We focus on questions that were asked in at least 4 waves.

For each of the 9 questions selected and for each of the waves in which those questions were posed, the columns of Table 2 show the fractions of respondents who do not respond (NR), who respond 0, 50, or 100, who respond with any other multiple of 10 percent (i.e., in $\mathbb{M}10 = \{10, 20, 30, 40, 60, 70, 80, 90\}$), who respond with any multiple of 5 percent that is not a multiple of 10 percent (i.e., in $\mathbb{M}5 = \{5, 15, 25, 35, 45, 55, 65, 75, 85, 95\}$), and who respond in two ranges of multiples of 1 percent that are not multiples of 5 or 10 percent (i.e., in 1-4 and in 96-99). In the column "Other" we report the residual fraction of respondents who respond with a multiple of 1 percent that does not lie in the 1-4 or 96-99 range.

By and large, HRS expectations questions feature low rates of item nonresponse in the personal health and personal finances domains (below 0.05) and higher rates of item nonresponse in the general economic conditions domain (typically between 0.05 and 0.10), with peaks of 0.25-0.30 rates of nonresponse to specific questions eliciting respondents' expectations of future performance of the stock market (e.g., see question P47 in Table 2).

The rates of 0, 50, and 100 vary across questions. For example, the fraction of 50 percent responses tends to be higher in the general economic conditions domain, where they range between 0.20 and 0.30, than in the remaining domains. Among the 9 questions shown in Table 2, the fractions of 0 and 100 are highest for specific questions belonging to the personal finances and personal health domains. For example, the fraction of 0 ranges between 0.35 and 0.50 for P14 (probability of losing own job during the next year) and for P32 (probability of moving to a nursing home in 5 years); whereas the fraction of 100 percent is highest for P5 (probability of leaving an inheritance of at least $10K), ranging between 0.324 and 0.447 across waves.

The high rates of 0, 50, and 100 in response to specific questions do not suggest any particular degree of rounding. For example, responses of 50 percent are consistent with any degree of rounding. Respondents who answered P47 (probability that the mutual fund will increase in value in the next year) might genuinely believe that it is equally likely that the stock market will increase or decrease in value in a 1-year time; they might mean that the chances that the stock market will go up are between 40 and 60 percent; or they might have epistemic uncertainty, using 50 percent to indicate a complete lack of knowledge.

Consistently high fractions of responses across questions and waves are multiples of 10 percent and, to a lesser extent, of 5 percent. For the 9 questions shown in Table 2, the fractions of $\mathbb{M}10$ and $\mathbb{M}5$ responses range respectively between 0.20 and 0.45 and between 0.05 and 0.15 across questions and waves. On the other hand, the fractions of cases where the response takes the value 1-4 or 96-99 are substantially smaller and range respectively between 0.002 and 0.035 and between 0.000 and 0.010 across questions and waves. Responses in the “Other” category occur even more infrequently and usually constitute 0.006 or less of cases.

The main takeaway from Table 2 is that the basic patterns found by Manski and Molinari (2010) using the 2006 data are confirmed for the remaining waves as well. Hence, these patterns are stable across waves.

2.2 Time Pattern of the Cross-Sectional Distributions of Response Tendencies across Questions

We now investigate whether the apparent time stability displayed by response patterns to individual questions also applies to response tendencies across multiple questions. We view the latter measure as more directly informative about whether respondents systematically vary in their tendency to round. Hence, in this subsection we investigate whether respondents’ tendencies to round their expectations reports vary across waves.

Following Manski and Molinari (2010), we compute the fractions of respondents displaying each of 7 mutually exclusive and exhaustive response patterns. Once again we extend their analysis to all waves between 2002 and 2014. Table 3 shows the empirical distributions of response tendencies in individual waves. Response patterns are indicated by column, from the most rounded (shown in the third column) to the least rounded (shown in the ninth and last column). Column 3 gives the fractions of respondents who respond all questions in the wave with a “Don’t know” or “Refuse” (NR). Column 4 gives the fractions of respondents who, when they respond, only use the values 0 and 100 in the corresponding wave. Column 5 gives the fractions of respondents who, when they respond, only use the values 0, 50, or 100. Columns 6 and 7 give the fractions of respondents who answer at least one question with a value in $\mathbb{M}10$ and $\mathbb{M}5$ respectively. Similarly, columns 8 and 9 give the fractions of respondents who respond to at least one question with a multiple of 1 percent that is not a multiple of 5 percent in 1-4 ∪ 96-99 and 6-94 respectively (the latter category is labelled “Some other”).

The set of expectations questions posed in Section P of the HRS varies considerably across waves. The bottom panel of Table 3 presents a version of the statistics where respondents are classified into one of the 7 response patterns using only the 12 questions that were asked in all 7 waves (i.e., P5, P6, P7, P16, P17, P18, P20, P28, P29, P32, P47, and P59).

A small fraction of respondents respond to none of the questions posed to them. This fraction ranges between 0.009 and 0.027 depending on the set of questions used to classify respondents. Between 0.019 and 0.101 of respondents uses only the values (0, 100). Similar fractions of respondents use only the values (0, 50, 100). The majority of respondents give at least one answer in $\mathbb{M}10$ or in $\mathbb{M}5$. The fraction of $\mathbb{M}10$ respondents ranges between 0.263 and 0.337 across waves when all questions asked in any single wave are used for classification and between 0.392 and 0.458 when only the set of questions in common to all waves is used. Similarly, the fraction of $\mathbb{M}5$ respondents ranges between 0.427 and 0.513 when all questions are used for classification and between 0.295 and 0.353 when only the common set is used.

The fractions of respondents who give at least one response that is a multiple of 1 percent but not of 5 percent in 1-4 ∪ 96-99 and in 6-94 are sizeable but considerably smaller, especially the latter. The former ranges between 0.101 and 0.144 when all questions are used for classification and between 0.054 and 0.092 when only the common set is used. The latter fraction ranges between 0.022 and 0.042 or between 0.011 and 0.020, depending on the set of questions used.

As revealed in Table 3, the empirical distribution of response tendencies across questions in any one wave is somewhat sensitive to the set of questions used to classify respondents in the corresponding wave. On the other hand, the basic observed patterns characterizing the distribution of response tendencies across questions in 2006 are confirmed for the other waves. Hence, once again, the main takeaway is that response tendencies across questions are stable across waves. Using the fixed and smaller set of questions that were asked in all waves for classification further reduces the variation of the observed distributions across waves.

The evidence presented in Tables 2 and 3 suggests that the main patterns of responses to specific questions and across questions are stable across waves between 2002 and 2014. However, these are aggregate patterns which may partly reflect sample composition. To address this issue we compute transition matrices of response tendencies across waves. Specifically, for each pair of waves indicated by column, Table 4 reports the fractions of respondents classified as belonging to any rounding category in the first wave who transitioned to the same rounding category in the second wave (1st row), who transitioned to a finer or coarser adjacent category (2nd row), and who transitioned to a more distant rounding category (3th row). The reported calculations use only the 12 questions in common to the 7 waves to classify respondents.

Between 0.406 and 0.436 of the respondents remain in the same rounding category across any pair of adjacent waves and between 0.373 and 0.386 transition to an adjacent category. Thus, overall between 0.788 and 0.813 of respondents transition to the same or an adjacent category. Even transitions between the first and last waves, with 14 years separating them, display high persistence, with over 78% of respondents transitioning to the same or an adjacent category.

The amount of stability observed in Table 4 is remarkable considering the criteria used to classify respondents in Tables 3 and 4. For instance, take a respondent whose most refined answer in 2002 is a multiple of 10 percent other than (0, 50, 100) and who is thus classified as "Some M10." If in 2004 the same respondent were observed to give a single answer that is a multiple of 5 percent but not of 10 percent, he would be now classified as "Some M5."

2.3 Individual-Level Patterns of Response Tendencies across Questions and Waves by Question Domain

The exploratory analysis presented above describes the relative prevalence of rounding patterns aggregated across the HRS respondents. To obtain further insight, we examine in depth the rounding behavior of particular respondents across questions and waves. This exploration yields important new findings, which we describe next.

We proceed by drawing a random subset of 100 HRS respondents and by generating histograms of the responses each respondent thus selected gave in each of the three question domains. Figure 2 illustrates using the respondent selected by the 9th random draw.

Inspection of the histograms across the 100 randomly drawn respondents suggests that many of them may be applying weakly coarser rounding in the middle of the 0-100 percent chance scale than in its tails. To better visualize this pattern we report a grouped version of the histograms. For example, Figure 3 presents the grouped versions of the histograms shown in Figure 2 for respondent #9. Specifically, in Figure 3 responses are grouped according to the following partition of the 0-100 scale, where 25 and 75 are used as the thresholds separating the center from the two symmetric tails: $\mathbb{M}1$-Tail = values in 1-24 ∪ 76-99 that are not divisible by 5; $\mathbb{M}1$-Center = values in [26, 74] that are not divisible by 5; $\mathbb{M}5$-Tail = {5, 15, 85, 95}; $\mathbb{M}5$-Center = {35, 45, 55, 65}; $\mathbb{M}10$-Tail = {10, 20, 80, 90}; $\mathbb{M}10$-Center = {30, 40, 60, 70}; $\mathbb{M}25$ = {25, 75}; $\mathbb{M}100 = \{0, 100\}$; $\mathbb{M}50 = \{50\}$.

There are two notable features in the distributions of responses given by respondent #9 in Figure 3. First, the high frequencies of 25 and 75 percent responses (grouped in $\mathbb{M}25$) relative to other multiples of 5 (grouped in $\mathbb{M}5$-T and $\mathbb{M}5$-C) suggest that 25 and 75 may have special status among multiples of 5. These percentages correspond respectively to “1 in 4” and “3 in 4” chances. Thus, they might be viewed by respondents as more rounded than other multiples of 5.

The second important feature emerging from the histograms shown in Figure 3 is that the relative frequencies of refined responses in the tail segments of the scale are generally higher than the frequencies of such responses in the corresponding center segment. For instance, the heights of the bars corresponding to $\mathbb{M}10$-T responses are systematically higher than those corresponding to $\mathbb{M}10$-C responses in all three question domains. The same pattern applies to the remaining response categories. This suggests that the more frequent use of multiples of 1 percent near the endpoints of the scale than toward the middle of the scale documented by earlier analyses of rounding might be the expression of a more general tendency of respondents to round more coarsely around the middle of the 0-100 scale than in its tails.

The histograms shown in Figure 3 —and the additional ones we created using the responses of the remaining 99 randomly selected HRS respondents— proved extremely useful for detecting potentially important features of respondents’ response patterns and their rounding tendencies. However, these histograms do not reveal how prevalent such features are across the whole sample of HRS respondents. To answer this question, in Table 6 we report the distributions of responses across respondents and waves for each question asked in Section P between 2002 and 2004 (see list in Figure 1 or Table 1). Response categories are defined as in Figure 3.

The two main features detected by inspecting the histograms are decisively confirmed in the general sample. In particular, a comparison of the relative frequencies of the $\mathbb{M}25$ responses (in column 5) with the relative frequencies of the remaining $\mathbb{M}5$ responses ($\mathbb{M}5$-C in column 9 and $\mathbb{M}5$-T in column 8) reveals that the fraction of 25 or 75 percent responses is always higher than the fraction of the remaining multiples of 5 percent in the center of the scale (i.e., of responses in {35, 45, 55, 65}). Moreover, for the large majority of questions across the three domains, the fraction of 25 or 75 percent is also higher than the fraction of multiples of 5 percent in the tails of the scale (i.e., of responses in {5, 15, 85, 95}).

Even more striking is the comparison of the relative frequencies of responses in the tails of the scale versus those in the center. Specifically, the fractions of $\mathbb{M}10$, $\mathbb{M}5$, and $\mathbb{M}1$ responses in the tails are visibly higher than the corresponding fractions of $\mathbb{M}10$, $\mathbb{M}5$, and $\mathbb{M}1$ responses in the center for nearly all questions in Table 6. Exceptions are questions P47 and P190, for which the fractions of $\mathbb{M}10$-C responses are slightly higher than the fractions of $\mathbb{M}10$-T responses.

3. Rounding Algorithm and Heterogeneity

The exploratory analysis of Section 2 reveals that HRS respondents differ systematically in their rounding practices, with a relatively small fraction of them habitually performing gross rounding and the majority of them sometimes giving more refined responses. In particular, using all waves between 2002 and 2014 we have established that the response tendencies of HRS respondents across questions are stable across waves. Furthermore, we have detected further patterns of responses that the earlier analysis by Manski and Molinari (2010) could not detect using only one wave of data. These include a relatively frequent use of 25 and 75 percent and a systematic use of more refined responses in the tails of the scale (i.e., below 25 percent and above 75 percent) than in its center (i.e., between 25 and 75 percent).

Generalizing the inferential approach proposed by Manski and Molinari (2010), in this section we develop a new algorithm that uses response tendencies of respondents across questions and waves to characterize how individual respondents round their responses to particular questions. The algorithm classifies each respondent into one of a set of mutually exclusive and exhaustive rounding categories and transforms each of the respondent's original point responses into an interval where the true latent belief is deemed to lie. With this accomplished, substantive analysis of expectations may proceed using the intervals thus constructed in place of the observed point responses.

Our algorithm relies on considerably weaker and hence more credible assumptions than inference that uses expectations reports at face value. Nevertheless, we cannot be certain that the intervals we construct using the algorithm always include the latent object of interest and, thus, that inference based on interval data is completely accurate. The algorithm is subject to two potential forms of misclassification. First, if a given survey response is less rounded than the interval assigned by the algorithm (i.e., the actual rounding interval is a subset of the algorithm's interval), then our use of the data is correct but yields inference that is less sharp than it would be if the true degree of rounding were known. Second, if the actual rounding interval is not completely contained in the algorithm's interval, then our use of data is incorrect. Still, use of the algorithm lowers the risk of the latter type of error relative to a more standard approach that takes survey responses at face value.

