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Stochastic Mortality, Subjective Survival Expectations, and Individual Saving Behavior

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Abstract Theoretical studies suggest that unexpected changes in future mortality and survival probabilities (stochastic mortality) are important determinants of individuals' decisions about consumption, saving, asset allocation, and retirement timing. Using data on subjective survival expectations elicited in the Survey of Health, Ageing and Retirement in Europe (SHARE) and corresponding life table data from the Human Mortality Database (HMD), we find evidence of respondents' awareness of stochastic mortality. We also find that respondents' saving behavior is influenced by stochastic mortality perceptions.

Keywords stochastic mortality, subjective survival expectations, forecast dispersion, savings behavior

JEL classifications D14, D84, D91, H31, J11

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For the past several decades, the industrialized world has experienced rapid improvements in life expectancy and mortality rates. However, annual rates of decline in mortality exhibit considerable variation, as illustrated in Figure 1 for males and females aged 65 and 85. The erratic path of mortality rates reflects the underlying complex interaction of external drivers, such as medical innovation, whose overall impact is clearly non-deterministic. The resulting unexpected changes in mortality are commonly referred to as *stochastic mortality* or *aggregate mortality risk*.

-- *Figure 1 here* --

Theoretical studies suggest that uncertainty regarding future mortality rates is an important determinant of individual consumption and saving decisions (Levhari and Mirman, 1977; Davies, 1981; Cocco and Gomes, 2009; De Nardi, French, and Jones, 2009), individual asset allocation decisions regarding annuities and longevity bonds (Albis and Thibault, 2008; Menoncin, 2008; Cocco and Gomes, 2009; Post, 2009; Stevens, 2009; Horneff, Maurer, Rogalla, 2010; Schulze and Post, 2010), and retirement timing decisions (Cocco and Gomes, 2009), as well as for equilibrium annuity prices (Van de Ven and Weale, 2008). In these models, individuals integrate into their decision process not only a prognosis on (mean) mortality rates and survival probabilities,[1] but also a prognosis on possible fluctuations in these rates. The presence of stochastic mortality is shown, for example, to increase individuals' savings for self-insurance against longevity shocks (Cocco and Gomes, 2009), to induce the use of longevity bonds as hedging instruments (Menoncin, 2008; Cocco and Gomes, 2009), and to increase investment in deferred annuities (Post, 2009; Stevens, 2009; Horneff, Maurer, Rogalla, 2010).

In this paper, we investigate whether individuals are aware of stochastic mortality and, if so, whether this awareness affects their actual savings behavior. To this end, we analyze survey data on subjective survival expectations elicited in the Survey of Health, Ageing and Retirement in Europe (SHARE) and corresponding life table data from the Human Mortality Database (HMD) (University of California and Max Planck Institute, 2009).

SHARE contains subjective point forecasts of individuals' survival probabilities. Such estimates have been shown to be informative with respect to the mean of objective survival

[1] This is the case in the standard life-cycle model incorporating uncertainty regarding the lifespan (Yaari, 1965).

probabilities. Similar to their objective counterparts, subjective survival estimates exhibit differentials according to, for example, age, gender, health, and socio-economic status (Hamermesh, 1985; Hurd and McGarry, 1995; Mirowsky and Ross, 2000; Khwaja, Sloan, and Chung, 2007; Popham and Mitchell, 2007; Delavande and Rohwedder, 2008). Subjective estimates are found to match the shape of survival functions of actual life tables, although they exhibit some underestimation at younger ages and some overestimation at older ages (Hamermesh, 1985; Elder, 2007; Hurd, Rohwedder, and Winter, 2009).[2] Furthermore, subjective estimates have predictive power for individuals' actual survival (Hurd, McFadden, and Gan, 1998; Hurd and McGarry, 2002; Siegel, Bradley, and Kasl, 2003; Winter, 2008), for the development of aggregate mortality rates (Hamermesh, 1985; Perozek, 2008), and for economic decisions regarding consumption, savings, bequests, and claiming retirement benefits (Coile et al., 2002; Gan et al., 2004; Hurd, Smith, and Zissimopoulos, 2004; Bloom et al., 2007; Delavande and Willis, 2008). In addition, in an experimental setting, it was shown that the processes underlying the formation of subjective expectations (including lifespan predictions) are indeed based on individuals' knowledge (Lewandowsky, Griffiths, and Kalish, 2009).

To study individuals' awareness of stochastic mortality, we test whether subjective survival probabilities elicited in SHARE are also informative with respect to the uncertainty surrounding the development of objective mortality rates. For this, we relate the dispersion in individuals' point forecasts to the uncertainty observed in objective mortality data. A similar approach is found in a large number of empirical studies that use dispersion of point forecasts as a proxy for uncertainty regarding economic variables, including, for example, macroeconomic variables such as inflation (Cukierman and Wachtel, 1979; Levi and Makin, 1979, 1980; Mullineaux, 1980; Makin; 1982; Brenner and Landskroner, 1983; Bomberger, 1996; Hayford, 2000), unemployment (Hayford, 2000), economic activity and growth (Hahm and Steigerwald, 1999; Vuchelen, 2004; Bloom, Floetotto, and Jaimovich, 2009; Bachmann, Elstner, and Sims, 2010), financial variables such as firm earnings and stock returns (Ajinkya and Gift, 1985; Imhoff and Lobo, 1992; Gebhardt, Lee, and Swaminathan, 2001; Zhang, 2006a, 2006b) and real estate performance (McAllister, Newell, and Matysiak, 2008), and the demand for consumer goods (Fisher and Raman, 1996; Gaur et al., 2007; Fuss and

[2] The evidence for specific causes of death is mixed: some studies find that individuals misperceive the risks related to specific causes of death (e.g., Lichtenstein et al., 1978; Morgan et al., 1983; Viscusi, 1990; Hakes and Viscusi, 2004; Armantier, 2006; Andersson and Lundborg, 2007; Bhattacharya, Goldman, and Sood, 2009); however, other studies report opposite results (Benjamin and Dougan, 1997; Viscusi, Hakes, and Carlin, 1997; Benjamin, Dougan, and Buschena, 2001).

Vermeulen, 2008). Methodologically, dispersion in point forecasts may reflect both perceived uncertainty underlying the forecast variable and disagreement among forecasters (who may feel certain about their estimate) (e.g., Zarnowitz and Lambros, 1987; Barron et al., 1998; Giordani and Söderlind, 2003; Engelberg, Manski, and Williams, 2009; Barron, Stanford, and Yu, 2009; Lahiri and Sheng, 2010). However, empirical studies that explicitly account for such distinction mostly find that forecast dispersion and uncertainty regarding the forecast variable are positively related (Zarnowitz and Lambros, 1987; Rich, Raymond, and Butler, 1992; Bomberger, 1996; Rich and Tracy, 2006; Barron, Stanford, and Yu, 2009; Lahiri and Sheng, 2010). Experimental studies further support these findings by documenting a positive relationship between past volatility of a target variable and the dispersion of corresponding forecasts (Harvey, 1995; Harvey, Ewart, and West 1997; Du and Budescu, 2007).

These results provide the foundation for our main research hypothesis:

Hypothesis 1: If individuals are aware of stochastic mortality, then the dispersion of subjective forecasts should be wider when uncertainty regarding the underlying mortality rates is high.[3]

We test this hypothesis by checking whether the mortality dispersion found in life table data from the Human Mortality Database corresponds to forecast dispersion observed in responses elicited in SHARE.[4] In a further step, we use data on SHARE respondents' wealth accumulation to study behavioral implications of stochastic mortality awareness in relation to forecaster uncertainty and forecaster disagreement.

Our results show that the dispersion of subjective estimates of survival probabilities is positively linked to the dispersion of objective survival rates, indicating an awareness of stochastic mortality among SHARE respondents. Our related analysis of respondents' saving behavior provides additional evidence that respondents are aware of and also act on stochastic mortality; however, disagreement effects are also found.

[3] In the sense of Kahneman and Tversky (1982), our hypothesis thus postulates a positive link between external and internal uncertainty with respect to survival probabilities.

[4] Ideally, we would like to have a data set that includes direct responses regarding subjective mortality uncertainty and contains information from a sample of individuals who exhibit considerable heterogeneity with respect to objective mortality uncertainty. We are not aware of data having the first property, but SHARE meets the second property very well. It covers a large number of countries with heterogeneous objective mortality uncertainty and provides key control variables. Survey design and sampling methods are harmonized across all countries, guaranteeing reliable cross-country comparisons.

Our real-world findings complement theoretical studies of individual decision making under stochastic mortality. They are highly relevant for the design of pension systems that emphasize individually managed retirement savings and asset allocation. The success of such systems crucially depends on individuals making informed decisions based, at least in part, on their awareness of stochastic mortality.

The remainder of this article is structured as follows. In Section 1, the data are described. Calculation of dispersion measures for SHARE and HMD data and explorative analyses are contained in Section 2. Awareness of stochastic morality is then formally analyzed in Section 3, followed by an analysis of estimation errors in Section 4. In Section 5, we link awareness of stochastic mortality to saving behavior. Section 6 summarizes and discusses our findings.