The new algorithm takes explicitly into account the data patterns we documented in Section 2. In Section 3.1 we describe the specific conditions used to determine a respondent's rounding category and we present the empirical distributions of the respondents' inferred rounding categories in the two scale segments and the three question domains. In addition, we study how rounding tendencies vary across basic characteristics of the respondents to inform researchers who may know the distribution of respondents' characteristics in their data set while not having a sufficient number of expectations to apply our proposed approach directly.

In Section 3.2 we explain how a respondent's point response to a specific question and the respondent's inferred rounding category are used to construct the interval associated with the observed point response. We present the sample distributions of the probability intervals thus constructed for a small set of questions spanning the three domains.

3.1 Determination of Respondent Rounding Categories and Analysis of Rounding Heterogeneity across Respondents

Based on the evidence accumulated in Section 2, we allow a respondent's rounding type to vary both across question domains and between the tails and center of the measurement scale. Thus, within a specific domain of questions, a respondent's rounding type is a bivariate vector of the form (tail, center) rounding, partitioning the 0-100 scale into two symmetric tails (0-24 and 76-100) and a center (25-75). We believe that our specific choice of tails and center reasonably reflects empirical patterns of HRS responses, but judgments need not be uniform. The algorithm can be easily adapted to different definitions of tails and center or extended to accommodate finer partitions of the 0-100 scale (e.g., outer tails, inner tails, center).

The new algorithm refines the earlier one posed by Manski and Molinari (2010) on multiple fronts. One refinement is to separate tail from center rounding. The other is to classify persons who only use the response values (0, 25, 50, 75, 100) as rounding to the nearest 25 percent rather than to the nearest 5 percent. A further difference between the two algorithms is that here we use a tighter criterion for assignment of a person to a more refined rounding type.

To explain the tighter criterion, consider categorization of a respondent as one who rounds to the nearest 10 percent (or to a more refined degree). Manski and Molinari assigned a respondent to this rounding category if all of the person's responses are multiples of 10 and at least one response is not a value in (0, 50, 100). We use here a slightly tighter criterion that requires observation of at least two responses that are multiples of 10 other than (0, 50, 100), of which one must be in the domain under consideration and the other may be in a different domain and may also be a less rounded response (i.e., a multiple of 5 or 1 that is not a multiple of 10).

Adding the new requirement reflects our desire for further credibility when assigning a person to a more refined rounding type. We want enhanced credibility because misclassification into an overly refined rounding category yields an inferential error (as the person's latent beliefs may not entirely lie within the overly refined interval). Whereas misclassification of a person into a rounding category less refined than their actual one does not yield an inferential error (as the less refined interval includes the actual one as a subset).[14]

The main criteria for classification of respondents are as follows:

[14] An extreme version of the first kind of error may occur when the data is taken at face value, implying a probability interval of width 0 around the observed expectations report. At the other extreme, the most conservative assumption would maintain that regardless of the values of individual responses, or the patterns of values across responses, the value of each response is consistent with any amount of rounding, implying a [0, 100] probability interval. Obviously, replacing all responses with the same [0, 100] range empties the data of any information content.

- **Center rounding type** Define x_n in {1, 5, 10, 50}, with $n = 1, \ldots, 4$. Respondent *j* is classified as rounding to the nearest x_n percent in the center within question domain *l* if one of the following two conditions holds: (i) they are observed to give at least two answers in the center that are multiples of x_n percent but not of $x_{n'}$ for any *n' < n* within domain *l*; or (ii) they are observed to give one answer in the center that is a multiple of x_n percent (but not of $x_{n'}$ for any *n' < n*) within domain *l* AND at least one answer in the center that is a multiple of $x_{n'}$ for any *n' ≤ n* within a second domain *l'* distinct from *l*.
- **Tail rounding type** Respondent *j* is classified as rounding to the nearest x_n percent in the tails within question domain *l* if one of the following two conditions holds: (i) they are observed to give at least two answers in the tails that are multiples of x_n percent but not of $x_{n'}$ for any *n' < n* within domain *l*; or (ii) they are observed to give one answer in the tails that is a multiple of x_n percent (but not of $x_{n'}$ for any *n' < n*) within domain *l* AND at least one answer in the tails OR center that is a multiple of $x_{n'}$ for any *n' ≤ n* within a second domain *l'* distinct from *l*.

Table 8 presents in a formal and compact way the complete algorithm used to determine a respondent's rounding type in the center of the 0-100 scale (panel A) and in its tails (panel B) within a given question domain. Specifically, Table 8A maps all logically possible response tendencies that may be observed in the center of the 0-100 scale into corresponding center rounding types. Table 8B maps all logically possible response tendencies that may be observed in the tails of the 0-100 scale into corresponding tail rounding types. For each question domain, each respondent is assigned a bivariate (tails, center) rounding type belonging to the cross product of the tail and center rounding types listed in the two panels of Table 8 (which relies on the partition of the 0-100 scale described in Table 7).[15]

We apply the algorithm described in Table 8 to all HRS respondents who responded to at least one expectations question in any question domain and in any wave between 2002 and 2014. Table 9 reports the empirical frequencies corresponding to the sample distribution of rounding types for each domain of questions among personal health, personal finances, and general economic conditions. Depending on the question domain, between 40.40% and 61.03% of respondents are inferred to apply finer rounding in the tails than in the center. Between 28.49%

[15] The Stata codes are available upon request.

and 38.73% of respondents apply the same degree of rounding in the tails and in the center. Between 2.90% and 6.71% of respondents apply coarser rounding in the tails than in the center.

The rounding type of a minority of respondents could not be determined either in the tails, or in the center, or both.[16] Nevertheless, the second stage of the algorithm assigns intervals to the observed point responses even for these respondents, as explained in Section 3.2.

Before describing how probability intervals are formed based on respondents' point responses and their inferred rounding types, we investigate whether the latter vary systematically by respondents' characteristics. This exercise sheds some light on the observed heterogeneity of respondents' tendencies to round. In addition, it may usefully inform researchers who analyze survey expectations but cannot assess rounding using our proposed approach (e.g., due to insufficient number of available expectations questions), about likely characteristics of respondents that are associated with coarser or more refined rounding behavior.

In Table 10 we present estimated coefficients of three bivariate ordered probit models, one per question domain, where the outcome variables are the respondent's bivariate vectors of tail and center rounding categories in the corresponding domains. As predictors we use dummy variables for the respondent's gender, age, educational attainment, and race. We allow the error terms of the latent variables underlying the inferred tail and center rounding categories to be correlated with each other. The correlation parameter "rho" is estimated along the other coefficients. The rounding categories are ordered from least coarse to most coarse. Thus, positive associations indicate a tendency to round more coarsely and *vice versa*.

We find that higher levels of educational attainment are unambiguously and statistically significantly associated with a tendency to give more refined responses (less rounding) across all scale segments and question domains. The patterns for the other predictors seem more varied.

For example, respondents belonging to the oldest age category (80+) have a statistically significant tendency to give more rounded responses than respondents belonging to the youngest one (50-59) across all scale segments and questions domains. On the other hand, respondents in the two intermediate age groups (i.e., 60-69 and 70-79) belong to rounding categories that may

[16] The vast majority of undetermined cases occur whenever, for a given respondent, we do not observe any answer in the relevant domain and scale segment. If we condition on respondents for whom we observe at least one answer in the relevant domain and scale segment, all cases of undetermined tail rounding type disappear and only few cases of undetermined center rounding type remain. The latter are all cases where for a given respondent we only observe one answer in the center in the relevant domain and no answers in the center in the remaining two domains.

be more refined, coarser, or statistically indistinguishable from those characterizing younger respondents, depending on the specific domain or scale segment. A potential interpretation of the observed age patterns is that individuals belonging to the intermediate age groups may have more direct experience and hence better knowledge of the topics covered by the questions than younger respondents, generating more refined responses among the middle groups. On the other hand, when individuals reach older ages cognitive decline may become a factor leading to coarser responses. The latter effect seems to kick in earlier in the center and later in the tails.

Male respondents appear to have a tendency to round significantly more coarsely than female respondents in the personal health and personal finances domains, but only in the tails. On the other hand, male respondents tend to round less coarsely than women respondents in the center in the general economic conditions domain. Finally, while respondents belonging to the residual race category (including Hispanic, Asian, and Pacific Islander) tend to round significantly more coarsely than white respondents, the differential rounding tendencies of black respondents relative to white respondents vary across question domains and scale segments.

The large, positive, and statistically significant estimates of the correlation parameter reveal that rounding tendencies are positively correlated across scale segments. Hence, respondents who give coarser responses in the tails are more likely to do so in the center and *vice versa*.

3.2 Forming Interval Expectations from Survey Responses and Rounding Categories

We now describe how observed percent-chance point reports are transformed into probability intervals. By construction, each interval contains the point response and is assumed to cover the unobserved true latent belief with certainty. The width of the assigned interval depends on the respondent's rounding type and may vary across responses given by the same respondent.

Table 11 (making use of the partition of the 0-100 scale described in Table 7) presents in a formal and compact way the complete portion of the algorithm used to assign intervals to observed point responses in the scale tails (panel A) and in the its center (panel B) within a given domain. Specifically, Table 11A maps all logically possible rounding types and responses that may be observed in the tails of the 0-100 scale into corresponding tail intervals. Similarly, Table

11B maps all logically possible rounding types and responses that may be observed in the center of the 0-100 scale into corresponding center intervals.[17]

We apply the algorithm described in Table 11 to all responses by HRS respondents who responded to at least one expectations question in any question domain and in any wave between 2002 and 2014. For the purpose of constructing the intervals, respondents who were classified as rounding more coarsely in the tails than in the center are now treated as respondents who were classified as rounding to the same degree in the tails and in the center.

Table 12 reports the distributions of interval width for the responses given in wave 2014 to the following three questions: the percent chance that the respondent will live to be 75 or older (P28), the percent chance that the respondent will work full time past age 62 (P17), and the percent chance that a mutual fund will increase in value within the next year (P47). The distribution of interval width for the probability of working past 62 displayed in the middle column of the table displays higher frequencies at lower width values than the distributions shown in the remaining columns, consistent with the pattern shown in Table 9.

4. Illustrative Applications

In this section we demonstrate how interval data on subjective expectations can be employed as either an outcome variable or a covariate in prediction analyses of substantive interest by means of two empirical applications. In section 4.1, we present an application to best linear prediction where the objective is to predict the labor supply expectations of working HRS respondents conditional on specified covariates. In section 4.2, we study the predictive power of longevity expectations and other covariates on hours worked of male HRS respondents. Hence, interval data play the role of predictors.

In both cases we are interested in studying how explicitly accounting for rounding in probabilistic expectations affects the conclusions that one can draw in empirical analysis.

4.1 Predicting Labor Supply Expectations of Older Workers

[17] The Stata codes are available upon request.?

As the American population ages and a larger fraction of "baby boomers" approach retirement age, we think it of interest to analyze how subjective expectations of HRS respondents for working full-time past age 62 vary with several covariates, including age, gender, coupledness status, household's wealth, race, and education.

In each of the HRS waves analyzed in this paper, respondents younger than 62 at the time of the interview were asked, *"Thinking about work in general and not just your present job, what do you think the chances are that you will be working full-time after you reach age 62?"*. See question P17 in Table 2 for the response distribution in each wave and in Table 6 for the response distribution with data pooled across waves. In our analysis, we compare the conclusions that can be drawn when the elicited expectations are taken at face value (as commonly done in the related literature; e.g., Honig, 1996, 1998), and when our algorithm is used to characterize rounding. We analyze data from each of the seven waves of the HRS going from 2002 to 2014, as well as for data pooled across waves. Here we present results for the pooled data, which yield a sample of size 24,052 after dropping respondents younger than forty and those for whom we do not observe some covariates.[18]

Table 12 reports the sample frequencies of the width of the intervals $[\upsilon_{jkt}^{L}, \upsilon_{jkt}^{U}]$ for $t = 2014$, when the intervals are constructed using our algorithm in Section 3. The intervals are relatively tight, with nearly 62% of observations having interval widths of 5 or less.[19]

When we take the elicited expectations of working past age 62 at face value, we report the results of best linear prediction under square loss (OLS analysis). In this case, we drop respondents who answered "Don't know" or "Refuse" to the probability chance question posed in P017. This assumes that nonresponse is random and yields a pooled sample of size 23,811.

When we use our algorithm to interpret the elicited expectations as intervals under the assumptions set forth in Section 3, conceptually we repeat the same exercise of best linear prediction under square loss considering all points in the interval outcome variable of each respondent to be feasible values of the quantity of interest. In this case, the resulting best linear predictor's parameter vector is not point identified. Rather, it is *partially identified*, meaning that there is a *set* of values (rather than a single value) for the parameter vector that are consistent with the available data and maintained assumptions. This set of values is called the parameters'

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[18] Results for each wave separately are available from the authors upon request.
[19] The distribution is similar for the pooled data (available upon request).

identification region. We estimate this region and build confidence intervals for it using the method proposed by Beresteanu and Molinari (2008). While Beresteanu and Molinari (2008, Section 4) and Beresteanu et al. (2012, Section 3.2) give a detailed discussion of the method, a technical appendix to the present paper provides a summary for the reader's convenience.

The results of our analysis are reported in Table 13. The first column shows the estimates and confidence intervals for the case in which elicited expectations are taken at face value. Standard errors are clustered at the household level. The results suggest an increased expectation to work full-time past age 62 for individuals who are closer to age 62, who are males, who have lower wealth, and who are more highly educated, while a reduced expectation to work past age 62 for less wealthy individuals and for non-whites.

The second through fifth columns report set estimates and confidence intervals for the case in which elicited expectations are interpreted as interval data according to our algorithm. The only difference between the empirical exercises reported in the two sets of columns (2-3 and 4-5) is that the set estimation in columns 2-3 maintains the assumption that nonresponse to the expectation question is random. This is done exclusively to provide intermediate results based on the same sample as that used in column 1, but we consider the assumption unrealistic in the present application. Hence, we focus on the results in columns 4-5.