1. Data, Sample Selection, and Generated Variables

1.1. Subjective Survival Expectations—SHARE

The Survey of Health, Ageing and Retirement in Europe (SHARE) is a rich micro-level data set covering European countries and Israel. We use Wave 2 of SHARE, which includes data collected between 2006 and 2007 for Austria, Belgium, Czechia, Denmark, France, Germany, Greece, Ireland, Italy, the Netherlands, Poland, Spain, Sweden, and Switzerland. We omit Greece and Ireland from our analysis because the Human Mortality Database does not contain data for Greece and SHARE is missing wealth and income variables for Ireland (as of July 2010). Our sample is comprised of 30,038 individual cases.

To elicit survival expectations, individuals in SHARE are asked the following question: "What are the chances that you will live to be age T or more?" The target age T is chosen conditional on the respondent's current age, x, as given in Table 1 (Hurd, Rohwedder, and Winter, 2009) and the response range is between 0 and 100. Due to this survey design, individuals are asked for age-specific survival probabilities referring to different forecast horizons ($T - x$).

-- *Table 1 here* --

We rescale the responses so that they range from 0 to 1 and treat them as probabilities (see, e.g., Hurd and McGarry, 2002). After removing those respondents who did not answer the survival expectations question as well as those cases where the target age variable given in the data set did not comply with Table 1, we have 26,497 valid cases for analysis.

An overview of demographic and economic characteristics of the selected respondents is given in Table 2; variables are defined in Table 3.

-- Table 2 here --

-- Table 3 here --

1.2. Objective Mortality Data—HMD

The Human Mortality Database provides harmonized mortality data for 37 countries. For the countries in our sample, we use the most recent gender- and age-specific time series for one-year probabilities of death, $q_{x,t}$, with t denoting the observation year, starting from 1950 if available (1956 for Germany; 1958 for Poland). To match subjective expectations and objective data, we construct for all time-horizon-age-gender-country combinations found in the SHARE data corresponding time series of multi-period mortality rates, $q_{x,t,T-x}$, using the HMD data (for simplicity's sake, country and gender indices are suppressed). Furthermore, we adapt to the forward-looking nature of SHARE responses by calculating forecasts for $q_{x,t,T-x}$ (and for multi-period rates of survival $p_{x,t,T-x}$) conditional on the survey year. To this end, we assume the following stochastic process for evolution of multi-period mortality rates over time: $q_{x,t,T-x} = q_{x,t-1,T-x} \cdot r_{x,t,T-x}$, where $r_{x,t,T-x}$ follows a lognormal distribution with mean $\mu_{x,T-x}$ and standard deviation $\sigma_{x,T-x}$. We estimate the parameters $\mu_{x,T-x}$ and $\sigma_{x,T-x}$ from the HMD data. This stochastic model reflects both trends and the uncertainty around trends in mortality progress (and thus survival probabilities) over time.

2. Calculation of Dispersion Measures

Mortality and survival rates vary with socio-demographic factors such as age, gender, and income and it is thus intuitive to expect dispersion in subjective survival expectations of respondents who are heterogeneous with respect to these factors. Since we are interested in response dispersion caused by uncertainty as to the mortality rate, we subdivide the sample into groups of individuals who can be expected to have homogenous mortality rates. To do so, we use all available information in the HMD database: age, gender, country, and, in addition, marital status ("couple").[5] Other factors known to have an impact on mortality rates (e.g., income) and, possibly, on dispersion for which the HMD data cannot account are included as control variables in regression analyses.

For every age-gender-country-couple group, we calculate a measure of the dispersion of responses by first calculating the standard deviation of responses for each group. To enable meaningful comparisons, especially between different age groups, we then normalize these standard deviations by the corresponding group-specific mean. That is, we choose the coefficient of variation (CV) as the measure of dispersion. We adopt the same approach for objective survival probability forecasts, where the CV for the prognosis of $p_{x,t,T-x}$ is calculated based on the stochastic mortality model introduced in the previous subsection.

Table 4 provides summary statistics for the data on the group level, including the dispersion measures. We restrict our analysis to groups containing at least two individuals, resulting in different countries having different numbers of groups.

-- *Table 4 here* --

Figure 2 is a preliminary look at the relationship between the uncertainty underlying objective survival probability and dispersion of subjective estimates.

-- *Figure 2 here* --

Figure 2 suggests a positive relationship between the two dispersion measures: a greater dispersion in subjective estimates of survival tends to coincide with greater dispersion in objective mortality data. A separate analysis by couple and gender (see Figure 3) shows that this tendency can also be found within these subgroups.

-- *Figure 3 here* --

[5] Key economic variables (e.g., net worth), used later in the econometric analysis are reported as household-level aggregates. Respondents living in a partnership appear wealthier, since both partners' entries for these variables refer to the combined amount.

Figure 4 shows the age-specific group averages of the two dispersion measures. Age-specific coefficients of variation in objective mortality rates are plotted in Panel A; those for the dispersion of subjective responses in Panel B.

-- Figure 4 here --

Figure 4 reveals that both dispersion measures are related to age. Elder (2007) argues that age is likely to have a detrimental effect on the cognitive abilities needed to estimate mortality rates. To understand more precisely to what extent the positive relationship shown in Figures 2 and 3 is due to the stochastic mortality perception link hypothesized in this paper, we next run regressions that control for age and other factors.

3. Regression Analyses of Subjective Dispersion

Using the grouped data described above, we now employ regressions to measure the impact of the actual uncertainty regarding future survival rates on the dispersion of individuals' subjective estimates of these rates. In this analysis, we control for key demographic characteristics and other factors potentially affecting dispersion in subjective survival estimates. In particular, we estimate the following equation with OLS:

$$SUB\_DISP_j = \alpha + \beta OBJ\_DISP_j + \boldsymbol{\delta}^{T}\mathbf{z}_j + \varepsilon_j \,, \tag{3.1}$$

where SUB_DISP_j depicts the measure of dispersion of subjective survival probabilities in group j (age-horizon-gender-country groups), OBJ_DISP_j depicts the objective uncertainty about the future survival rate for group j (estimated from time-series models for $q_{x,t,T-x}$), and $\mathbf{z}_j$ is a vector of group-specific control variables. In addition to the variables used for grouping, we chose net worth, income, education, self-perceived health, and grip strength as additional socio-demographic control variables based on empirical findings on mortality differentials (e.g., Smith, Taylor, and Sloan, 2001; Hurd and McGarry, 2002; Brown, 2003; Elder, 2007; Sullivan and von Wachter, 2009; Andersen-Ranberg et al., 2010). We also include numeracy score as a control variable to account for possible differences in cognitive ability. For these variables we use their group-specific dispersion as a control variable.[6] We thus control for the possibility that heterogeneity in these factors could cause additional

[6] Depending on whether it is relative differences (scale variables such as net worth) or absolute differences that are more informative (ordinal variables such as numeracy score), we use either the coefficient of variation (CV) or the standard deviation (Std) as a dispersion measure.

dispersion of subjective survival probability estimates within a group. Since variables in Equation (3.1) are generated, we use bootstrap standard errors (Efron and Tibshirani, 1993). Results for three models that differ by the number of control variables they include, are given in Table 5.

-- *Table 5 here* --

Results for all models show that dispersion in objective survival probabilities is positively and strongly significantly related to dispersion in subjective survival estimates of SHARE respondents. The dispersion in subjective survival estimates increases significantly with age, possibly reflecting a decrease in cognitive ability as mentioned by Elder (2007) in his analysis of survival expectation levels. The dispersion also increases with the length of the forecast horizon (even though we are using a normalized dispersion measure), which indicates that it is more difficult to forecast events in the more distant future (Lahiri and Sheng, 2010). Respondents who are one-half of a couple have a lower dispersion in subjective survival estimates, but no significant effect is found for gender. Nor do differences in group size have any impact on dispersion. Adding socio-economic and cognitive control variables that account for mortality dispersion unrelated to stochastic mortality in Models (2) and (3) improves model fit as measured by the R^2, while the coefficient for the dispersion in objective survival probabilities remains positive and strongly significant.

In conclusion, results of the regression analysis in which we control for key variables related to the dispersion in objective mortality probabilities (e.g., age, gender, wealth, income) and cognitive abilities (e.g., age, numeracy) confirm the findings of the univariate analysis: our data exhibit a significant and positive relationship between the dispersion in objective survival probabilities and subjective estimates. This finding supports *Hypothesis 1* as it is an indication that the SHARE respondents are aware of stochastic mortality.

4. Analysis of Estimation Error Level

In this section, we analyze the level of the estimation error, that is, we study the difference between subjective and objective estimates of survival probability for each respondent. Previous literature establishes a relationship between survival probability estimation error and various individual characteristics, one of the most important of which is age: younger people tend to underestimate actual survival rates, older people tend to overestimate them (e.g., Hamermesh, 1985; Elder, 2007; Hurd, Rohwedder, and Winter, 2009). Related to this phenomenon are findings from the financial analyst dispersion literature showing that greater objective uncertainty is associated with larger levels of estimation errors (see, e.g., Zhang, 2006a). We thus now investigate whether dispersion of objective rates plays a role with respect to survival probability estimation error levels.