The results reveal that the strength of the conclusions that can be drawn is weaker when we interpret elicited expectations as intervals than when we take them at face value. This is to be expected, as there is an intrinsic trade-off between the strength and the credibility of inference. Despite this, however, our analysis –under considerably weaker assumptions– continues to find that males and individuals with higher education have higher expectations, while blacks have lower expectations, to work past age 62.

4.2 Longevity Expectations and Hours Worked [This section is under revision.]

Individuals' life horizon and the related mortality risk are key ingredients of any economic model of life-cycle behaviors. This raises the question of whether life horizon and mortality risk as *perceived* by individuals are empirically important determinants of their labor supply, saving and investment decisions, etc. (e.g., Hamermesh (1985)). Previous work has examined the effect of subjective survival probabilities on retirement and Social Security claiming behaviors of older

Americans (e.g., Hurd et al. (2004), Delavande et al. (2006)). Here we focus on the relationship between subjective survival probabilities and hours worked.[20]

In all waves of the HRS, respondents were asked to report their longevity expectations by means of one of or both the following questions, depending on the respondent's age at the time of the survey. Respondents under 65 were asked, *"What is the percent chance that you will live to be* [X] *or more?"* with X equal to 75 (question P28) and 85 (question P29). Respondents aged 65 through 90 were asked, *"What is the percent chance that you will live to be* [X] *or more?"* where X takes a value in {80, 85, 90, 95, 100} depending on the respondent's age (question P29). The sample distribution of responses to P28 in each wave is displayed in Table 2, and the sample distributions of responses to P28 and P29 pooled across waves are shown in Table 6. Table 12 reports the sample frequencies of the width of the algorithm intervals $[\upsilon_{jkt}^{L}, \upsilon_{jkt}^{U}]$, constructed around respondents' point responses to question P28 in the 2014 HRS wave.

We focus here on working male individuals aged 50 through 69, who were asked to report their percent chance of living past 80 or 85. Our outcome variable is weekly hours worked.[21] And our predictors are interval-valued longevity expectations, age, and coupledness status. As in the first application, the exercise is one of best linear prediction of the outcome variable given covariates. Once again, we are interested in comparing the conclusions that can be drawn when rounding is explicitly addressed with those obtained when rounding is ignored. Econometrically, the key difference between this application and the earlier one is that now the interval-valued variable is used as a covariate. In this case, the inferential problem is more difficult than in the case where the interval-valued variable is used as an outcome of a regression model, because the estimator is no longer linear in the interval data.

Manski and Tamer (2002) study the problem of inference on regressions with interval data on a regressor. That is, the problem is one of inferring, say $E(y\,|\,\upsilon, x)$, when υ is unobserved but is known to lie in some interval $[\upsilon^{L}, \upsilon^{U}]$with probability 1. The latter assumption is called Interval (I). Under assumption (I), two additional ones – Monotonicity (M) and Mean Independence

[20] Recent evidence indicates that bad health reduces both employment and hours worked; the latter effect operates mainly through the employment margin (French and Jones, 2017). However, we are not aware of any study investigating the relationship between longevity subjective expectations and hours worked.

[21] Hours worked were measured in question J172 as following: *"How many hours a week do you usually work [on this job/in this business]?"* This question was asked only of respondents who answered "yes" to question J20, *"Are you doing any work for pay at the present time?"*.

(MI), and a parametric model for $E(y \mid \upsilon, x)$, Manski and Tamer (2002) derive the identification region for the parameters of the model and discuss estimation methods. Once again we summarize the theory for the reader's convenience in the technical appendix.

We estimate the model using Chernozhukov et al. (2013)'s inferential approach.[22] Once again, we present results for the pooled data, which yield a sample of size 16287 after dropping respondents with missing covariates. In the interest of space, we present results graphically in Figure 4.[23] Specifically, each panel of Figure 4 reports on the y-axis the mean weekly hours of work predicted using a linear regression model estimated by least squares taking the longevity expectations data at face value ("OLS"), alongside the estimated bounds ("Bounds") obtained using interval expectations to account for rounding and implemented using the Chernozhukov et al. (2013, 2015)'s inferential method and Stata code. Additionally, the graphs display 95% confidence intervals for both the OLS and Bounds estimates. Within each panel, the predicted hours worked are displayed as a function of respondents' point expectations (shown on the x-axis). Different panels show estimates for different sub-samples, corresponding to different age-coupledness status combinations.

The figures suggest that predicted mean hours worked increase weakly in the perceived likelihood of living past 80 (85), they decrease markedly as age increases, and do not seem to differ significantly across coupledness statuses.

5 Conclusion

In this paper, we have studied the nature of rounding in numerical reports of probabilistic expectations, a type of survey measure that has become widely used in empirical economic analysis of individual and household decisions under uncertainty. Our exploratory analysis of the responses to all expectations questions asked in the HRS core questionnaire between 2002 and 2014 confirms some of the earlier findings based on individual waves of data and establishes new findings relying on the use of several waves of data.

[22] The approach can be implemented using a Stata package described in Chernozhukov et al. (2015).
[23] Results for each wave separately as well as in table form are available from the authors upon request. As in application 1, when we take the elicited longevity expectations at face value, we drop respondents who answered "Don't know" or refused to answer the probability chance question posed.

We propose an inferential approach that interprets expectations reports as interval data and that explicitly incorporates the documented patterns of responses across waves, question domains, and location within the measurement scale. Next, we demonstrate how interval data on subjective expectations can be employed in prediction analyses of substantive interest by means of two empirical applications where interval data are alternatively used as an outcome variable or a covariate. Finally, to assess the importance of rounding we compare empirical findings when rounding is ignored and when it is accounted for using our proposed approach.

The main tenet of the analysis is that observed response patterns across questions and waves carry information about individual respondents' rounding practices. Observed response patterns, however, do not reveal whether individual respondents round their reports to simplify communication or to convey partial knowledge. Consistent with the first interpretation, in the analysis we have assumed that respondents have well-formed latent point beliefs. If instead the relevant latent objects were sets or ranges of beliefs, the algorithm would still work as intended as long as the algorithm's interval completely includes the latent interval. On the other hand, the interpretation of the estimates would be less transparent, as it would require that the object of interest of the prediction exercise be a random set or some feature of a random set.

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Appendix

A1. Technical Appendix to Section 4.1

Consider best linear prediction of υ given x under square loss, where υ is a well-defined latent subjective expectation. (Thus, we implicitly assume that respondents round to simplify communication rather than to express ambiguity.) $x = [1\ x_1\ x_2\ \ldots\ x_{d-1}] \in \mathbb{R}^d$ is a row vector of covariates, and $[\upsilon^L, \upsilon^U]$ are constructed as in Section 4 with the subscripts jkt dropped for simplicity. Beresteanu and Molinari show that the best linear predictor (BLP) is

$$H[\beta] = \left\{b \in \mathbb{R}^d : b = [E(x'x)]^{-1}E[x'\upsilon], \upsilon \in \left[\upsilon^L, \upsilon^U\right] \textit{with probability } 1\right\},$$

where H[·] denotes the identification region of the functional in brackets and where we assumed that the matrix $E(x'x)$ is nonsingular and that the variables υ, υ^L, υ^U, and x have bounded fourth moments. Intuitively, this identification region is obtained by considering all points in $[\upsilon^L, \upsilon^U]$, that is all feasible values for υ, and by computing the BLP parameters associated with each of these points. Beresteanu and Molinari (2008) show that the region resulting from this construction is sharp; that is, it exhausts all the available information given the data and the maintained assumptions.

This characterization of the identification region is computationally easy to implement (see Beresteanu et al. (2010)).[1] The projection of H[β] onto each of its components can be obtained extending to the interval outcome case the algebra of partitioned regression. Beresteanu and Molinari (2008, Corollary 4.5) show that for each $s = 1, \ldots, d$,

$$\widehat{H}_n[\beta_s] = \frac{1}{\sum_{j=1}^{n} \tilde{x}_{js}^2}\left[\sum_{j=1}^{n} min\{\tilde{x}_{js}\upsilon_j^L, \tilde{x}_{js}\upsilon_j^U\}, \sum_{j=1}^{n} max\{\tilde{x}_{js}\upsilon_j^L, \tilde{x}_{js}\upsilon_j^U\}\right]$$

is a consistent estimator (with respect to the Hausdorff distance[2]) for the population identification region $H[\beta_s]$, where β_s denotes the s–th component of the vector β. In the above expression, $\tilde{x}_{is}$ denotes the residuals obtained after projecting x_s on the other covariates in x. Beresteanu et al. (2012) show how to construct an appropriate estimate of the difference in best linear predictors associated with two different values of the covariates, x^1 and x^2, i.e. for

[1] A STATA code is available at https://molinari.economics.cornell.edu/programs.html.

[2] Given two sets A and B, the Hausdorff distance between them equals

$$\rho_H(A, B) = max\left(\sup_{a\in A}\inf_{b\in B}\|a-b\|, \sup_{b\in B}\inf_{a\in A}\|a-b\|\right).$$

$$H[(x^1)'\beta - (x^2)'\beta] = \{r \in \mathbb{R}: r = (x^1 - x^2)'\beta, \beta \in H[\beta]\}.$$

For the special case that x^1 and x^2 differ only in one component s and by one unit (with $x_s^1 = x_s^2 - 1$), they show that $H[(x^1)'\beta - (x^2)'\beta] = H[\beta_s]$. (See Stoye (2007) for related findings.)

To conclude, we note that the recent literature on inference in partially identified models has proposed two conceptually distinct types of confidence intervals for partially identified parameters. Imbens and Manski (2004), Stoye (2009), and Andrews and Soares (2010), among others, propose confidence intervals that (asymptotically) uniformly cover each point in the identification region, rather than the entire region, with at least a pre-specified probability. On the other hand, Horowitz and Manski (2000), Chernozhukov et al. (2007), and Beresteanu and Molinari (2008), among others, give confidence sets that (asymptotically) cover the entire identification region with a pre-specified probability. Imbens and Manski (2004, Lemma 1), show that confidence sets that asymptotically cover the entire identification region with a pre-specified probability constitute valid but potentially conservative confidence sets for the partially identified parameter. In our empirical analysis, we report Beresteanu-Molinari confidence sets that (asymptotically) cover the entire identification region with probability 95%. These confidence sets are obtained by bootstrap methods. In particular, for $b = 1, \dots, B$, bootstrap data $\{v_j^{Lb}, v_j^{Ub}, x_j^b\}_{j=1}^n$ is drawn with replacement from the sample, the region $\widehat{H}_n[\beta_s^b]$ is obtained, and the value r_n^b equal to the (directed) Hausdorff distance[3] from $\widehat{H}_n[\beta_s]$ to $\widehat{H}_n[\beta_s^b]$, normalized by $\sqrt{n}$, is computed. The critical value $c_{n\alpha} = inf\{t: J_n^b(t) \geq 1 - \alpha\}$, where $J_n^b(\cdot)$ is the empirical distribution of r_n^b. For each component $s = 1, \dots, d$ of β, the confidence intervals are given by

$$\left[\frac{\sum_{j=1}^n min\{\tilde{x}_{js}v_j^L, \tilde{x}_{js}v_j^U\}}{\sum_{j=1}^n \tilde{x}_{js}^2} - \frac{c_{n\alpha}}{\sqrt{n}}, \frac{\sum_{j=1}^n max\{\tilde{x}_{js}v_j^L, \tilde{x}_{js}v_j^U\}}{\sum_{j=1}^n \tilde{x}_{js}^2} + \frac{c_{n\alpha}}{\sqrt{n}}\right]$$

A2. Technical Appendix to Section 4.2

[3] Given two sets A and B, the directed Hausdorff distance between them equals

$$\rho_H(A, B) = \sup_{a \in A} \inf_{b \in B} \|a - b\|.$$

We are interested in learning the conditional expectation $E(y|x,\upsilon)$, where y is the outcome of interest, υ is a well-defined latent subjective expectation,[4] and $x = [1\ x_1\ x_2\ ...\ x_{d-1}] \in \mathbb{R}^d$ is a row vector of covariates. Let $[\upsilon^L, \upsilon^U]$ be constructed as in Section 4 with the subscripts jkt dropped for simplicity. Manski and Tamer (2002) assume that $P\left(\upsilon^L \leq \upsilon \leq \upsilon^U\right) = 1$, that $E(y|x,\upsilon)$ exists and is weakly increasing in υ, and that $E\left(y|x,\upsilon,\upsilon^L,\upsilon^U\right) = E(y|x,\upsilon)$. Under these assumptions, they show (Proposition 1) that

$$\sup_{\upsilon^U \leq V} E(y|x,\upsilon^L,\upsilon^U) \leq E(y|x,\upsilon = V) \leq \inf_{\upsilon^L \geq V} E(y|x,\upsilon^L,\upsilon^U),$$

and they establish that these bounds are sharp. The conditional expectation $E(y|x,\upsilon^L,\upsilon^U)$, which is identified by the data, can be consistently estimated either by nonparametric methods, or using a best linear approximation as in the previous section,[5] and asymptotic distribution results are readily available for these estimators. However, a simple plug-in estimator which replaces $E(y|x,\upsilon^L,\upsilon^U)$ with a consistent estimator in the above expression produces a substantial finite sample bias, as noted by Manski and Pepper (2000), and characterization of the asymptotic distribution of the resulting bounds is complicated by the fact that they are the infimum and supremum of an estimated function. We therefore employ the recently proposed inferential method of Chernozhukov et al. (2013) and the companion STATA package (Chernozhukov et al., 2015) to obtain half-median unbiased estimators of the bounds, and confidence intervals that asymptotically cover each point in the bounds with probability at least $1-\alpha$. Specifically, denoting

$$\vartheta_{n,L} \equiv \sup_{\upsilon^U \leq V} E(y|x,\upsilon^L,\upsilon^U), \qquad \vartheta_{n,U} \equiv \inf_{\upsilon^L \geq V} E(y|x,\upsilon^L,\upsilon^U),$$

the Chernozhukov et al.'s procedure provides an interval $[\hat{\vartheta}_{n,L}(p), \hat{\vartheta}_{n,U}(p)]$ such that

$$\liminf_{n\to\infty} P_n\left\{\left[\vartheta_{n,L}, \vartheta_{n,U}\right] \subset \left[\hat{\vartheta}_{n,L}(p), \hat{\vartheta}_{n,U}(p)\right]\right\} \geq 1-p$$

for $p = \frac{1}{2}$ (half-median unbiased estimator) and for $p = 1-\alpha$ (confidence interval with $1-\alpha$ coverage).

[4] Thus, we again implicitly assume that respondents round to simplify communication rather than to express ambiguity.

[5] In our empirical exercise we use a best linear approximation, with age and coupledness as our x variables.

Figure 1. Probabilistic Expectations Questions in the HRS (Section P, Waves 2002-2014)

#	Question	Wave						
		2002	2004	2006	2008	2010	2012	2014
PERSONAL HEALTH (3-9 Qs in each wave, 10 across waves)								
P19	Health limit work during next 10 years	Y	-	-	-	-	-	-
P28	**Live to be 75 or more**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**
P29	**Live to be age X or more**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**
P32	**Move to nursing home ever (if age<65) / in the next 5 years (if age >= 65)**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**
P103	Live independently at 75	-	-	Y	Y	-	-	-
P104	Free of serious mental problems at 75	-	-	Y	Y	-	-	-
P106	Live independently at X	-	-	Y	Y	-	-	-
P107	Free of serious problems in thinking/reasoning at X	-	-	Y	Y	-	Y	Y
P108	Same health in 4 years	-	-	Y	Y	-	-	-
P109	Worse health in 4 years	-	-	Y	Y	-	-	-
PERSONAL FINANCES (11-23 Qs in each wave, 31 across waves)								
P4	Income keep up inflation for next 5 years	Y	Y	Y	-	-	-	-
P5	**Leave inheritance >=$10,000**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**
P6	**Leave inheritance >=$100,000**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**
P7	**Leave any inheritance**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**
P8	Receive inheritance during next 10 years	Y	Y	Y	-	-	-	-
P14	Lose job next year	Y	Y	Y	-	Y	Y	Y
P15	Finding a job in few month in case of job-loss	Y	Y	Y	-	Y	Y	Y
P16	**Working for pay in the future**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**
P17	**Working full time after age 62**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**
P18	**Working full time after age 65**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**
P20	**Finding a job in few months if unemployed**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**
P30	Give $5,000 to others over next 10 years	Y	Y	Y	-	-	-	-
P31	Receive $5,000 from others over next 10 years	Y	Y	Y	-	-	-	-
P59	**Leave inheritance >=$500,000**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**
P70	Medical expenses use up savings in next 5 years	-	Y	Y	Y	-	-	-
P71	Give $1,000 to others during next 10 years	-	Y	Y	-	-	-	-
P72	Give $10,000 to others during next 10 years	-	Y	Y	-	-	-	-
P73	Give $20,000 to others during next 10 years	-	Y	Y	-	-	-	-
P74	Receive $2,500 from others over next 10 years	-	Y	Y	-	-	-	-
P75	Receive $1,000 from others over next 10 years	-	Y	Y	-	-	-	-
P76	Receive $10,000 from others over next 10 years	-	Y	Y	-	-	-	-
P111	Soc. Sec. will be worse over next 10 years - current own benefits	-	-	Y	Y	Y	Y	Y
P112	Soc. Sec. will be worse over next 10 years - future own benefits	-	-	Y	Y	Y	Y	Y
P166	Home worth more by next year	-	-	-	-	Y	Y	Y
P168	Home worth more/less by random "X" by next year	-	-	-	-	Y	Y	Y
P175	Out-of-pocket medical expense >$1,500 during next year	-	-	-	-	Y	Y	Y
P176	Out-of-pocket medical expense >$500 during next year	-	-	-	-	Y	Y	Y
P177	Out-of-pocket medical expense >$3,000 during next year	-	-	-	-	Y	Y	Y
P178	Out-of-pocket medical expense >$8,000 during next year	-	-	-	-	Y	Y	Y
P181	Any work after age 70	-	-	-	-	-	Y	Y
P182	Working full time after age 70	-	-	-	-	-	Y	Y
GENERAL ECONOMIC CONDITIONS (2-7 Qs in each wave, 12 across waves)								
P34	U.S. have economic depression during next 10 years	Y	Y	Y	Y	-	-	-
P47	**Mutual funds increase in value by next year**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**
P110	Social Security in general will become worse in next 10 years	Y	-	Y	Y	Y	Y	-
P114	Mutual funds increase more than the cost of living over next 10 years	-	-	Y	-	-	-	-
P115	Mutual funds increase 8% more than the cost of living over next 10 years	-	-	Y	-	-	-	-
P116	Cost of living increases more than 5% over next 10 years	-	-	Y	Y	-	-	-
P150	Mutual funds increase by 20% (10%, or a random X%) by next year	Y	-	-	Y	Y	Y	Y
P180	Mutual funds decrease by 20% by next year	-	-	-	-	Y	Y	Y
P183	Medicare less generous in next 10 years	-	-	-	-	-	Y	Y
P190	Stock Market increase in value in 12 months of today	-	-	-	-	-	-	Y
P192	Stock Market increse by 20% (in 12 months)	-	-	-	-	-	-	Y
P193	Stock Market decrease by 20% (in 12 months)	-	-	-	-	-	-	Y
	Total N of Questions	**22**	**26**	**38**	**25**	**25**	**29**	**31**

Table 1: Number of Waves, Observations, and Respondents by Question

Question: percent chance that…	N waves asked	N total obs. (across waves)	N Rs asked (across waves)
		Personal Health	
P19: Health limit work next 10 years	1	5475	5475
P28: Live to be age 75 or more	7	56497	17868
P29: Live to be age X or more	7	118404	27638
P32: Move to nursing home in 5 y	7	74696	26095
P103: Live independently at 75	2	7590	5693
P104: Free of serious mental… at 75	2	7590	5693
P106: Live independently at X	2	15291	13228
P107: Free of serious think/reason…	4	33518	15599
P108: Same health in 4 years	2	16253	12509
P109: Worse health in 4 years	2	16232	12512
		General Economic Conditions	
P34: U.S. have economic depression	4	50661	19598
P47: Mutual funds up /next y	7	105714	27279
P110: SS in general will be worse	5	71770	24868
P114: Mutual fund up /more than living	1	16680	16680
P115: Mutual fund up 8% /more than…	1	16652	16652
P116: Cost living up /more than 5%	2	32431	17781
P150: Mutual funds up by 20/10/ X%	5	42092	20051
P180: Mutual funds down by 20%	3	31658	17826
P183: Medicare less generous in 10 y	2	36524	19938
P190: Stock market up by next year	1	8615	8615
P192: Stock market up by 20%	1	5430	5430
P193: Stock market down by 20%	1	5306	5306

NOTE: N of total observations includes all answers by any respondent in any wave to the corresponding question, including don’t know/refuse. The set of questions each respondent is asked and observed to answer may vary across waves as a function of aspects of survey design such as the decision of designers to introduce new questions or to eliminate existing ones, the respondent’s time-varying characteristics used for skip logic, etc. Additionally, new cohorts of respondents have been added over time, while a portion of respondents from the initial cohorts have left the study due to death or other reasons.

Table 1 (Continued): Number of Waves, Observations, and Respondents by Question

Question: percent chance that…	N waves asked	N total obs. (across waves)	N Rs asked (across waves)
		Personal Finances	
P4: Income keep up inflation in 5 y	3	51559	20852
P5: Leave inheritance ≥ $10K	7	116769	28252
P6: Leave inheritance ≥ $100K	7	95625	25360
P7: Leave any inheritance	7	19716	9426
P8: Receive inheritance in 10 y	3	51559	20852
P14: Lose job next year	6	32743	12220
P15: Find job in few months/loss	6	32727	12220
P16: Work for pay in the future	7	66855	20902
P17: Work full time after age 62	7	36603	13325
P18: Work full time after age 65	7	37062	13158
P20: Find job in few months/unemployed	7	8206	5182
P30: Give $5K to others in 10 y	3	50528	20633
P31: Receive $5K… in 10 y	3	50528	20633
P59: Leave inheritance ≥ $500K	7	73872	21339
P70: Med expenses use up savings	3	50478	19583
P71: Give $1K to others in 10 y	2	21024	13717
P72: Give $10K to others in 10 y	2	12904	8981
P73: Give $20K to others in 10 y	2	11155	7838
P74: Receive $2.5K… in 10 y	2	30644	18014
P75: Receive $1K… in 10 y	2	30397	17924
P76: Receive $10K… in 10 y	2	3270	2786
P111: SS worse/current own benefits	5	51023	16477
P112: SS worse/future own benefits	5	26753	10599
P166: Home worth more next year	3	28067	11422
P168: Home worth more/less by X	3	26394	11168
P175: OP med exp ≥ $1.5K next year	3	56760	21771
P176: OP med exp ≥ $500 next year	3	10962	7482
P177: OP med exp ≥ $3K next year	3	44022	19526
P178: OP med exp ≥ $8K next year	3	36369	17453
P181: Any work after age 70	2	17057	9915
P182: Work full time after age 70	2	10384	6856

NOTE: N of total observations includes all answers by any respondent in any wave to the corresponding question, including don't know/refuse. The set of questions each respondent is asked and observed to answer may vary across waves as a function of aspects of survey design such as the decision of designers to introduce new questions or to eliminate existing ones, the respondent's time-varying characteristics used for skip logic, etc. Additionally, new cohorts of respondents have been added over time, while a portion of respondents from the initial cohorts have left the study due to death or other reasons.

Table 2: Responses by Question and Wave in the 2002-2014 HRS

			Fraction of responses equal to or in:								
Question: percent chance that…	Wave	N	NR	0	1-4	50	96-99	100	𝕄10	𝕄5	Other
P5: leave inheritance ≥ $10,000	2002	16119	0.050	0.154	0.004	0.074	0.007	0.443	0.205	0.060	0.002
(personal finances)	2004	18249	0.037	0.162	0.004	0.083	0.008	0.404	0.241	0.059	0.002
	2006	17191	0.053	0.159	0.004	0.067	0.008	0.447	0.209	0.052	0.001
	2008	16060	0.050	0.153	0.004	0.067	0.010	0.431	0.236	0.046	0.002
	2010	20397	0.037	0.172	0.007	0.080	0.009	0.344	0.296	0.053	0.003
	2012	19359	0.039	0.170	0.007	0.085	0.009	0.329	0.306	0.053	0.003
	2014	17647	0.037	0.167	0.006	0.086	0.008	0.324	0.319	0.050	0.003
P14: lose job during next year	2002	4220	0.022	0.479	0.021	0.122	0.002	0.018	0.244	0.091	0.002
(personal finances)	2004	5629	0.013	0.450	0.021	0.128	0.000	0.019	0.277	0.091	0.001
	2006	4797	0.020	0.461	0.026	0.107	0.001	0.018	0.274	0.090	0.003
	2010	6785	0.018	0.323	0.028	0.141	0.001	0.022	0.356	0.106	0.004
	2012	6093	0.017	0.322	0.033	0.140	0.001	0.022	0.363	0.099	0.002
	2014	5219	0.015	0.323	0.035	0.126	0.001	0.018	0.376	0.103	0.003
P15: find equally good job	2002	4220	0.022	0.183	0.009	0.165	0.006	0.142	0.353	0.120	0.001
(personal finances)	2004	5629	0.013	0.176	0.012	0.158	0.003	0.138	0.387	0.112	0.002
	2006	4797	0.017	0.173	0.014	0.152	0.004	0.143	0.383	0.112	0.003
	2010	6769	0.013	0.188	0.022	0.148	0.004	0.069	0.435	0.118	0.004
	2012	6093	0.014	0.166	0.018	0.164	0.003	0.076	0.447	0.108	0.003
	2014	5219	0.014	0.141	0.016	0.166	0.002	0.083	0.463	0.112	0.003
P17: work full time after age 62	2002	3219	0.012	0.194	0.005	0.139	0.005	0.220	0.312	0.111	0.001
(personal finances)	2004	4528	0.007	0.161	0.008	0.156	0.004	0.163	0.387	0.112	0.003
	2006	5238	0.011	0.299	0.011	0.133	0.004	0.142	0.305	0.093	0.002
	2008	3870	0.026	0.160	0.012	0.134	0.006	0.202	0.357	0.099	0.004
	2010	7828	0.008	0.152	0.014	0.151	0.006	0.143	0.415	0.108	0.004
	2012	6647	0.010	0.148	0.016	0.147	0.005	0.136	0.434	0.098	0.005
	2014	5294	0.006	0.147	0.015	0.142	0.005	0.137	0.443	0.099	0.005

NOTE: N = sample size, NR = nonresponse, 𝕄10 = multiple of 10 but not (0, 50, 100), 𝕄5 = multiple of 5 but not of 10.