We use two alternative measures of the respondent's estimation error (see Table 3). Both measures are defined in relative terms; again, this is done to enable comparison of each group's estimates on a similar scale. The first and more intuitive measure defines the estimation error as the difference between the subjective and the objective estimate of survival probability, divided by the objective probability. This measure distinguishes between positive and negative deviations of subjective estimates from the objective probabilities. On average, within groups, positive and negative values can cancel out, and thus the second measure defines the estimation error as the absolute (positive) value of the difference between the subjective and objective estimates of the survival probability, divided by the objective probability. As expected, the second measure tends to be larger on average (see Table 4).

Results obtained using the first measure confirm findings in the literature: higher age leads to more optimism about survival prospects (see Figure 5).

-- *Figure 5 here* --

Figure 6 shows that the level of estimation error (especially in absolute terms, i.e., using the second definition) increases when the dispersion of objective mortality rates increases.

-- *Figure 6 here* --

To disentangle the effects dispersion in objective mortality rates, age, and other control variables have on the level of estimation error, we estimate the following regression model:

$$EST\_ERR\_LEVEL_j = \alpha + \beta OBJ\_DISP_j + \boldsymbol{\delta}^{\mathrm{T}}\mathbf{z}_j + \varepsilon_j. \tag{4.1}$$

Model (4.1) uses the same set of control variables as Model (3.1), but we now also include age^2 to account for the non-linear age effect on the estimation error observed in Figure 5.[7] Another difference from the previous regressions is that in Model (4.1) we include the control variables in their levels (instead in their dispersion), because we are interested in measuring an effect on a survival-rate-level variable as well.

Regression results for both error level measures yield significant and positive coefficients for the dispersion of objective survival rates. However, the estimation results are highly sensitive to outliers (compare Figure 6, Panels A and B), and standard diagnostic tests clearly reject the normality assumption for the regression residuals. Taking the logarithm of the estimation error (which is possible only for the second measure, which is always positive), however, yields a much more stable model and reveals a more linear relationship (compare Figure 6, Panel C). Regression results for the logarithm of the estimation error level are provided in Table 6.

-- *Table 6 here* --

With respect to age (age and age^2), we find a u-shaped impact on the absolute estimation error level, confirming (from age 49 onward) the positive age effect found in the literature. Moreover, we observe that a longer forecast horizon makes it more difficult for individuals to estimate their survival probability, as reflected by increased errors in the level. With respect to the dispersion in subjective forecasts, there is a significant positive effect of the objective dispersion on the estimation error, which accords with the effects found in the financial analyst literature.

5. Stochastic Mortality and Individuals' Saving Behavior

The results discussed in Section 3 evidence a positive relationship between the dispersion in objective survival data and the dispersion in individuals' subjective survival expectations. Building on findings from the literature on forecast dispersion, we argue that this is evidence that individuals are aware of stochastic mortality. This argument is based by empirical studies on financial analyst forecasts that identify a positive relationship between forecast dispersion and uncertainty regarding the forecast variable (Zarnowitz and Lambros, 1987; Rich,

[7] Adding an age^2 term to Equation (3.1) yields no significant results.

Raymond, and Butler, 1992; Bomberger, 1996; Rich and Tracy, 2006; Barron, Stanford, and Yu, 2009; Lahiri and Sheng, 2010). However, we do not ignore the argument made by Zarnowitz and Lambros (1987) and Engelberg, Manski, and Williams (2009) that any dispersion in forecasts can be caused by both forecaster uncertainty (driven by the underlying uncertainty of the forecast variable) and disagreement among forecasters (who may feel certain about their prediction). To identify the drivers of survival probability dispersion, we use data on SHARE respondents' saving behavior and follow a systematic testing procedure (described below). This analysis thus relates to the question of whether respondents are not only aware of but also act on the existence of stochastic mortality, that is, whether they adjust their savings behavior.

Previous literature shows that both a longer expected lifespan (Bloom et al., 2007) and higher perceived background risk (e.g., Carroll, 1997; Courbage and Rey, 2007; Cocco and Gomes, 2009; Menegatti, 2009) should increase savings. Our analysis of dispersion in subjective survival estimates utilizes these findings to discriminate between forecast uncertainty and disagreement. We structure our analysis according to three mutually exclusive research hypotheses.

Hypothesis 2: Uncertainty in objective survival probability causes uncertainty of individuals regarding their individual survival rate expectation, but does not cause disagreement between individuals.

Hypothesis 3: Uncertainty in objective survival probability causes disagreement between individuals, but each individual is certain about his or her survival rate expectation.

Hypothesis 4: Uncertainty in objective survival probability causes both forecast uncertainty and disagreement between individuals with respect to subjective expectations.

We test these hypotheses by analyzing individuals' saving behavior, as each of the hypotheses is expected to have a different effect on savings behavior. Under *Hypothesis 2*, individuals will accumulate more (buffer stock or precautionary) savings the higher the perceived uncertainty (as indicated by forecast dispersion). However, we should not expect savings differentials between individuals, that is, savings dispersion should not be related to forecast dispersion. Under *Hypothesis 3*, individuals are not aware of stochastic mortality, so higher dispersion should not lead to higher average savings—unless there is a general bias in the level of survival prospect estimation related to uncertainty, for which we control. But, since individuals have different opinions with respect to survival prospects, we expect a positive relationship between forecast dispersion and savings dispersion. Under *Hypothesis 4*, we expect both level and dispersion effects of forecast dispersion on individual savings. Figure 7 summarizes the conceptual framework underlying *Hypotheses 2–4*.

-- *Figure 7 here* --

To test *Hypotheses 2–4*, we estimate two simultaneous equation models (SEM), the first of model incorporating the savings level, the second one the savings dispersion. The SEM for the savings level contains the following three equations:

$$SUB\_DISP_j = \alpha_1 + \beta_1 OBJ\_DISP_j + \boldsymbol{\delta}_1^{\mathrm{T}}\mathbf{z}_{1j} + \varepsilon_{1j}\,, \tag{5.1}$$

$$EST\_ERR\_LEVEL_j = \alpha_2 + \beta_2 OBJ\_DISP_j + \boldsymbol{\delta}_2^{\mathrm{T}}\mathbf{z}_{2j} + \varepsilon_{2j}\,, \tag{5.2}$$

$$SAVE\_LEVEL_j = \alpha_3 + \gamma_1 SUB\_DISP_j + \gamma_2 EST\_ERR\_LEVEL_j + \boldsymbol{\delta}_3^{\mathrm{T}}\mathbf{z}_{3j} + \varepsilon_{3j}\,, \tag{5.3}$$

Equation (5.1) reestablishes the link analyzed in Section 3 (Equation (3.1)) between objective and subjective survival expectation dispersion. Similarly, Equation (5.2) incorporates the findings of Section 4, where, by means of Equation (4.1), we identified a positive link between objective dispersion and the survival probability estimation error level. This equation for the level of estimation error is necessary in our model because in Equation (5.3) we want to control for the possibility that even under pure disagreement (*Hypothesis 3*), objective dispersion may lead to some estimation bias with respect to the survival probability level. These estimation errors could very well have an impact on saving levels if individuals are using an either too long or too short future lifetime as the basis for their saving plans. Thus, without this control, it would be impossible to discriminate between *Hypotheses 2* and *3*. Finally, in Equation (5.3), the overall impact of subjective dispersion and estimation error levels on the savings level is modeled. Again, the vector $\mathbf{z}$ contains group-specific control variables.

We use two alternative indicators to measure savings: the total net worth of a respondent and the respondent's financial assets (see Table 3). Net worth is a very broad measure of wealth accumulation and includes items such as real estate or cars that are in part also consumption goods. Financial assets are less comprehensive but avoid the latter issue.

The savings level simultaneous equation model is estimated via three-stage least squares (3SLS); the estimation results can be found in Table 7.

-- *Table 7 here* --

Results for the model's key equation (Equation (5.3)) show a significant positive link between dispersion in survival probability estimates and the amount of financial assets. No such link is found for the broader savings measure net worth.

In a next step, we specify a simultaneous equation model for savings dispersion:

$$SUB\_DISP_j = \alpha_1 + \beta_1 OBJ\_DISP_j + \boldsymbol{\delta}_1^{\mathrm{T}}\mathbf{z}_{1j} + \varepsilon_{1j}\,, \tag{5.4}$$

$$SAVE\_DISP_j = \alpha_2 + \gamma SUB\_DISP_j + \boldsymbol{\delta}_2^{\mathrm{T}}\mathbf{z}_{2j} + \varepsilon_{2j}\,, \tag{5.5}$$

Again, we incorporate the relation between objective dispersion and subjective dispersion first described in Equation (3.1), now labeled equation (5.4). The overall impact of the dispersion of subjective estimates on savings dispersion is modeled in Equation (5.5) using the coefficient of variation for net worth or financial assets as the dependent variable. In contrast to the savings level SEM, there is no need for including an equation for the estimation error. Here, such an equation would refer to the estimation error dispersion, thus in principle resembling Equation (5.4).[8] Results of the 3SLS estimation of the savings dispersion SEM are given in Table 8.