Table 2 (Continued): Responses by Question and Wave in the 2002-2014 HRS

			Fraction of responses equal to or in:								
Question: percent chance that…	Wave	N	NR	0	1-4	50	96-99	100	M10	M5	Other
P28: live to be 75 or more	2002	7200	0.048	0.038	0.002	0.223	0.005	0.178	0.359	0.144	0.003
(personal health)	2004	9037	0.035	0.049	0.003	0.230	0.004	0.165	0.372	0.139	0.002
	2006	6713	0.040	0.053	0.004	0.222	0.005	0.152	0.375	0.144	0.004
	2008	5567	0.038	0.041	0.004	0.207	0.005	0.156	0.394	0.148	0.006
	2010	10498	0.041	0.059	0.005	0.206	0.006	0.143	0.402	0.133	0.006
	2012	9482	0.035	0.064	0.006	0.221	0.006	0.135	0.406	0.124	0.004
	2014	8084	0.029	0.064	0.006	0.226	0.006	0.136	0.414	0.115	0.004
P32: move to nursing home in 5 years	2002	9177	0.082	0.491	0.014	0.111	0.001	0.006	0.207	0.088	0.002
(personal health)	2004	12629	0.063	0.444	0.012	0.144	0.001	0.008	0.232	0.095	0.002
	2006	10044	0.075	0.463	0.021	0.101	0.000	0.007	0.231	0.100	0.002
	2008	10106	0.061	0.433	0.020	0.089	0.000	0.007	0.281	0.106	0.002
	2010	15512	0.045	0.393	0.025	0.130	0.001	0.016	0.284	0.103	0.003
	2012	9870	0.046	0.402	0.023	0.120	0.000	0.012	0.289	0.105	0.003
	2014	9367	0.037	0.400	0.028	0.113	0.000	0.013	0.304	0.102	0.003
P34: U.S. have economic depression	2002	184	0.103	0.054	0.016	0.299	0.000	0.082	0.359	0.071	0.016
(general economic conditions)	2004	17996	0.069	0.084	0.005	0.264	0.002	0.056	0.384	0.134	0.003
	2006	16754	0.078	0.066	0.006	0.238	0.002	0.060	0.404	0.142	0.004
	2008	15727	0.060	0.044	0.005	0.194	0.006	0.137	0.409	0.141	0.004
P110: Social Security will be less generous	2006	16754	0.065	0.048	0.003	0.231	0.005	0.120	0.387	0.139	0.002
(general economic conditions)	2008	15727	0.064	0.049	0.002	0.223	0.006	0.111	0.395	0.147	0.003
	2010	20208	0.046	0.048	0.005	0.191	0.010	0.187	0.379	0.130	0.005
	2012	19081	0.043	0.051	0.004	0.210	0.008	0.175	0.387	0.118	0.004
P47: mutual fund increase in value	2002	7260	0.206	0.079	0.004	0.239	0.000	0.040	0.306	0.122	0.003
(general economic conditions)	2004	17996	0.148	0.058	0.004	0.264	0.001	0.041	0.359	0.121	0.004
	2006	16754	0.240	0.042	0.003	0.231	0.001	0.036	0.339	0.106	0.003
	2008	15727	0.197	0.057	0.004	0.216	0.001	0.028	0.374	0.119	0.004
	2010	20208	0.111	0.062	0.006	0.238	0.001	0.037	0.420	0.122	0.005
	2012	19081	0.119	0.058	0.005	0.271	0.000	0.033	0.401	0.108	0.005
	2014	8828	0.097	0.052	0.007	0.273	0.000	0.041	0.414	0.109	0.006

Table 3: Response Tendencies in the 2002-2014 HRS

		Response pattern						
Wave	N	All NR	All 0 or 100	All 0, 50 or 100	Some 𝕄10	Some 𝕄5	Some 1-4 or 96-99	Some other
Based on the 12 questions asked in all waves								
2002	16032	0.022	0.101	0.101	0.392	0.320	0.054	0.011
2004	18250	0.015	0.062	0.084	0.418	0.353	0.056	0.013
2006	17191	0.027	0.072	0.077	0.409	0.336	0.065	0.014
2008	16060	0.021	0.068	0.063	0.417	0.340	0.072	0.018
2010	20400	0.010	0.053	0.050	0.426	0.350	0.092	0.020
2012	19360	0.015	0.051	0.058	0.445	0.328	0.083	0.020
2014	17647	0.012	0.065	0.062	0.458	0.295	0.090	0.018
Based on all questions asked in each wave								
2002	16032	0.014	0.023	0.039	0.324	0.459	0.119	0.022
2004	18250	0.010	0.019	0.032	0.337	0.467	0.108	0.026
2006	17191	0.025	0.019	0.023	0.263	0.513	0.117	0.039
2008	16060	0.021	0.025	0.019	0.290	0.511	0.101	0.033
2010	20400	0.009	0.029	0.022	0.316	0.442	0.144	0.038
2012	19360	0.014	0.027	0.021	0.317	0.443	0.139	0.038
2014	17647	0.012	0.026	0.022	0.329	0.427	0.142	0.042

NOTE: N = sample size, NR = nonresponse, 𝕄10 = multiple of 10 but not (0, 50, 100), 𝕄5 = multiple of 5 but not of 10. The following 12 questions were asked in all HRS waves between 2002 and 2014: P47: mutual fund increase in value; P28: live to be 75 or more; P29: live to be X or more; P5: live inheritance ≥ \$10,000; P6: live inheritance ≥ \$100,000; P59: live inheritance ≥ \$500,000; P7: leave any inheritance; P16: work for pay in the future; P17: work full time after age 62; P18: work full time after age 65; P32: move to nursing home in 5 years; P20: finding a job in few months if unemployed.

Table 4: Transitions of Response Tendencies across Waves

Transition waves:	2002 to 2004	2004 to 2006	2006 to 2008	2008 to 2010	2010 to 2012	2012 to 2014	2002 to 2014
	Frequency (based on the 12 questions asked in all waves)						
% transitions to:							
same category	0.406	0.420	0.406	0.415	0.436	0.433	0.389
adjacent category	0.386	0.383	0.383	0.385	0.377	0.373	0.392
more distant category	0.209	0.197	0.212	0.201	0.187	0.194	0.218
N (100%)	14183	16126	15231	13732	18260	16923	8348
same or adjacent	0.792	0.803	0.788	0.800	0.813	0.806	0.782

NOTE: The percentages shown in the table are calculated from transition matrices of response tendencies defined in terms of the following categories: All NR, All (0, 100), All (0, 50, 100), Some $\mathbb{M}10$, Some $\mathbb{M}5$, Some 1-4 or 96-99, Some other. The following 12 questions were asked in all HRS waves between 2002 and 2014: P47: mutual fund increase in value; P28: live to be 75 or more; P29: live to be X or more; P5: live inheritance ≥ \$10,000; P6: live inheritance ≥ \$100,000; P59: live inheritance ≥ \$500,000; P7: leave any inheritance; P16: work for pay in the future; P17: work full time after age 62; P18: work full time after age 65; P32: move to nursing home in 5 years; P20: finding a job in few months if unemployed.

Table 5: Numbers of Questions Asked and Answered by Wave and Question Domain

Wave Question Domain	2004	2006	2008	2010	2012	2014	All Waves
				Number of Questions			
personal finances	21	23	11	18	20	20	113
personal health	3	9	9	3	4	4	32
gen. economic cond.	2	6	5	4	5	7	29
total	26	38	25	25	29	31	174
				Average Number of Questions Asked			
personal finances	11.2	12.3	5.2	8.4	9.2	9.1	55.4
personal health	1.9	3.3	4.7	2.1	2.3	2.3	16.6
gen. economic cond.	1.8	5.4	4.3	3	4	3.1	21.6
total	14.9	21	14.2	13.5	15.5	14.5	93.6
				Average Number of Questions Answered			
personal finances	11	11.9	5	8.2	9	9	54.1
personal health	1.8	3.1	4.4	2	2.2	2.2	15.7
gen. economic cond.	1.6	4.5	3.9	2.9	3.8	3.8	19.6
total	14.4	19.5	13.3	13.1	15	15	89.4

Figure 2. Distribution of Responses across Waves (2002-2014) of an Individual Respondent by Domain

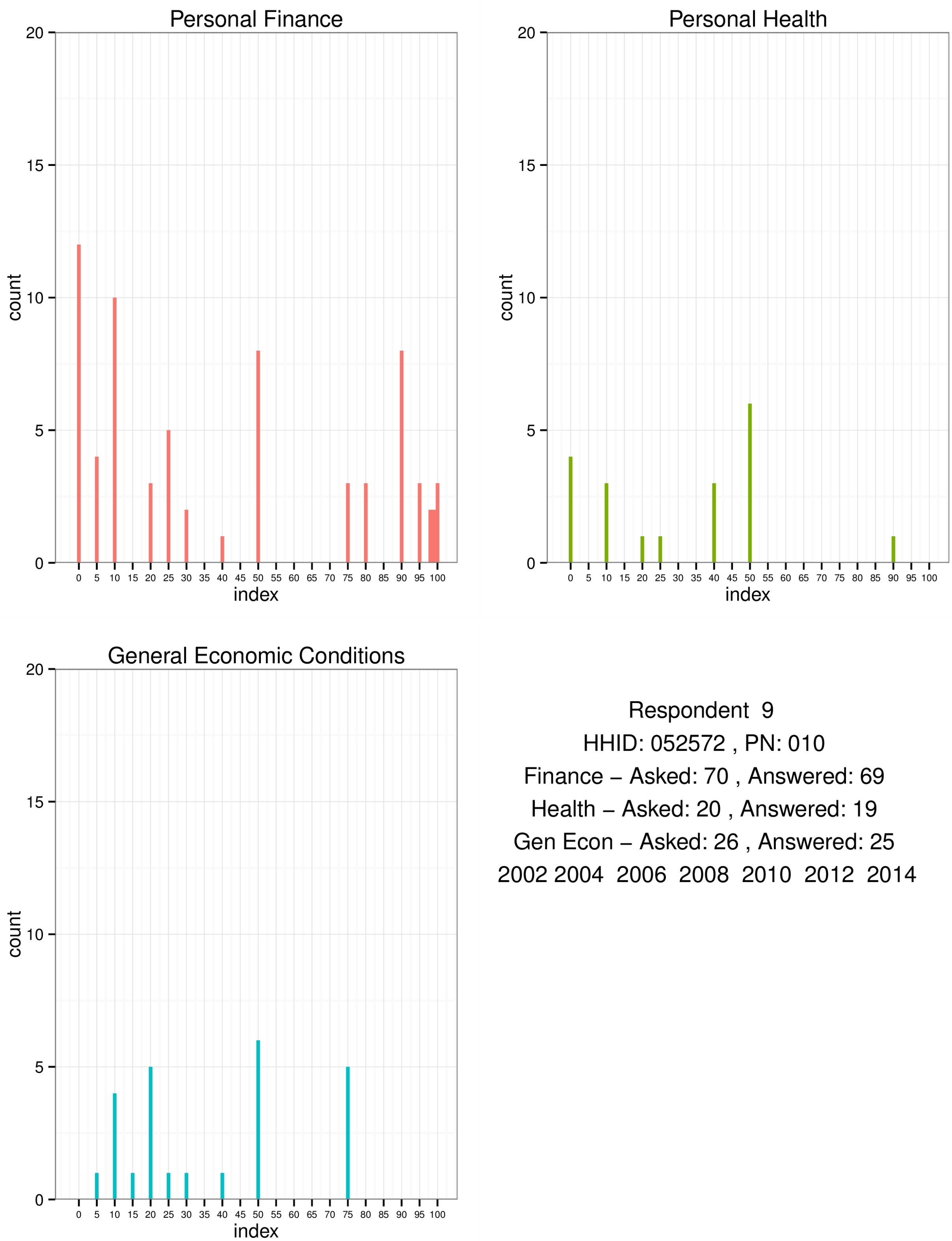

Figure 3. Distribution of Responses across Waves (2002-2014) of an Individual Respondent by Domain: Grouped Version

NOTE**:** Responses are grouped into the following 9 categories: answers in 𝕄1-T=1-24 ∪ 76-99 that are not divisible by 5; answers in 𝕄1-C=[26, 74] that are not divisible by 5; answers in 𝕄1-T={5, 15, 85, 95}; answers in 𝕄5-C={35, 45, 55, 65}; answers in 𝕄10-T={10, 20, 80, 90}; answers in 𝕄10-C={30, 40, 60, 70}; answers in 𝕄25={25, 75}; answers in 𝕄100={0, 100}; answers in 𝕄50={50}.