-- *Table 8 here* --

Results of the savings dispersion SEM are similar with respect to the two savings indicators: that is, there is a positive and significant link between dispersion of subjective survival estimates and financial assets, and no significant effect for net worth.

These results lead to two possible conclusions regarding *Hypotheses 2–4*. First, if net worth is the appropriate indicator for savings, all three hypotheses are rejected. This finding would imply that while the subjective survival probability estimation of SHARE respondents is indeed distorted by objective mortality dispersion, respondents do not act on this at all. If, on

[8] The level of the estimation error is a deterministic additive transformation of the subjective survival probability estimate. This transformation does not contribute additional dispersion.

the other hand, financial assets are the appropriate indicator for savings, *Hypotheses 2 and 3* are rejected and we can conclude that the impact of stochastic mortality on respondents is twofold: both uncertainty and disagreement play a role in the formation of (subjective survival) expectations. Given that net worth encompasses consumption goods, and that the goodness of fit of the net worth SEMs (see AIC and BIC) is inferior, we lean toward the second interpretation (*Hypothesis 4*) of our regression results: SHARE respondents are aware of stochastic mortality, stochastic mortality causes forecaster uncertainty as well as disagreement, and respondents adjust their savings behavior in response to the perceived risk of stochastic mortality.[9]

6. Summary and Conclusions

Annual rates of decline in mortality exhibit considerable variation, which is well described by the term *stochastic mortality*. Theoretical studies indicate that stochastic mortality is an important determinant for individual decisions on consumption, saving, asset allocation, and retirement timing, as well as for equilibrium annuity prices. Our analysis of subjective survival expectations elicited in the SHARE survey and objective mortality data from the Human Mortality Database reveals that SHARE respondents are aware of stochastic mortality. This awareness is reflected in the dispersion of respondents' subjective estimates, which co-varies systematically with dispersion in actual population mortality rate changes. Awareness, in turn, translates into savings behavior, resulting in higher savings when uncertainty is higher.

These findings have particular relevance for the design of pension systems that emphasize individually managed retirement savings and asset allocations. In such systems, it is essential that individuals make informed decisions based on sound expectations about asset returns, returns to human capital, and mortality fluctuations. Although we find that individuals adjust savings in response to stochastic mortality we cannot judge at this moment, whether the response is sufficient or whether it is biased by behavioral factors documented in the savings literature and whether the adjustment of savings is the best possible response at all. Based on the theoretical findings of Cocco and Gomes (2009) this question could provide a fruitful are for future research, as responding only partially correctly to stochastic mortality was shown to

[9] We also tested for the behavioral impact of stochastic mortality on private annuity purchases. SHARE respondents show the "normal" annuitization behavior, i.e., voluntary annuitization is rather. Only 18.8% of the

imply considerable individual welfare costs in the domain of investments into (hypothetical) longevity bonds.

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Table 1 Assignment of individual target age T in SHARE

Current age of respondent, x	Target age, T
≤65	75
66–69	80
70–74	85
75–79	90
80–84	95
85–94	100
95–99	105
100–104	110
105+	120

Table 2 Summary statistics for sample selected from SHARE Wave 2 data

	Country																							
	Austria N = 1,290		Belgium N = 2,923		Czechia N = 2,211		Denmark N = 2,437		France N = 2,322		Germany N = 2,401		Italy N = 2,723		Netherlands N = 2,415		Poland N = 2,224		Spain N = 1,757		Sweden N = 2,415		Switzerland N = 1,379	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Demographics																								
Age, *x*	66.04	65.00	63.85	62.00	62.86	61.00	63.06	61.00	63.50	62.00	64.09	63.00	64.72	64.00	63.06	61.00	63.11	61.00	65.21	64.00	65.07	63.00	63.98	63.00
Gender	0.59	1.00	0.54	1.00	0.58	1.00	0.55	1.00	0.57	1.00	0.54	1.00	0.54	1.00	0.55	1.00	0.56	1.00	0.54	1.00	0.53	1.00	0.55	1.00
Couple	0.63	1.00	0.75	1.00	0.71	1.00	0.76	1.00	0.72	1.00	0.81	1.00	0.83	1.00	0.80	1.00	0.77	1.00	0.80	1.00	0.77	1.00	0.72	1.00
Education	2.92	3.00	2.80	3.00	2.50	2.00	3.40	3.00	2.58	3.00	3.41	3.00	1.92	1.00	2.83	2.00	2.28	3.00	1.64	1.00	2.78	3.00	2.93	3.00
Health and Cognition																								
Self-Perceived Health	3.02	3.00	2.95	3.00	3.33	3.00	2.54	2.00	3.12	3.00	3.18	3.00	3.26	3.00	2.93	3.00	3.85	4.00	3.40	3.00	2.75	3.00	2.56	3.00
Grip Strength	35.20	33.00	35.68	34.00	36.21	34.00	34.91	33.00	34.25	32.00	37.19	35.00	33.15	31.00	36.20	35.00	33.56	32.00	30.61	29.00	36.79	35.00	35.74	34.00
Numeracy	3.73	4.00	3.41	3.00	3.56	4.00	3.66	4.00	3.32	3.00	3.75	4.00	2.99	3.00	3.75	4.00	2.98	3.00	2.62	3.00	3.71	4.00	3.87	4.00
Economic Indicators PPP adj. €																								
Income	38,143	22,762	42,744	22,689	20,385	13,033	32,647	28,237	60,880	28,772	33,365	25,020	37,127	19,093	41,293	29,175	37,758	9,304	79,345	15,422	32,818	27,811	40,149	30,766
Pension Income	8,807	7,017	5,953	0	3,701	5,015	3,362	0	6,379	205	6,627	0	3,881	0	6,323	0	2,987	2,071	4,161	0	4,810	0	7,000	0
Financial Wealth	34,288	10,507	99,183	37,055	12,256	5,286	120,028	53,296	66,967	20,461	54,269	24,062	23,069	5,795	83,430	29,455	14,708	0	35,619	6,094	90,796	42,797	145,616	60,836
Net Worth	195,232	145,029	344,129	253,566	196,963	84,854	505,219	193,343	392,823	261,324	233,296	148,659	296,063	197,387	417,854	201,692	76,585	42,319	337,753	226,544	744,723	153,740	475,794	217,036
Survival Expectation																								
Forecast Horizon	14.79	14.00	16.22	15.00	16.38	15.00	16.50	15.00	16.41	15.00	15.58	14.00	15.42	14.00	16.16	15.00	16.40	15.00	15.69	14.00	15.26	14.00	16.11	14.00
Subj. Survival Probabiliy	0.59	0.60	0.58	0.60	0.43	0.50	0.69	0.80	0.62	0.60	0.60	0.60	0.67	0.70	0.66	0.70	0.48	0.50	0.61	0.60	0.62	0.70	0.66	0.70

Note: Summary statistics were calculated based on the unweighted data.

Table 3 Definition of variables

Variable	Definition
Age	Age of respondent
Gender	Gender: 0 = male, 1 = female
Couple	Marital status: 0 = married or partnership, 1 = otherwise
Education	International Standard Classification of Education (ISCED 97) (0 = no education … 6 = Ph.D.)
Self-Perceived Health	Self-perceived health ("US version") (1 = excellent … 5 = poor)
Grip Strength	Maximum grip strength measurement of hands
Numeracy	Numeracy score (mathematical performance) (1 = bad … 5 = good)
Income	Total, purchasing power adjusted, Euro, net income of household, including income from employment, self-employment, pensions, invalidity or unemployment benefits, alimony or other private regular payments, long-term care insurance, housing allowances, child benefits, poverty relief, real estate (incl. imputed rents), land or forestry, and capital income
Pension Income	Total, purchasing power adjusted, Euro, old-age pension income of household, including old-age pensions from government, occupational schemes, and private annuities
Pension Share	Pension income divided by income
Financial Wealth	Total, purchasing power adjusted, Euro, financial wealth of household including bank accounts, government and corporate bonds, stocks, mutual funds, individual retirement accounts, contractual savings for housing, and life insurance policies
Net Worth	Total, purchasing power adjusted, Euro, net worth of household, including real assets (real estate, share owned of businesses, cars), financial assets (bank accounts, government and corporate bonds, stocks, mutual funds, individual retirement accounts, contractual savings for housing, and life insurance policies) minus the value of mortgages and financial liabilities
Forecast Horizon	Forecast horizon for estimate of subjective survival probability = T (as defined in Table 1) minus age
Subjective Survival Probability	Response to the question: "What are the chances that you will live to be age T or more?" divided by 100
Relative Estimation Error	Subjective survival probability minus objective estimate of the survival probability divided by the objective probability
Relative Absolute Estimation Error	ABS(Subjective survival probability minus objective estimate of the survival probability) divided by the objective probability
Group Size	Number of respondents in an age-gender-country-couple group

Table 4 Summary statistics for SHARE Wave 2 and HMD grouped data

	Country																							
	Austria		Belgium		Czechia		Denmark		France		Germany		Italy		Netherlands		Poland		Spain		Sweden		Switzerland	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
	N = 141		N = 167		N = 158		N = 167		N = 164		N = 142		N = 159		N = 160		N = 150		N = 151		N = 166		N = 146	
Group Size	9.00	8.00	17.37	12.00	13.87	10.00	14.48	9.00	13.99	11.00	16.70	9.50	16.99	9.00	14.96	7.00	14.66	10.00	11.45	7.00	14.37	9.00	9.21	7.00
Age, x	67.84	68.00	67.41	67.00	66.15	66.00	66.95	67.00	67.56	67.50	66.65	66.50	66.69	67.00	67.29	67.00	67.32	67.00	67.88	68.00	68.17	68.00	66.92	67.00
Gender	0.55	1.00	0.53	1.00	0.54	1.00	0.53	1.00	0.55	1.00	0.56	1.00	0.53	1.00	0.54	1.00	0.53	1.00	0.56	1.00	0.54	1.00	0.57	1.00
Couple	0.52	1.00	0.52	1.00	0.53	1.00	0.53	1.00	0.53	1.00	0.54	1.00	0.53	1.00	0.54	1.00	0.52	1.00	0.54	1.00	0.51	1.00	0.56	1.00
Forecast Horizon	15.14	14.00	15.86	14.00	16.16	14.00	15.99	14.00	15.70	14.00	15.57	14.00	15.92	14.00	15.71	14.00	15.35	14.00	15.43	14.00	15.44	14.00	15.79	14.00
CV Subj. Estimate	0.56	0.47	0.57	0.46	0.74	0.62	0.54	0.46	0.56	0.46	0.59	0.47	0.49	0.42	0.49	0.42	0.69	0.64	0.58	0.49	0.65	0.50	0.46	0.37
CV Obj. Probability	0.04	0.02	0.04	0.03	0.06	0.05	0.05	0.03	0.03	0.02	0.04	0.03	0.03	0.03	0.03	0.02	0.07	0.05	0.03	0.01	0.03	0.02	0.03	0.01
Relative Estimation Error	0.46	-0.16	0.49	-0.19	0.33	-0.34	0.65	0.05	0.19	-0.21	0.22	-0.19	0.49	-0.12	0.69	-0.09	0.77	-0.26	0.55	-0.16	0.17	-0.14	0.34	-0.13
Relative Abs. Est. Error	0.98	0.36	1.04	0.35	1.15	0.48	1.05	0.36	0.77	0.35	0.81	0.36	0.94	0.34	1.10	0.32	1.44	0.48	1.11	0.37	0.77	0.38	0.77	0.30
Std Relative Est. Error	0.96	0.36	1.16	0.34	1.24	0.37	1.10	0.44	0.85	0.32	0.84	0.34	0.83	0.37	1.01	0.36	1.44	0.42	1.15	0.38	0.98	0.38	0.70	0.31
Std Rel. Abs. Est. Error	0.77	0.27	0.97	0.27	1.01	0.29	0.83	0.28	0.67	0.26	0.66	0.28	0.66	0.26	0.84	0.26	1.24	0.32	0.91	0.29	0.71	0.27	0.55	0.23

Note: N denotes the number of groups with more than one individual. For calculation of group-based measures, the SHARE weights are not applied. Groups are based on age, gender, country, and couple. Mean and median values are calculated across all data points.

Table 5 OLS regression results for SHARE/HMD grouped data; dependent variable: coefficient of variation of group-specific subjective survival probabilities

	(1)		(2)		(3)	
	Coef.	Bootstr. std. err.	Coef.	Bootstr. std. err.	Coef.	Bootstr. std. err.
Group Size	-0.0002	0.0005	-0.0004	0.0006	-0.0006	0.0005
Age	0.0197	0.0017 ***	0.0196	0.0018 ***	0.0187	0.0016 ***
Gender	-0.0063	0.0124	-0.0060	0.0121	-0.0071	0.0123
Couple	-0.0402	0.0159 **	-0.0402	0.0172 **	-0.0396	0.0167 **
Forecast Horizon	0.0211	0.0030 ***	0.0209	0.0028 ***	0.0188	0.0026 ***
CV Obj. Prob.	2.7109	0.4667 ***	2.7745	0.4775 ***	3.0258	0.4502 ***
CV Net Worth			-0.0006	0.0042	0.0001	0.0037
CV Income			0.0128	0.0063 **	0.0116	0.0059 **
CV Education					-0.0167	0.0166
CV Self-Perc. Health					0.0224	0.0227
CV Grip					0.0713	0.0988
CV Numeracy					0.0243	0.0242
Constant	-1.1528	0.1465 ***	-1.1512	0.1425 ***	-1.1057	0.1346 ***
N	1,871		1,869		1,814	
Adjusted R^2	0.4530		0.4517		0.4738	

* significant at 10%, ** significant at 5%, *** significant at 1% level

Table 6 OLS regression results for SHARE/HMD grouped data; dependent variable: log of group-specific relative absolute estimation

	Coef.	Bootstr. std. err.
Group Size	0.0053	0.0012 ***
Age	-0.1696	0.0312 ***
Age^2	0.0017	0.0002 ***
Gender	-0.0486	0.0728
Couple	-0.1093	0.0311 ***
Forecast Horizon	0.0404	0.0084 ***
CV Obj. Prob.	5.3994	0.9148 ***
Net Worth	0.0000	0.0000
Income	0.0000	0.0000 *
Education	-0.0295	0.0232
Self-Perc. Health	0.1082	0.0299 ***
Grip	0.0006	0.0045
Numeracy	0.0008	0.0318
Constant	5.3994	0.9148 ***
N	1,878	
Adjusted R^2	0.7394	

* significant at 10%, ** significant at 5%, *** significant at 1% level

Table 7 Simultaneous equation model (SEM) for the savings level; two savings indicators; three-stage least squares estimation results for SHARE/HMD grouped data

	Net Worth Level SEM		Financial Assets Level SEM	
	Coef.	Bootstr. std. err.	Coef.	Bootstr. std. err.
Dependent Variable	*Equ. (5.1): SUB_DISP = CV Sub. Surv. Prob.*			
Group Size	0.0000	0.0006	0.0008	0.0008
Age	0.0199	0.0018 ***	0.0217	0.0022 ***
Gender	-0.0154	0.0125	-0.0163	0.0122
Couple	-0.0493	0.0163 ***	-0.0631	0.0178 ***
Forecast Horizon	0.0214	0.0029 ***	0.0244	0.0035 ***
CV Obj. Prob.	2.7713	0.5338 ***	2.4717	0.6379 ***
CV Net Worth	0.0045	0.0069		
CV Financial Wealth			0.0389	0.0147 ***
CV Income	0.0010	0.0061	-0.0029	0.0068
Std Education	-0.0115	0.0156	-0.0095	0.0143
Std Self-Perc. Health	-0.0002	0.0214	0.0101	0.0214
CV Grip	0.1685	0.1134	0.0344	0.0834
Std Numeracy	0.0498	0.0235 **	0.0492	0.0210 **
Constant	-1.2430	0.1662 ***	-1.4328	0.2039 ***
Dependent Variable	*Equ. (5.2): EST_ERR_LEVEL = Log of Rel. Abs. Est. Error*			
Group Size	0.0047	0.0013 ***	0.0029	0.0013 **
Age	-0.1793	0.0330 ***	-0.1902	0.0317 ***
Age^2	0.0017	0.0002 ***	0.0017	0.0002 ***
Gender	-0.1173	0.0695 *	-0.0679	0.0725
Couple	-0.1700	0.0647 ***	-0.2243	0.0647 ***
Forecast Horizon	0.0278	0.0092 ***	0.0209	0.0099 **
CV Obj. Prob.	6.0105	1.1911 ***	8.5586	1.3978 ***
Net Worth	0.0000	0.0000		
Financial Wealth			0.0000	0.0000 **
Income	0.0000	0.0000	0.0000	0.0000 **
Education	-0.0178	0.0219	-0.0745	0.0339 **
Self-Perc. Health	0.0963	0.0533 *	0.1839	0.0659 ***
Grip	-0.0060	0.0045	-0.0018	0.0044
Numeracy	0.0144	0.0331	-0.0529	0.0395
Constant	2.4252	1.2870 *	2.9545	1.2881 **
	Equ. (5.3): SAVE_LEVEL =			
Dependent Variable	*Net Worth*		*Financial Assets*	
Age	-77,101.93	90,453.40	-13,901.18	7,953.13 *
Age^2	702.77	761.83	138.75	68.93 **
Gender	61,134.27	98,960.68	-7,527.86	9,923.17
Couple	136,999.70	31,966.52 ***	17,260.66	4,220.21 ***
Education	6,442.72	25,489.04	10,795.39	3,024.21 ***
Self-Perc. Health	-110,267.70	39,409.49 ***	-21,181.81	5,053.80 ***
Grip	8,272.12	6,163.64	-37.25	600.52
Numeracy	-624.41	44,278.87	16,107.92	5,169.82 ***
Income	0.06	0.19	0.07	0.03 **
Pension Share	-326,994.50	154,026.30 **	-70,500.73	18,282.52 ***
Log Rel. Abs. Est. Error	-585,907.20	517,039.30	-120,435.30	50,674.15 **
Sub. Surv. Prob.	1,959,536.00	1,550,873.00	318,596.20	166,630.40 *
CV Sub. Surv. Prob.	2,475,178.00	2,096,772.00	427,053.90	210,575.60 **
Constant	-676,065.30	2,170,192.00	-166,987.80	219,431.90
N	1,773		1,768	
AIC	54,176		46,691	
BIC	54,401		46,916	