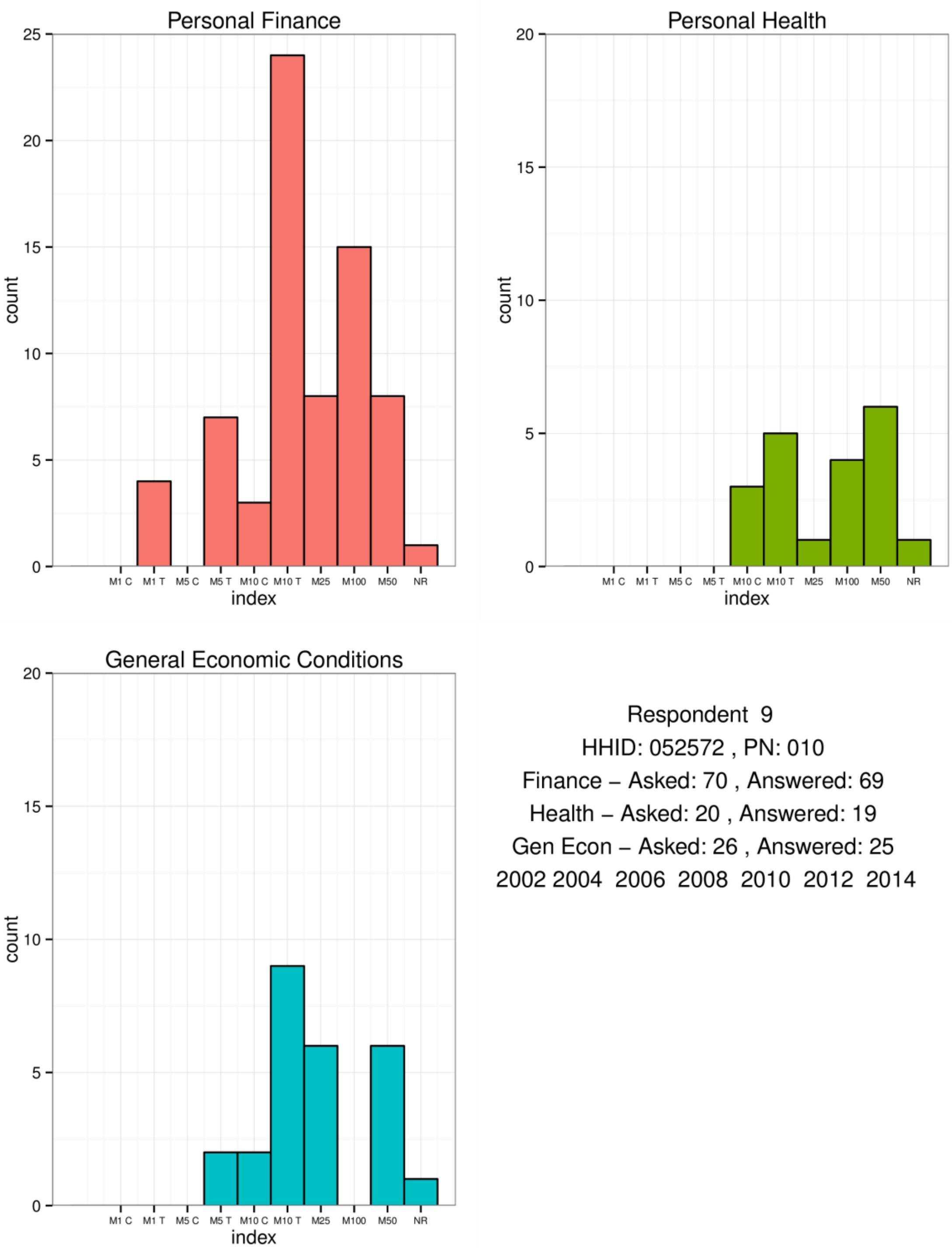

Table 6: Responses by Question and across Waves in the 2002-2014 HRS

Question: percent chance that…	N total obs.	Percentage of responses in: NR	𝕄50	𝕄100	𝕄25	𝕄10 T	𝕄10 C	𝕄5 T	𝕄5 C	𝕄1 T	𝕄1 C
						Personal Health					
P19: Health limit work next 10 years	5475	0.044	0.311	0.153	0.087	0.217	0.144	0.031	0.007	0.005	0.001
P28: Live to be age 75 or more	56497	0.038	0.219	0.204	0.082	0.270	0.120	0.042	0.010	0.013	0.001
P29: Live to be age X or more	118404	0.050	0.211	0.191	0.075	0.236	0.156	0.049	0.013	0.018	0.001
P32: Move to nursing home in 5 y	74696	0.059	0.120	0.426	0.039	0.206	0.062	0.060	0.003	0.023	0.001
P103: Live independently at 75	7590	0.031	0.190	0.136	0.115	0.292	0.152	0.056	0.016	0.012	0.001
P104: Free of serious mental… at 75	7590	0.034	0.210	0.099	0.130	0.259	0.183	0.052	0.020	0.011	0.002
P106: Live independently at X	15291	0.060	0.219	0.144	0.100	0.234	0.166	0.046	0.015	0.015	0.001
P107: Free of serious think/reason…	33518	0.062	0.227	0.135	0.088	0.229	0.179	0.049	0.014	0.016	0.001
P108: Same health in 4 years	16253	0.048	0.226	0.151	0.097	0.263	0.151	0.044	0.009	0.010	0.001
P109: Worse health in 4 years	16232	0.069	0.228	0.146	0.077	0.272	0.143	0.043	0.008	0.014	0.001
						General Economic Conditions					
P34: U.S. have economic depression	50661	0.069	0.234	0.148	0.083	0.228	0.170	0.041	0.014	0.011	0.001
P47: Mutual funds up /next y	105714	0.157	0.247	0.093	0.076	0.185	0.193	0.025	0.014	0.008	0.001
P110: SS in general will be worse	71770	0.054	0.212	0.200	0.087	0.235	0.151	0.035	0.011	0.014	0.001
P114: Mut fund up /more than living	16680	0.281	0.182	0.096	0.063	0.178	0.157	0.026	0.010	0.006	0.001
P115: Mut fund up 8% /more than…	16652	0.307	0.162	0.076	0.061	0.187	0.150	0.033	0.010	0.012	0.001
P116: Cost living up /more than 5%	32431	0.077	0.151	0.210	0.089	0.252	0.152	0.045	0.010	0.013	0.001
P150: Mutual funds up by 20/10/ X%	42092	0.034	0.156	0.090	0.070	0.314	0.237	0.063	0.017	0.018	0.002
P180: Mutual funds down by 20%	31658	0.019	0.179	0.098	0.061	0.318	0.225	0.064	0.017	0.016	0.002
P183: Medicare less generous in 10 y	36524	0.039	0.219	0.216	0.075	0.246	0.150	0.032	0.008	0.014	0.001
P190: Stock market up by next year	8615	0.077	0.335	0.090	0.058	0.185	0.202	0.026	0.011	0.016	0.001
P192: Stock market up by 20%	5430	0.021	0.151	0.108	0.054	0.342	0.199	0.084	0.012	0.028	0.001
P193: Stock market down by 20%	5306	0.013	0.183	0.115	0.048	0.314	0.210	0.076	0.012	0.026	0.002

NOTE: 𝕄50={50}, 𝕄100={0, 100}, 𝕄25={25, 75}, 𝕄10-T={10, 20, 80, 90}, 𝕄10-C={30, 40, 60, 70}, 𝕄5-T={5, 15, 85, 95}, 𝕄5-C={35, 45, 55, 65}, 𝕄1-T=multiples of 1 that are not multiples of 5 in 1-24 ∪ 76-99, 𝕄1-C=multiples of 1 that are not multiples of 5 in 26-74.

Table 6 (Continued): Responses by Question and across Waves in the 2002-2014 HRS

Question: percent chance that…	N total obs.	Percentage of responses in: NR	$\mathbb{M}50$	$\mathbb{M}100$	$\mathbb{M}25$ C	$\mathbb{M}10$ T	$\mathbb{M}10$ C	$\mathbb{M}5$ T	$\mathbb{M}5$ C	$\mathbb{M}1$ T	$\mathbb{M}1$ C
					Personal Finances						
P4: Income keep up inflation in 5 y	51559	0.066	0.196	0.226	0.069	0.249	0.136	0.036	0.007	0.015	0.001
P5: Leave inheritance ≥ \$10K	116769	0.046	0.083	0.518	0.028	0.228	0.051	0.028	0.001	0.017	0.000
P6: Leave inheritance ≥ \$100K	95625	0.014	0.100	0.490	0.037	0.228	0.072	0.035	0.002	0.022	0.000
P7: Leave any inheritance	19716	0.020	0.053	0.763	0.013	0.098	0.021	0.020	0.001	0.012	0.000
P8: Receive inheritance in 10 y	51559	0.032	0.043	0.755	0.016	0.091	0.024	0.023	0.001	0.014	0.000
P14: Lose job next year	32743	0.017	0.129	0.405	0.028	0.261	0.060	0.067	0.003	0.031	0.000
P15: Find job in few months/loss	32727	0.015	0.158	0.276	0.056	0.287	0.128	0.053	0.004	0.022	0.000
P16: Work for pay in the future	66855	0.018	0.055	0.672	0.021	0.139	0.037	0.035	0.001	0.021	0.000
P17: Work full time after age 62	36603	0.011	0.144	0.333	0.055	0.268	0.120	0.043	0.006	0.020	0.001
P18: Work full time after age 65	37062	0.011	0.144	0.280	0.058	0.282	0.130	0.057	0.008	0.028	0.001
P20: Find job in few months/unemployed	8206	0.012	0.211	0.184	0.061	0.277	0.174	0.050	0.012	0.019	0.001
P30: Give \$5K to others in 10 y	50528	0.024	0.120	0.505	0.050	0.187	0.065	0.035	0.002	0.011	0.000
P31: Receive \$5K… in 10 y	50528	0.023	0.047	0.674	0.020	0.143	0.026	0.047	0.001	0.019	0.000
P59: Leave inheritance ≥ \$500K	73872	0.011	0.090	0.490	0.034	0.216	0.073	0.046	0.003	0.037	0.000
P70: Med expenses use up savings	50478	0.060	0.141	0.316	0.060	0.246	0.109	0.048	0.006	0.014	0.000
P71: Give \$1K to others in 10 y	21024	0.007	0.097	0.551	0.044	0.186	0.060	0.041	0.002	0.013	0.000
P72: Give \$10K to others in 10 y	12904	0.011	0.212	0.322	0.072	0.219	0.124	0.026	0.006	0.007	0.001
P73: Give \$20K to others in 10 y	11155	0.011	0.152	0.334	0.061	0.265	0.100	0.057	0.005	0.015	0.000
P74: Receive \$2.5K… in 10 y	30644	0.004	0.021	0.723	0.019	0.134	0.023	0.053	0.001	0.022	0.000
P75: Receive \$1K… in 10 y	30397	0.003	0.042	0.686	0.024	0.141	0.031	0.051	0.001	0.021	0.000
P76: Receive \$10K… in 10 y	3270	0.015	0.243	0.321	0.052	0.198	0.134	0.022	0.009	0.006	0.001
P111: SS worse/current own benefits	51023	0.036	0.246	0.197	0.080	0.246	0.138	0.037	0.007	0.012	0.001
P112: SS worse/future own benefits	26753	0.020	0.205	0.186	0.085	0.255	0.179	0.040	0.014	0.014	0.001
P166: Home worth more next year	28067	0.030	0.202	0.165	0.045	0.361	0.146	0.033	0.005	0.011	0.001
P168: Home worth more/less by X	26394	0.035	0.112	0.259	0.029	0.348	0.120	0.070	0.004	0.024	0.000
P175: OP med exp ≥ \$1.5K next year	56760	0.031	0.143	0.340	0.051	0.261	0.109	0.043	0.004	0.017	0.000
P176: OP med exp ≥ \$500 next year	10962	0.017	0.114	0.642	0.025	0.126	0.043	0.020	0.001	0.012	0.000
P177: OP med exp ≥ \$3K next year	44022	0.012	0.132	0.235	0.058	0.318	0.126	0.082	0.006	0.033	0.000
P178: OP med exp ≥ \$8K next year	36369	0.009	0.079	0.260	0.037	0.327	0.092	0.120	0.005	0.071	0.000
P181: Any work after age 70	17057	0.010	0.118	0.374	0.042	0.259	0.101	0.058	0.005	0.034	0.000
P182: Work full time after age 70	10384	0.003	0.100	0.264	0.038	0.323	0.108	0.097	0.007	0.060	0.000

Table 7: Partition of the 0-100 Percent Chance Scale in Two Symmetric Tails and a Center

	LT (Left Tail)	RT (Right Tail)	T (Tail)	C (Center)	Union
(𝕄100,𝕄50)	{ 0 }	{ 100 }	𝕄100-LT ∪ 𝕄100-RT	{ 50 }	𝕄100 ∪ 𝕄50
𝕄25	∅	∅	∅	{ 25, 75 }	𝕄25
𝕄10	{ 10, 20 }	{ 80, 90 }	𝕄10-LT ∪ 𝕄10-RT	{ 30, 40, 60, 70}	𝕄10-T ∪ 𝕄10-C
𝕄5	{ 5, 15 }	{ 85, 95 }	𝕄5-LT ∪ 𝕄5-RT	{ 35, 45, 55, 65 }	𝕄5-T ∪ 𝕄5-C
𝕄1	1-4 ∪ 6-9 ∪ 11-14 ∪ 16-19 ∪ 21-24	76-79 ∪ 81-84 ∪ 86-89 ∪ 91-94 ∪ 96-99	𝕄1-LT ∪ 𝕄1-RT	26-29 ∪ 31-34 ∪ 36-39 ∪ 41-44 ∪ 46-49 ∪ 51-54 ∪ 56-59 ∪ 61-64 ∪ 66-69 ∪ 71-74	𝕄1-T ∪ 𝕄1-C
Union	𝕄100-LT ∪ 𝕄10-LT ∪ 𝕄5-LT ∪ 𝕄1-LT	𝕄100-RT ∪ 𝕄10-RT ∪ 𝕄5-RT ∪ 𝕄1-RT	𝕄100 ∪ 𝕄10-T ∪ 𝕄5-T ∪ 𝕄1-T	𝕄50 ∪ 𝕄25 ∪ 𝕄10-C ∪ 𝕄5-C ∪ 𝕄1-C	0-100 (entire scale)

Table 8A. Portion of the Algorithm Determining the Rounding Type of Respondent *j* in the Center for Questions of Domain *l*