* significant at 10%, ** significant at 5%, *** significant at 1% level

Table 8 Simultaneous equation model (SEM) for the dispersion in savings; two indicators for the saving level; three-stage least squares estimation results for SHARE/HMD grouped data

	Net Worth Dispersion SEM		Financial Assets Dispersion SEM	
	Coef.	Bootstr. std. err.	Coef.	Bootstr. std. err.
Dependent Variable	*Equ. (5.4): SUB_DISP = CV Sub. Surv.Prob.*			
Group Size	-0.0053	24.9818	0.0011	0.0040
Age	0.0210	3.7960	0.0174	0.0041 ***
Gender	-0.0601	61.3421	-0.0051	0.0228
Couple	0.0131	259.7296	-0.0598	0.0411
Forecast Horizon	0.0200	9.0266	0.0159	0.0097
CV Obj. Prob.	2.4415	3201.7050	3.8105	1.4412 ***
CV Net Worth	0.3414	1586.0620		
CV Financial Wealth			-0.1242	0.2885
CV Income	0.0411	690.7319	0.0244	0.0322
Std Education	-0.0213	55.6996	-0.0217	0.0176
Std Self-Perc. Health	-0.0359	183.2232	0.0130	0.0282
CV Grip	0.1872	516.1696	0.1500	0.2106
Std Numeracy	-0.0601	367.2323	0.0430	0.0271
Constant	-1.4994	1731.2690	-0.8643	0.6716
	Equ. (5.5): SAVE_DISP =			
Dependent Variable	*CV Net Worth*		*CV Financial Assets*	
Age	0.0346	0.0298	0.1357	0.0177 ***
Age^2	-0.0003	0.0003	-0.0011	0.0002 ***
Gender	0.1618	0.0858 *	0.0927	0.0258 ***
Couple	0.0225	0.0578	0.0712	0.0265 ***
Std Education	0.0176	0.0469	0.0173	0.0283
Std Self-Perc. Health	0.1823	0.0820 **	-0.0489	0.0417
CV Grip	-0.1434	0.2899	0.5692	0.1648 ***
Std Numeracy	0.2843	0.0904 ***	0.0374	0.0396
CV Income	-0.0579	0.3614	0.1390	0.0231 ***
CV Sub. Surv. Prob.	0.0990	0.7164	0.5883	0.2028 ***
Constant	-0.2094	1.2000	-3.3370	0.5665 ***
N	1,773		1,768	
AIC	7,232		2,752	
BIC	7,364		2,884	

* significant at 10%, ** significant at 5%, *** significant at 1% level

Figure 1 One-year realized probabilities of death, data source: Human Mortality Database

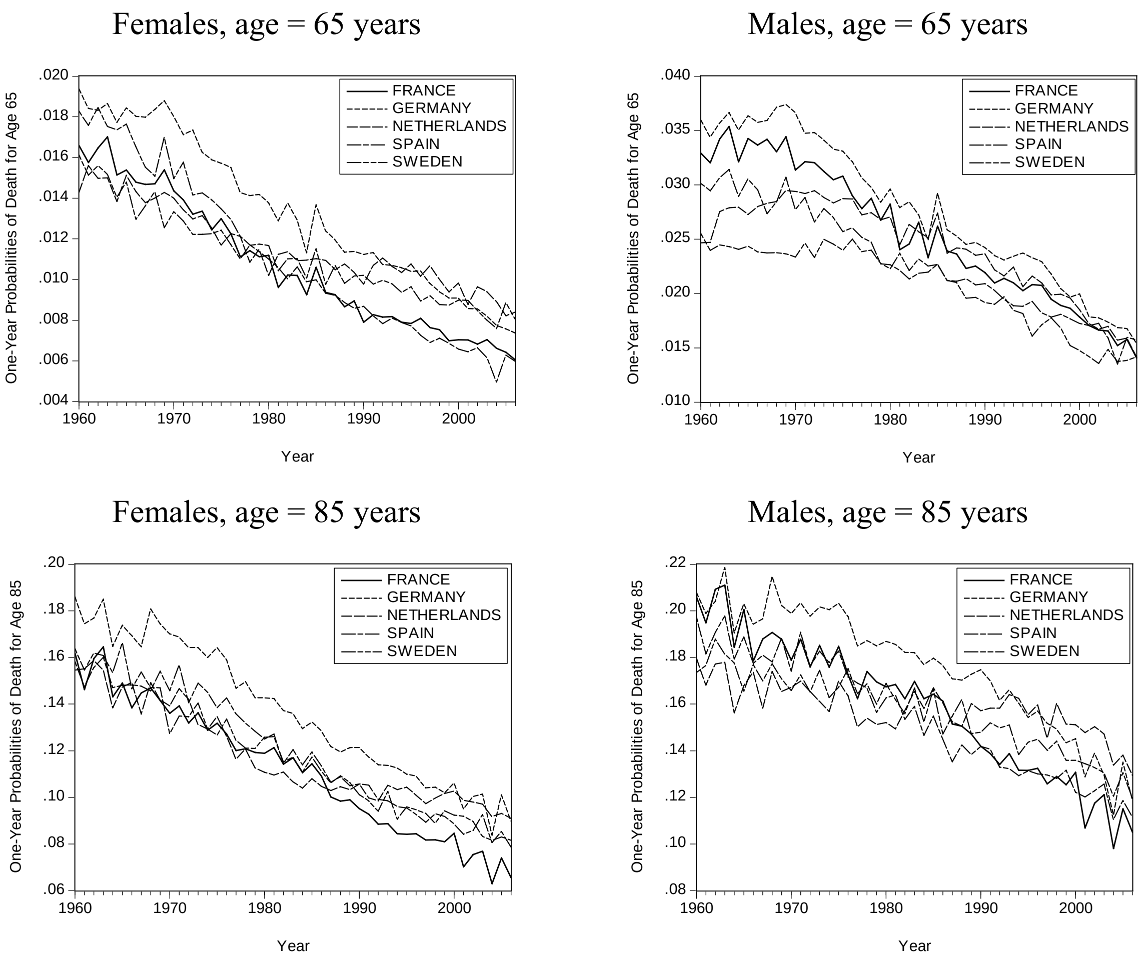
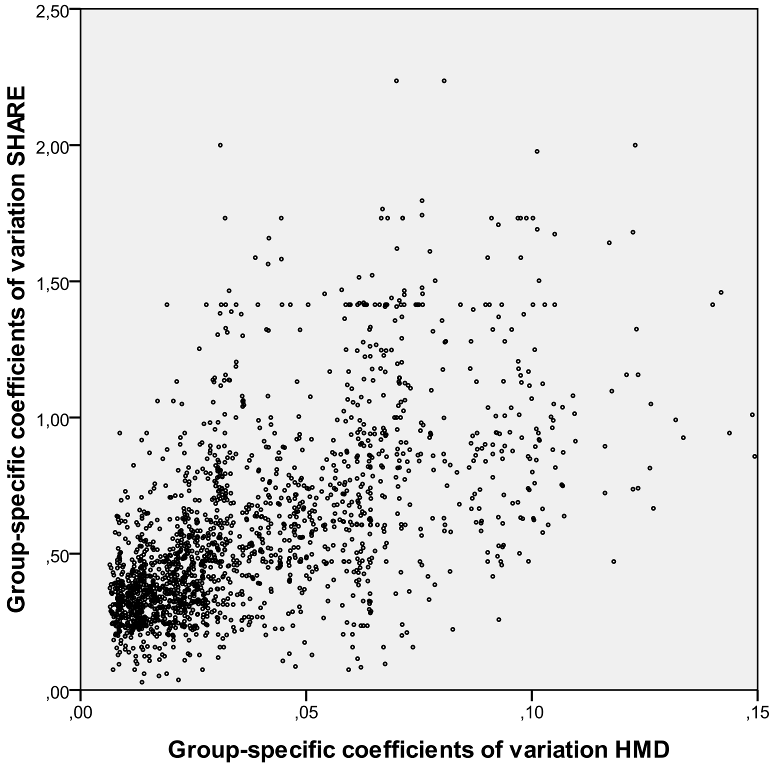
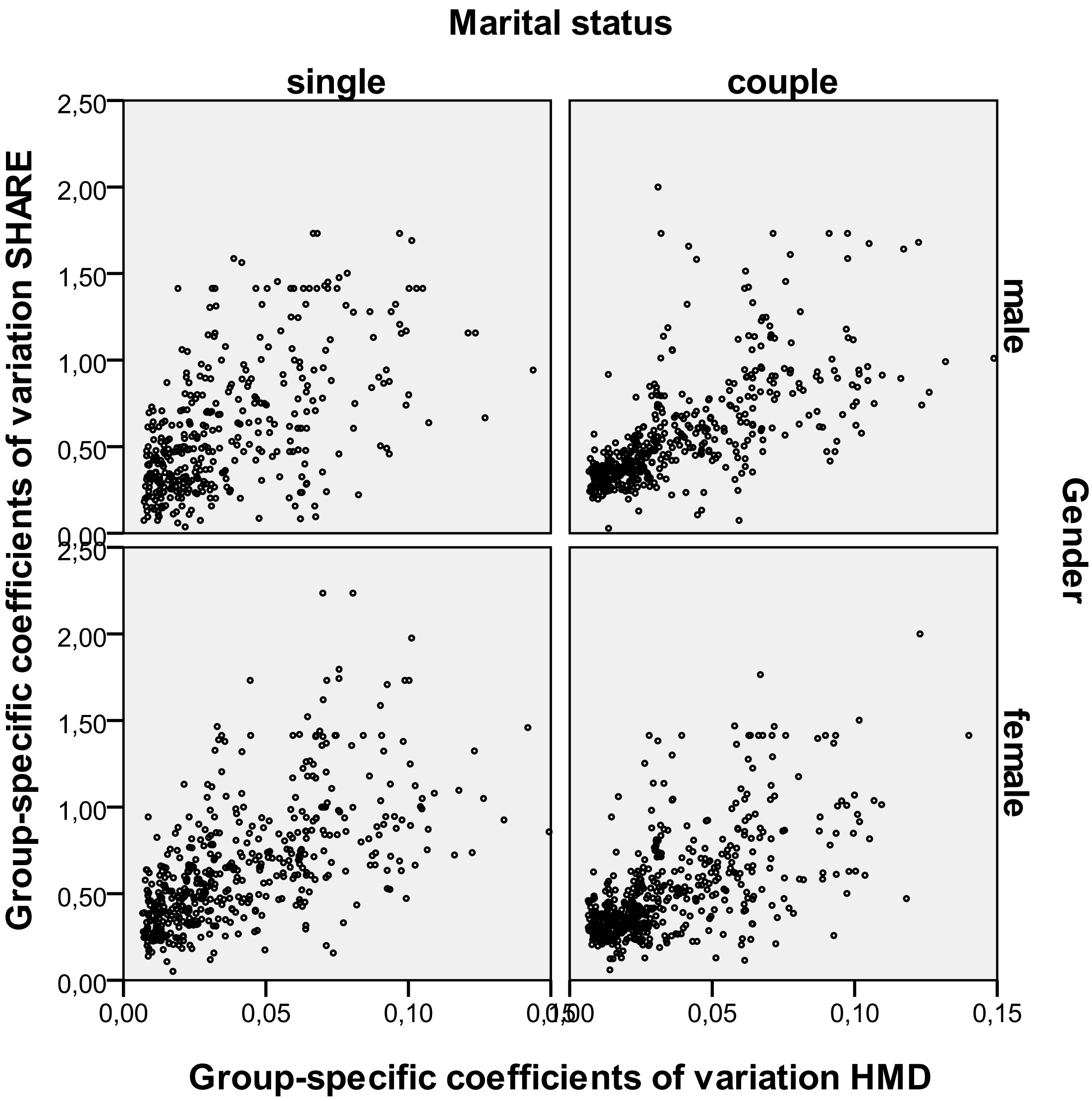