AND ∃ domain $l' \neq l$ s.t. / **START: IF**	$\#(\Upsilon_{l'} \cap \mathbb{M}1\text{-C}) \geq 1$	$\#(\Upsilon_{l'} \cap \mathbb{M}1\text{-C}) = 0$	$\#(\Upsilon_{l'} \cap \mathbb{M}5\text{-C}) \geq 1$	$\#(\Upsilon_{l'} \cap \mathbb{M}5\text{-C}) = 0$	$\#(\Upsilon_{l'} \cap \mathbb{M}10\text{-C}) \geq 1$	$\#(\Upsilon_{l'} \cap \mathbb{M}10\text{-C}) = 0$	$\#(\Upsilon_{l'} \cap \mathbb{M}25) \geq 1$	$\#(\Upsilon_{l'} \cap \mathbb{M}25) = 0$	$\#(\Upsilon_{l'} \cap \mathbb{M}50) \geq 1$	$\#(\Upsilon_{l'} \cap \mathbb{M}50) = 0$	All NR
$\#(\Upsilon_l \cap \mathbb{M}1\text{-C}) \geq 2$	*j* is $\boldsymbol{\mathcal{M}}$1-C										
$\#(\Upsilon_l \cap \mathbb{M}1\text{-C}) = 1$	$\boldsymbol{\mathcal{M}}$1-C	IF *j* is still UNCLASSIFIED, GO to the NEXT row									
$\#(\Upsilon_l \cap \{\mathbb{M}1\text{-C} \cup \mathbb{M}5\text{-C}\}) \geq 2$	*j* is $\boldsymbol{\mathcal{M}}$5-C										
$\#(\Upsilon_l \cap \{\mathbb{M}1\text{-C} \cup \mathbb{M}5\text{-C}\}) = 1$	$\boldsymbol{\mathcal{M}}$5-C		$\boldsymbol{\mathcal{M}}$5-C	IF *j* is still UNCLASSIFIED, GO to the NEXT row							
$\#(\Upsilon_l \cap \{\mathbb{M}1\text{-C} \cup \mathbb{M}5\text{-C} \cup \mathbb{M}10\text{-C}\}) \geq 2$	*j* is $\boldsymbol{\mathcal{M}}$10-C										
$\#(\Upsilon_l \cap \{\mathbb{M}1\text{-C} \cup \mathbb{M}5\text{-C} \cup \mathbb{M}10\text{-C}\}) = 1$	$\boldsymbol{\mathcal{M}}$10-C		$\boldsymbol{\mathcal{M}}$10-C		$\boldsymbol{\mathcal{M}}$10-C	IF *j* is still UNCLASSIFIED, GO to the NEXT row					
$\#(\Upsilon_l \cap \{\mathbb{M}1\text{-C} \cup \mathbb{M}5\text{-C} \cup \mathbb{M}10\text{-C} \cup \mathbb{M}25\}) \geq 2$	*j* is $\boldsymbol{\mathcal{M}}$25										
$\#(\Upsilon_l \cap \{\mathbb{M}1\text{-C} \cup \mathbb{M}5\text{-C} \cup \mathbb{M}10\text{-C} \cup \mathbb{M}25\}) = 1$	$\boldsymbol{\mathcal{M}}$25		$\boldsymbol{\mathcal{M}}$25		$\boldsymbol{\mathcal{M}}$25		$\boldsymbol{\mathcal{M}}$25	IF *j* is still UNCLASSIFIED, GO to the NEXT row			
$\#(\Upsilon_l \cap \{\mathbb{M}1\text{-C} \cup \mathbb{M}5\text{-C} \cup \mathbb{M}10\text{-C} \cup \mathbb{M}25 \cup \mathbb{M}50\}) \geq 2$	*j* is $\boldsymbol{\mathcal{M}}$50										
$\#(\Upsilon_l \cap \{\mathbb{M}1\text{-C} \cup \mathbb{M}5\text{-C} \cup \mathbb{M}10\text{-C} \cup \mathbb{M}25 \cup \mathbb{M}50\}) = 1$	$\boldsymbol{\mathcal{M}}$50		$\boldsymbol{\mathcal{M}}$50		$\boldsymbol{\mathcal{M}}$50		$\boldsymbol{\mathcal{M}}$50		$\boldsymbol{\mathcal{M}}$50	*j* type is $\boldsymbol{\mathcal{U}}$ndetermined, END	
All NR	*j* type is $\boldsymbol{\mathcal{U}}$ndetermined, END										

NOTE: Υ_l is the set of responses given by a hypothetical respondent *j* in domain *l*. 𝕄1-C, 𝕄5-C, 𝕄10-C, 𝕄25, and 𝕄50 are sets partitioning the center of the 0-100 scale, defined in Table 6. $\boldsymbol{\mathcal{M}}$1-C, $\boldsymbol{\mathcal{M}}$5-C, $\boldsymbol{\mathcal{M}}$10-C, $\boldsymbol{\mathcal{M}}$25, $\boldsymbol{\mathcal{M}}$50, and '$\boldsymbol{\mathcal{U}}$ndetermined' denote rounding types in the center. $\boldsymbol{\mathcal{M}}$1-C denotes a respondent who rounds to the nearest 1 percent in the center, $\boldsymbol{\mathcal{M}}$5-C denotes a respondent who rounds to the nearest 5 percent in the center, and so on. $\boldsymbol{\mathcal{U}}$ndetermined denotes respondents who could not be classified to belong to any of the preceding center types.

Table 8B. Portion of the Algorithm Determining the Rounding Type of Respondent *j* in the Tails for Questions of Domain *l*

START: IF \ **AND** ∃ domain $l' \neq l$ s.t.	$\#(\Upsilon_{l'} \cap \{\mathbb{M}1\text{-T} \cup \mathbb{M}1\text{-C}\}) \geq 1$	$\#(\Upsilon_{l'} \cap \{\mathbb{M}1\text{-T} \cup \mathbb{M}1\text{-C}\}) = 0$	$\#(\Upsilon_{l'} \cap \{\mathbb{M}5\text{-T} \cup \mathbb{M}5\text{-C}\}) \geq 1$	$\#(\Upsilon_{l'} \cap \{\mathbb{M}5\text{-T} \cup \mathbb{M}5\text{-C}\}) = 0$	$\#(\Upsilon_{l'} \cap \{\mathbb{M}10\text{-T} \cup \mathbb{M}10\text{-C}\}) \geq 1$	$\#(\Upsilon_{l'} \cap \{\mathbb{M}10\text{-T} \cup \mathbb{M}10\text{-C}\}) = 0$	$\#(\Upsilon_{l'} \cap \mathbb{M}25) \geq 1$	$\#(\Upsilon_{l'} \cap \mathbb{M}25) = 0$	$\#(\Upsilon_{l'} \cap \{\mathcal{M}100 \cup \mathcal{M}50\}) \geq 1$	$\#(\Upsilon_{l'} \cap \{\mathcal{M}100 \cup \mathcal{M}50\}) = 0$	All NR
$\#(\Upsilon_l \cap \mathbb{M}1\text{-T}) \geq 2$	*j* is $\mathcal{M}$1-T										
$\#(\Upsilon_l \cap \mathbb{M}1\text{-T}) = 1$	$\mathcal{M}$1-T	IF *j* is still UNCLASSIFIED, GO to NEXT row									
$\#(\Upsilon_l \cap \{\mathbb{M}1\text{-T} \cup \mathbb{M}5\text{-T}\}) \geq 2$	*j* is $\mathcal{M}$5-T										
$\#(\Upsilon_l \cap \{\mathbb{M}1\text{-T} \cup \mathbb{M}5\text{-T}\}) = 1$	$\mathcal{M}$5-T		$\mathcal{M}$5-T	IF *j* is still UNCLASSIFIED, GO to NEXT row							
$\#(\Upsilon_l \cap \{\mathbb{M}1\text{-T} \cup \mathbb{M}5\text{-T} \cup \mathbb{M}10\text{-T}\}) \geq 2$	*j* is $\mathcal{M}$10-T										
$\#(\Upsilon_l \cap \{\mathbb{M}1\text{-T} \cup \mathbb{M}5\text{-T} \cup \mathbb{M}10\text{-T}\}) = 1$	$\mathcal{M}$10-T		$\mathcal{M}$10-T		$\mathcal{M}$10-T	IF *j* is still UNCLASSIFIED, GO to NEXT row					
$\#(\Upsilon_l \cap \{\mathbb{M}1\text{-T} \cup \mathbb{M}5\text{-T} \cup \mathbb{M}10\text{-T} \cup \mathbb{M}25 \cup \mathcal{M}100\}) \geq 2$	*j* is $\mathcal{M}$100										
$\#(\Upsilon_l \cap \{\mathbb{M}1\text{-T} \cup \mathbb{M}5\text{-T} \cup \mathbb{M}10\text{-T} \cup \mathbb{M}25 \cup \mathcal{M}100)\} = 1$	$\mathcal{M}$100		$\mathcal{M}$100		$\mathcal{M}$100		$\mathcal{M}$100		$\mathcal{M}$100	*j* type is $\mathcal{U}$ndetermined, END	
All NR	*j* type is $\mathcal{U}$ndetermined, END										

NOTE: Υ_l is the set of responses given by a hypothetical respondent *j* in domain *l*. $\mathbb{M}$1-T, $\mathbb{M}$5-T, $\mathbb{M}$10-T, and $\mathbb{M}$100 are sets partitioning the tails of the 0-100 scale, defined in Table 6. $\mathcal{M}$1-T, $\mathcal{M}$5-T, $\mathcal{M}$10-T, $\mathcal{M}$100, and '$\mathcal{U}$ndetermined' denote rounding types in the tails. $\mathcal{M}$1-T denotes a respondent who rounds to the nearest 1 percent in the tails, $\mathcal{M}$5-T denotes a respondent who rounds to the nearest 5 percent in the tails, and so on. $\mathcal{U}$ndetermined denotes respondents who could not be classified to belong to any of the preceding t types.

Table 9. Distribution of Rounding Types by Domain

Rounding Type	Percent Personal Health	Percent Personal Finances	Percent General Economic Conditions
(M1-T, M1-C)	0.17	0.33	0.26
(M1-T, M5-C)	**1.07**	**3.03**	**1.22**
(M1-T, M10-C)	**6.08**	**15.84**	**5.73**
(M1-T, M25)	**1.33**	**1.72**	**0.80**
(M1-T, M50)	**1.27**	**1.31**	**0.86**
(M1-T, None/Undet.)	1.02	0.50	0.42
(M5-T, M1-C)	*0.07*	*0.08*	*0.11*
(M5-T, M5-C)	2.60	2.97	3.65
(M5-T, M10-C)	**16.05**	**23.47**	**16.98**
(M5-T, M25)	**3.20**	**2.95**	**2.29**
(M5-T, M50)	**2.53**	**1.75**	**1.35**
(M5-T, None/Undet.)	1.39	0.53	0.55
(M10-T, M1-C)	*0.13*	*0*	*0.16*
(M10-T, M5-C)	*1.84*	*0.73*	*2.47*
(M10-T, M10-C)	25.92	22.75	32.50
(M10-T, M25)	**5.91**	**5.09**	**5.24**
(M10-T, M50)	**7.98**	**5.88**	**5.93**
(M10-T, None/Undet.)	4.35	2.36	2.70
(M100, M1-C)	*0*	*0*	*0.01*
(M100, M5-C)	*0.16*	*0.03*	*0.14*
(M100, M10-C)	*2.89*	*1.04*	*1.96*
(M100, M25)	*1.62*	*1.01*	*1.08*
(*M100*, M50)	3.90	2.45	2.32
(*M100*, None/Undet.)	4.74	3.42	2.47
(None/Undet., M1-C)	0.01	0	0.01
(None/Undet., M5-C)	0.20	0.01	0.24
(None/Undet., M10-C)	1.27	0.01	2.50
(None/Undet., M25)	0.47	0.00	0.92
(None/Undet., M50)	0.92	0	2.06
(None/Undet., None/Undet.)	0.91	0.75	3.06
Total	100	100	100
Sample size	28044	28252	28172
Tails finer than center	**45.42**	**61.03**	**40.40**
Tails same as center	32.60	28.49	38.73
Tails coarser than center	*6.71*	*2.90*	*5.94*
No/Undet. T and/or C	15.27	7.58	14.93

Table 10. Bivariate Ordered Probit of (Tail, Center) Rounding Categories on Respondent's Characteristics, by Question Domain

	Personal Health		Personal Finances		Gen. Econ. Conditions	
	Tail Type	Center Type	Tail Type	Center Type	Tail Type	Center Type
Male	0.0306**	-0.0203	0.0321**	0.0166	0.0137	-0.0346**
	(0.0146)	(0.0152)	(0.0139)	(0.0149)	(0.0147)	(0.0154)
Aged 60-69	-0.1860***	-0.1343***	-0.0062	0.0217	-0.1064***	-0.0962***
	(0.0177)	(0.0191)	(0.0171)	(0.0186)	(0.0182)	(0.0192)
Aged 70-79	-0.1409***	0.0784***	0.1732***	0.2271***	-0.7937***	0.0562***
	(0.0196)	(0.0203)	(0.0187)	(0.0201)	(0.0196)	(0.0205)
Aged 80+	0.1768***	0.5320***	0.5862***	0.6615***	0.2228***	0.4162***
	(0.0257)	(0.0252)	(0.0237)	(0.0248)	(0.0258)	(0.0257)
High school	-0.1749***	-0.1996***	-0.2507***	-0.2776***	-0.1250***	-0.2324***
	(0.0210)	(0.0206)	(0.0194)	(0.0203)	(0.0211)	(0.0210)
Some college	-0.1607***	-0.2081***	-0.2969***	-0.3290***	-0.1289***	-0.2820***
	(0.0346)	(0.0359)	(0.0326)	(0.0351)	(0.0347)	(0.0367)
Bachelor	-0.3400***	-0.4218***	-0.4566***	-0.4950***	-0.2714***	-0.4588***
	(0.0264)	(0.0276)	(0.0253)	(0.0271)	(0.0268)	(0.0277)
Graduate	-0.4362***	-0.5580***	-0.5459***	-0.5586***	-0.3513***	-0.5527***
	(0.0290)	(0.0311)	(0.0281)	(0.0306)	(0.0294)	(0.0313)
Black	0.0846***	0.1947***	-0.0548***	0.0212	-0.0036	0.0477**
	(0.0211)	(0.0216)	(0.0193)	(0.0209)	(0.0209)	(0.0217)
Other race	0.1586***	0.2031***	0.1264***	0.0897***	0.1220***	0.1128***
	(0.0296)	(0.0315)	(0.0280)	(0.0302)	(0.0306)	(0.0312)
Rho	0.2698***		0.3799***		0.2985***	
	(0.0086)		(0.0073)		(0.0092)	
N	22,821		25,015		22,983	