Figure 2 Scatter plot of group-specific coefficients of variation of HMD and SHARE data



Note: Each point represents one group of individuals with a certain characteristic in the dimensions of age, gender, country, and couple.

Figure 3 Scatter plot of group-specific coefficients of variation of HMD and SHARE data



Note: Each point represents one group of individuals with fixed characteristic in the dimensions age, gender, country, and couple.

Figure 4 Mean group-specific coefficients of variation of HMD (Panel A) and SHARE (Panel (B) data, data grouped according to age, gender, country, and couple; mean calculated over gender and couple

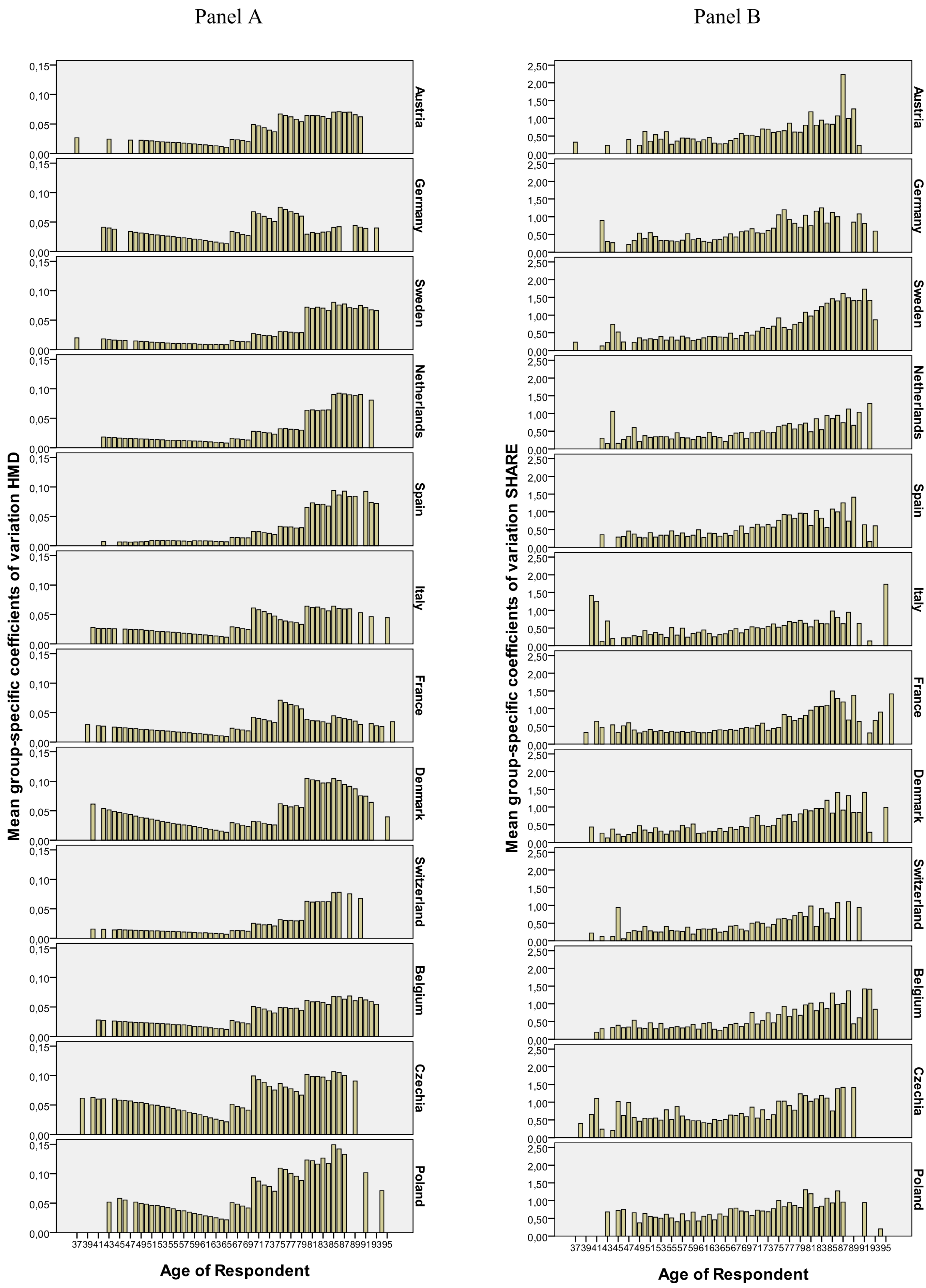


Figure 5 Mean group-specific relative estimation error, data grouped according to age, gender, country, and couple; mean calculated over gender and couple

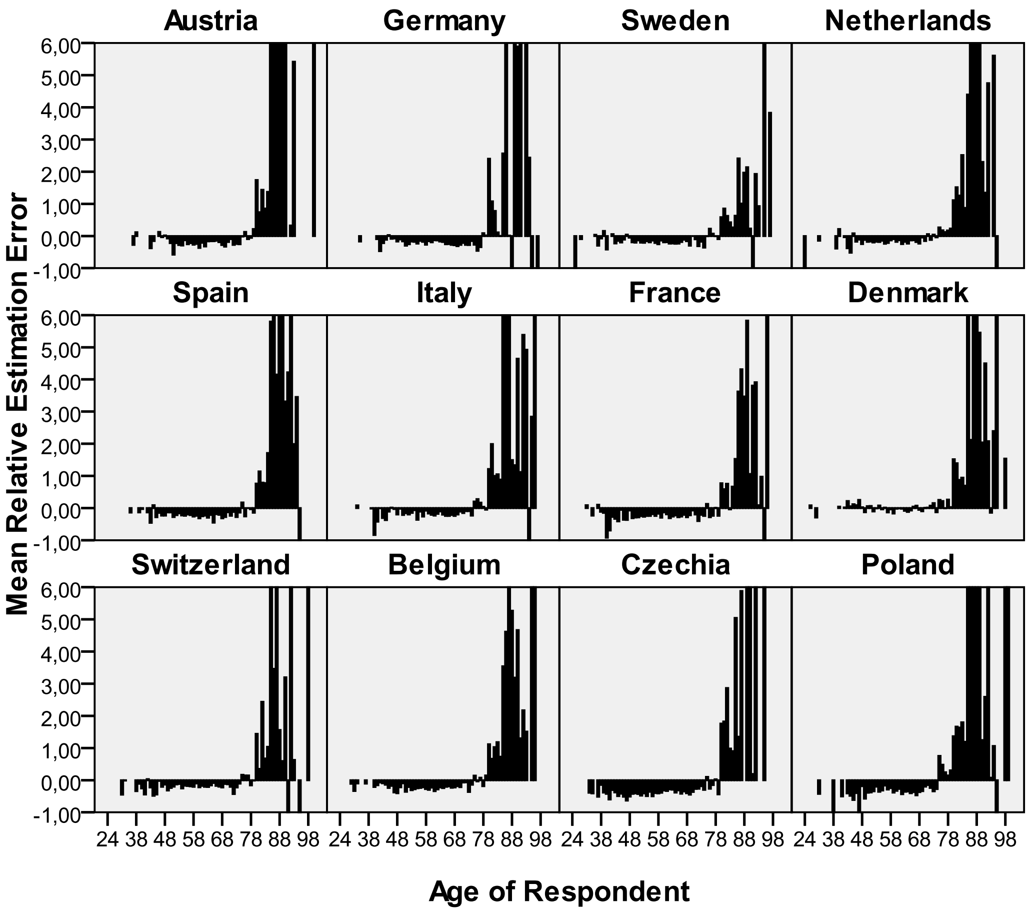
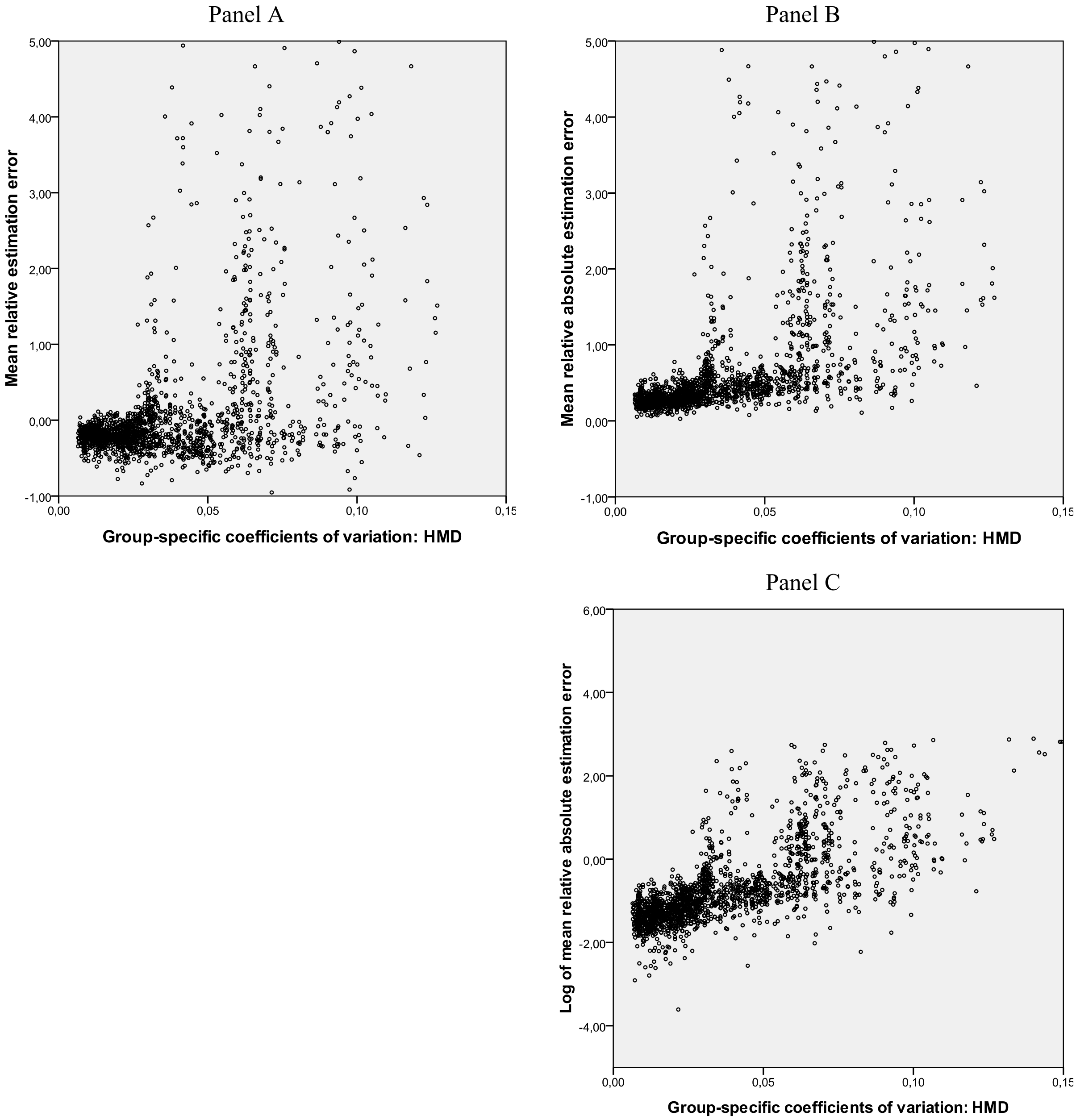
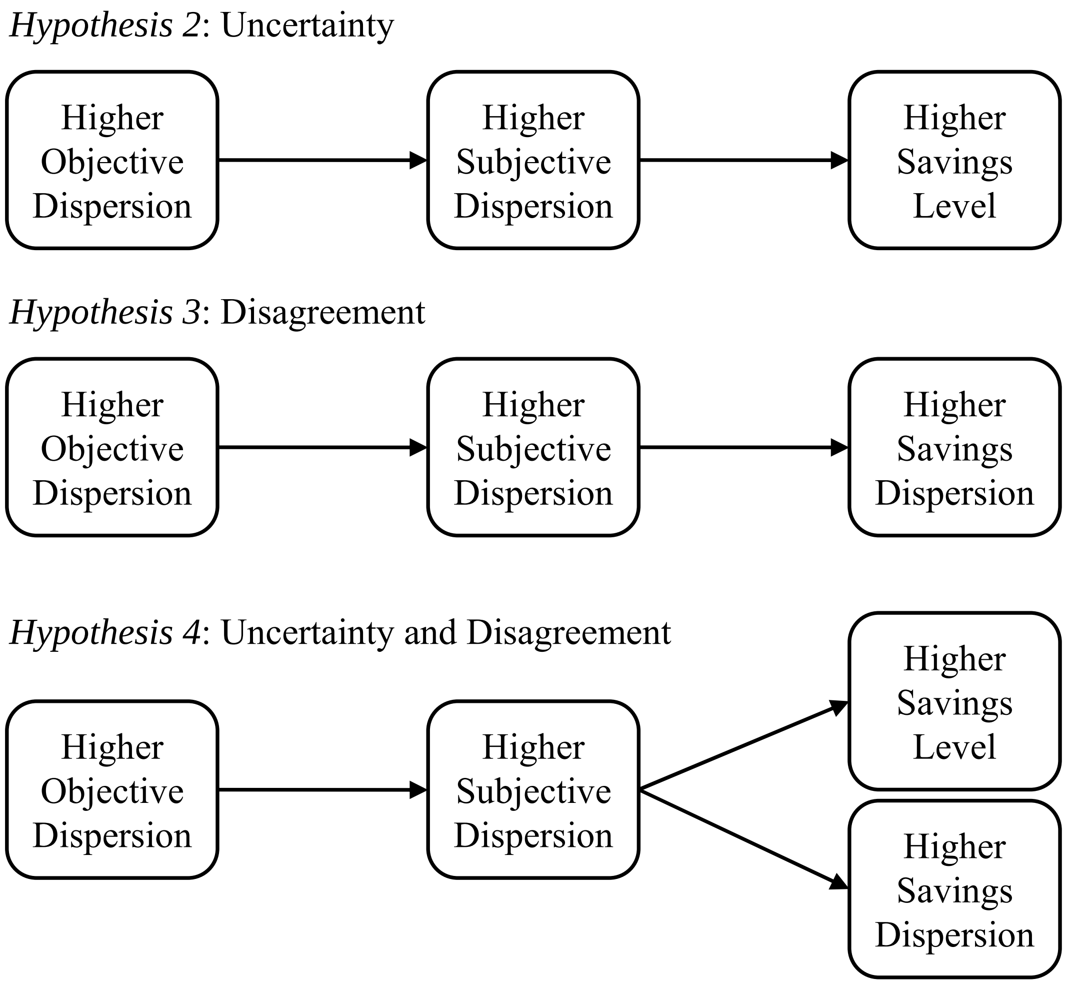


Figure 6 Scatter plots of group-specific coefficients of variation of HMD data and estimation errors in SHARE data, relative estimation error (Panel A), relative absolute estimation error (Panel B), and logarithm of relative absolute estimation error (Panel C)



Note: Each point represents one group of individuals with fixed characteristic in the dimensions age, gender, country, and couple.

Figure 7 Conceptual links underlying savings-behavior-related research hypotheses



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