NOTES: (i) Respondents whose tail or center rounding category is undetermined are excluded from this analysis. (ii) Omitted dummies are 'Female,' 'Aged 50-59,' 'No degree,' and 'White.' 'Rho' is the parameter capturing the correlation between the error terms of the tail and center latent equations. (iii) Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 11A. Portion of the Algorithm Assigning Probability Intervals, $\left[\upsilon^{T}_{jktL},\upsilon^{T}_{jktU}\right]$, to Point Responses in the Tails by Respondent *j* to Questions in Domain *l*, υ^{T}_{jkt}, by Rounding Type

Tails Type \ Center Type	$\mathcal{M}$1-C	$\mathcal{M}$5-C	$\mathcal{M}$10-C	$\mathcal{M}$25	$\mathcal{M}$50	No or $\mathcal{U}$ndetermined center type
$\mathcal{M}$1-T	υ^{T}_{jkt}	υ^{T}_{jkt}	υ^{T}_{jkt}	υ^{T}_{jkt}	υ^{T}_{jkt}	υ^{T}_{jkt}
$\mathcal{M}$5-T	SAME AS ($\mathcal{M}$1-T, $\mathcal{M}$1-C)	$[\max(0,\upsilon^{T}_{jkt}-2.5),$ $\min(\upsilon^{T}_{jkt}+2.5,100)]$	$[\max(0,\upsilon^{T}_{jkt}-2.5),$ $\min(\upsilon^{T}_{jkt}+2.5,100)]$	$[\max(0,\upsilon^{T}_{jkt}-2.5),$ $\min(\upsilon^{T}_{jkt}+2.5,100)]$	$[\max(0,\upsilon^{T}_{jkt}-2.5),$ $\min(\upsilon^{T}_{jkt}+2.5,100)]$	$[\max(0,\upsilon^{T}_{jkt}-2.5),$ $\min(\upsilon^{T}_{jkt}+2.5,100)]$
$\mathcal{M}$10-T	SAME AS ($\mathcal{M}$1-T, $\mathcal{M}$1-C)	SAME AS ($\mathcal{M}$5-T, $\mathcal{M}$5-C)	$[\max(0,\upsilon^{T}_{jkt}-5),$ $\min(\upsilon^{T}_{jkt}+5,100)]$	$[\max(0,\upsilon^{T}_{jkt}-5),$ $\min(\upsilon^{T}_{jkt}+5,100)]$	$[\max(0,\upsilon^{T}_{jkt}-5),$ $\min(\upsilon^{T}_{jkt}+5,100)]$	$[\max(0,\upsilon^{T}_{jkt}-5),$ $\min(\upsilon^{T}_{jkt}+5,100)]$
$\mathcal{M}$100	SAME AS ($\mathcal{M}$1-T, $\mathcal{M}$1-C)	SAME AS ($\mathcal{M}$5-T, $\mathcal{M}$5-C)	SAME AS ($\mathcal{M}$10-T, $\mathcal{M}$10-C)	$[\max(0,\upsilon^{T}_{jkt}-12.5),$ $\min(\upsilon^{T}_{jkt}+12.5,100)]$	$[\max(0,\upsilon^{T}_{jkt}-25),$ $\min(\upsilon^{T}_{jkt}+25,100)]$	$[\max(0,\upsilon^{T}_{jkt}-50),$ $\min(\upsilon^{T}_{jkt}+50,100)]$
No or $\mathcal{U}$ndet. tail type	SAME AS ($\mathcal{M}$1-T, $\mathcal{M}$1-C)	SAME AS ($\mathcal{M}$5-T, $\mathcal{M}$5-C)	SAME AS ($\mathcal{M}$10-T, $\mathcal{M}$10-C)	SAME AS ($\mathcal{M}$100, $\mathcal{M}$25)	SAME AS ($\mathcal{M}$100, $\mathcal{M}$50)	$[0,100]$
All NR responses regardless of type	$[0,100]$	$[0,100]$	$[0,100]$	$[0,100]$	$[0,100]$	$[0,100]$

NOTE: $\mathcal{M}$1-T, $\mathcal{M}$5-T, $\mathcal{M}$10-T, $\mathcal{M}$100, and '$\mathcal{U}$ndetermined' denote rounding types in the tails. υ^{T}_{jkt} denotes a hypothetical response respondent *j* gave in the tails of the 0-100 scale when answering a question in domain *l*. $\left[\upsilon^{T}_{jktL},\upsilon^{T}_{jktU}\right]$ denotes the probability interval assigned to the point response by the algorithm. The boundary conditions ensure that the lower and upper bounds of the probability interval lie in the tails of the 0-100 scale.

Table 11B. Portion of the Algorithm Assigning Probability Intervals, $\left[\upsilon^{C}_{jktL},\upsilon^{C}_{jktU}\right]$, to Point Responses in the Center by Respondent *j* to Questions in Domain *l*, υ^{C}_{jkt}, by Rounding Type

Center Type / Tails Type	$\mathcal{M}$1-C	$\mathcal{M}$5-C	$\mathcal{M}$10-C	$\mathcal{M}$25	$\mathcal{M}$50	No or $\mathcal{U}$ndet. center type or any NR
$\mathcal{M}$1-T	υ^{C}_{jkt}	$[\max(\max\Upsilon^{LT}_{j},\upsilon^{C}_{jkt}-2.5), \min(\upsilon^{C}_{jkt}+2.5,\min\Upsilon^{RT}_{j})]$	$[\max(\max\Upsilon^{LT}_{j},\upsilon^{C}_{jkt}-5), \min(\upsilon^{C}_{jkt}+5,\min\Upsilon^{RT}_{j})]$	$[\max(\max\Upsilon^{LT}_{j},\upsilon^{C}_{jkt}-12.5), \min(\upsilon^{C}_{jkt}+12.5,\min\Upsilon^{RT}_{j})]$	$[\max(\max\Upsilon^{LT}_{j},\upsilon^{C}_{jkt}-25), \min(\upsilon^{C}_{jkt}+25,\min\Upsilon^{RT}_{j})]$	$[0,100]$
$\mathcal{M}$5-T	AS ($\mathcal{M}$1T, $\mathcal{M}$1C)	$[\max(\max\Upsilon^{LT}_{j}+2.5,\upsilon^{C}_{jkt}-2.5), \min(\upsilon^{C}_{jkt}+2.5,\min\Upsilon^{RT}_{j}-2.5)]$	$[\max(\max\Upsilon^{LT}_{j}+2.5,\upsilon^{C}_{jkt}-5), \min(\upsilon^{C}_{jkt}+5,\min\Upsilon^{RT}_{j}-2.5)]$	$[\max(\max\Upsilon^{LT}_{j}+2.5,\upsilon^{C}_{jkt}-12.5), \min(\upsilon^{C}_{jkt}+12.5,\min\Upsilon^{RT}_{j}-2.5)]$	$[\max(\max\Upsilon^{LT}_{j}+2.5,\upsilon^{C}_{jkt}-25), \min(\upsilon^{C}_{jkt}+25,\min\Upsilon^{RT}_{j}-2.5)]$	$[0,100]$
$\mathcal{M}$10-T	AS ($\mathcal{M}$1T, $\mathcal{M}$1C)	SAME AS ($\mathcal{M}$5-T, $\mathcal{M}$5-C)	$[\max(\max\Upsilon^{LT}_{j}+5,\upsilon^{C}_{jkt}-5), \min(\upsilon^{C}_{jkt}+5,\min\Upsilon^{RT}_{j}-5)]$	$[\max(\max\Upsilon^{LT}_{j}+5,\upsilon^{C}_{jkt}-12.5), \min(\upsilon^{C}_{jkt}+12.5,\min\Upsilon^{RT}_{j}-5)]$	$[\max(\max\Upsilon^{LT}_{j}+5,\upsilon^{C}_{jkt}-25), \min(\upsilon^{C}_{jkt}+25,\min\Upsilon^{RT}_{j}-5)]$	$[0,100]$
$\mathcal{M}$100	AS ($\mathcal{M}$1T, $\mathcal{M}$1C)	SAME AS ($\mathcal{M}$5-T, $\mathcal{M}$5-C)	SAME AS ($\mathcal{M}$10-T, $\mathcal{M}$10-C)	$[\upsilon^{C}_{jkt}-12.5,\upsilon^{C}_{jkt}+12.5]$	$[\max(25,\upsilon^{C}_{jkt}-25), \min(\upsilon^{C}_{jkt}+25,75)]$	$[0,100]$
No or $\mathcal{U}$ndet. tail type	AS ($\mathcal{M}$1T, $\mathcal{M}$1C)	SAME AS ($\mathcal{M}$5-T, $\mathcal{M}$5-C)	SAME AS ($\mathcal{M}$10-T, $\mathcal{M}$10-C)	SAME AS ($\mathcal{M}$100, $\mathcal{M}$25)	SAME AS ($\mathcal{M}$100, $\mathcal{M}$50)	$[0,100]$

NOTE: $\mathcal{M}$1-C, $\mathcal{M}$5-C, $\mathcal{M}$10-C, $\mathcal{M}$50, and '$\mathcal{U}$ndetermined' denote rounding types in the tails. υ^{C}_{jkt} denotes a hypothetical response respondent *j* gave in the center of the 0-100 scale when answering a question in domain *l*. $\left[\upsilon^{C}_{jktL},\upsilon^{C}_{jktU}\right]$ denotes the probability interval assigned to the point response by the algorithm. The boundary conditions ensure that the lower and upper bounds of the probability interval lie in the center of the 0-100 scale. Υ^{LT}_{j} denotes the set of responses respondent *j* gave in the left tail (i.e., in 0-24) when answering questions in domain *l*. Υ^{RT}_{j} denotes the set of respondent *j*'s responses in the right tail (i.e., in 76-100).

Table 12. Distribution of Range Size for Specific Expectations Questions in the 2014 HRS

Range Size	Percent Live to be 75 or older (P28 in Personal Health)	Percent Work full time past age 62 (P17 in Personal Finances)	Percent Mutual funds increase in value (P47 in General Economic Conditions)
0	7.17	20.95	6.04
2.5	3.71	9.05	2.02
3.5	0.09	0.09	0
4.5	0.04	0.08	0.02
5	27.72	31.72	23.82
6	0.01	0.02	0
7.5	0.99	1.38	1.55
9	0.02	0.02	0
10	42.96	32.58	48.11
12.5	1.53	0.34	0.77
15	0.38	0.19	0.36
17.5	0.06	0.13	0.11
20	0.05	0.02	0.02
22.5	0.06	0.11	0.09
25	4.40	1.57	3.77
27.5	0.02	0	0
30	0.02	0.02	0.01
32.5	0	0.02	0
35	0.01	0	0
40	0	0	0.02
42.5	0.01	0	0
50	7.71	1.1	3.56
60	0.01	0	0
100	2.99	0.62	9.72
Total	100	100	100
Sample size	8084	5294	8828

Table 13. BLP Prediction of Retirement Expectations: Point Estimates vs. Set Estimates with Pooled HRS 2002-2014 Data

	OLS Estimates I	Set Estimates I		Set Estimates II	
	(MCAR imposed)	LB	UB	LB	UB
Age	0.1638221**	-0.40359618	0.72120951	-0.49438537	0.81096113
	(0.0306357, 0.2970086)	(-0.51768266, 0.8352959)		(-0.59444688, 0.91102264)	
Coupled	-2.69401***	-8.5773441	3.2791972	-9.601387	4.4009574
	(-4.13476, -1.25326)	(-9.6554672, 4.357320)		(-10.652129, 5.4516997)	
Male	8.217222***	2.1835235	13.957973	1.1364714	14.764102
	(7.001744, 9.4327)	(1.2709936, 14.870503)		(0.20237046, 15.698203)	
Negative wealth	6.181168***	-1.6446953	13.57578	-4.1145186	15.453035
	(4.398587, 7.963748)	(-3.2408944, 15.17198)		(-5.7203313, 17.058848)	
Below median wealth	6.211564***	-1.5954425	13.586249	-3.9163622	15.298648
	(4.489798, 7.933331)	(-2.9979902, 14.98879)		(-5.4242413, 16.806527)	
Above median wealth	-0.4700764	-9.3488693	8.1918129	-11.563376	9.8588751
	(-2.52093, 1.580777)	(-10.974637, 9.817580)		(-13.132089, 11.427588)	
Black	-9.865536***	-16.065535	-3.352129	-17.245896	-2.2000895
	(-11.51149, -8.21958)	(-17.215125, -2.20253)		(-18.352668, -1.0933171)	
Other race	-4.820859***	-11.57924	2.1776555	-13.275225	4.2223185
	(-6.837141, -2.804578)	(-12.99555, 3.5939652)		(-14.769607, 5.7167003)	
High school	10.53563***	3.0626705	17.33757	0.26331536	19.123686
	(8.701606, 12.36965)	(1.5481337, 18.852107)		(-1.1983042, 20.585305)	
Some college	13.47746***	4.707323	21.511786	1.9292065	23.212118
	(10.72894, 16.22598)	(2.7421172, 23.47699)		(0.0494954, 25.091829)	
Bachelor degree	17.09265***	7.972854	25.300611	5.2205032	27.02243
	(14.68995, 19.49534)	(6.0970397, 27.17642)		(3.5435262, 28.699407)	
Graduate degree	19.15506***	9.7651245	27.608368	7.0036548	29.342804
	(16.35548, 21.95463)	(7.8350385, 29.53845)		(5.0635249, 31.282934)	
Constant	26.07626***	-5.8897704	59.66448	-10.564714	65.969594
	(18.32665, 33.82588)	(-12.641148, 66.41585)		(-16.584584, 71.989465)	
N	23,811	23,811		24,052	

NOTE: OLS and SetBLP estimates I calculated after dropping DK/RF responses to the point PC question. SetBLP estimates II include DK/RF responses to the point PC question. 95% confidence intervals in parenthesis. OLS CIs clustered at the HH level. SetBLP estimates calculated using 501 bootstrap repetitions. Beresteanu and Molinari (2008)'s confidence sets based on directed Hausdorff. Omitted dummies are '0 wealth,' 'white,' and 'no degree.'

Figure 4: Predicted Hours of Work per Week