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How Much Does Risk Tolerance Change?

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Abstract

Stability of preferences is central to how economists study behavior. This paper uses panel data on hypothetical gambles over lifetime income in the Health and Retirement Study to quantify changes in risk tolerance over time and differences across individuals. Maximum-likelihood estimation of a correlated random effects model utilizes information from 12,000 respondents in the 1992–2002 HRS. The results are consistent with constant relative risk aversion and career selection based on preferences. While risk tolerance changes with age and macroeconomic conditions, persistent differences across individuals account for over 70% of the systematic variation.

1 INTRODUCTION

> "One does not argue over tastes for the same reason that one does not argue over the Rocky Mountains—both are there, will be there next year, too, and are the same to all men." Stigler and Becker (1977)

This paper approaches the fundamental debate on preference stability as an empirical question. Hypothetical gambles asked repeatedly to the same individuals over ten years provide a unique lever for this direct study of changes in risk tolerance. The gambles pose a well-defined risky choice that is comparable both across individuals and over time. The odds of the gambles are explicit, the stakes over lifetime income are large, albeit hypothetical, and most importantly for this study, the attributes of the gambles do not change over time. As a result, the panel of gamble responses offers a unique view of the changes in risk preference measured at the individual level.

To quantify risk preferences, I use gamble responses across the 1992 to 2002 waves of the Health and Retirement Study (HRS).[1] The placement of the gambles in the HRS with its rich individual and household information is crucial for measuring the systematic variation in risk preference. Throughout the paper, I refer to systematic variation as the variation (within or between individuals) that is associated with differences in observables. Yet, even with a rich set of observables there is substantial idiosyncratic variation in the gamble responses that remains unexplained. To interpret the gamble responses, I adapt the framework from Barsky et al. (1997) and Kimball et al. (2008) that maps the gambles to the coefficient of relative risk tolerance. I provide the first direct test with the HRS gambles of whether an individual's risk tolerance changes over time and whether individuals exhibit

[1]The Health and Retirement Study began in 1992 as a large biennial panel survey of Americans over the age of 50 and their spouses. Further information on the survey and the data are available at http://hrsonline.isr.umich.edu.

constant relative risk aversion.[2] My analysis of the gamble responses also is the first to incorporate the detailed information in the HRS on individuals over the panel period in a multi-variate model of risk tolerance. This additional information allows me to investigate the drivers of preference change, the degree of selection on preference type, and the measurement error in the gambles. I model risk tolerance with a time varying component and a time-constant component and use the panel to separate within-person and across-person variation in preferences. Specifically, I estimate a correlated random effects model of risk tolerance with 18,625 gamble responses from 12,003 individuals between ages 45 and 70.[3]

My results suggest that less than 30% of the systematic variation in risk tolerance—for this sample of older adults in the 1990s—is associated with time-varying attributes. In particular, the changes in household income and wealth over the decade do not alter an individual's measured willingness to take risk (consistent with CRRA utility). Likewise, major life events of a job displacement and the diagnosis of a serious health condition that likely reduce expected lifetime income also have little impact on measured risk tolerance. My analysis does identify two quantitatively important changes: risk tolerance declines modestly with age and increases with an improvement in macroeconomic conditions. Nonetheless, time-constant attributes, including gender,race, and education, are the largest source of the systematic variation. The results are also consistent with past selection of risky careers and high debt levels based on the individual's risk tolerance type. While risk preferences do change predictably over time in this sample of older adults, persistent difference across individuals are a much more important source of systematic variation.

This decomposition of the systematic variation pertains only to within-person and across-time differences in the gamble responses that are associated with observable attributes. It is important to stress that this systematic variation is notably smaller than either the idiosyncratic, time-constant variation or the unexplained, transitory variation from the gambles. While these features of the data are in my statistical model which utilizes the panel of gambles and incorporates survey response errors, in my interpretation of the results, I focus on the systematic (or predictable) patterns in risk tolerance.

The plan of the paper is as follows. Section 2 discusses the hypothetical gambles in the HRS. Section 3 uses expected utility theory to map the gamble responses to the coefficient of relative risk tolerance and then develops the statistical model of risk tolerance based on the gamble responses. Section 4 presents the results from maximum-likelihood estimation of the model. Section 5 discusses the credibility of the data and compares the results to the literature. The final section offers conclusions.

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[2]Barsky et al. (1997) and Kimball et al. (2008) both assume that any changes in an individual's gamble responses over time are noise and that constant relative risk aversion is a good approximation for utility. Furthermore these papers focus on the *level* of individual risk tolerance that is based only on the gamble responses.

[3]Individuals in the sample answer these gambles in 1.6 survey waves on average while they participate in 4.7 HRS waves on average. The lower frequency of gamble responses owes to the targeted (and randomized) delivery of the gambles. With six years on average between pairs of gamble responses, the data is informative of changes in risk tolerance over time.

2 GAMBLES OVER LIFETIME INCOME

The Health and Retirement Study uses hypothetical gambles over lifetime income to elicit risk attitudes. In a short series of questions, individuals choose between two jobs; one job guarantees current lifetime income and the other job offers an unpredictable, but on average higher lifetime income. In the 1998 HRS, individuals consider the following scenario:

> Suppose that you are the only income earner in the family. Your doctor recommends that you move because of allergies, and you have to choose between two possible jobs.
>
> The first would guarantee your current total family income for life. The second is possibly better paying, but the income is also less certain. There is a 50–50 chance the second job would double your total lifetime income and a 50–50 chance that it would cut it by a third. Which job would you take—the first job or the second job?

Individuals who accept the first risky job then consider a job with a larger downside risk of one-half, while those who reject the first risky job are asked about a job with a smaller downside risk of one-fifth. If they reject the first two risky jobs, individuals consider a third risky job that could cut their lifetime income by one-tenth. Likewise, if they accept both risky jobs, individuals consider a third risky job that could cut their lifetime income by three-quarters.[4] I use these responses to order individuals in a small number of categories. Table 1 relates the gamble response category to the downside risks that the individual accepts and rejects. The category numbers are increasing in an individual's willingness to accept income risk, so the gamble responses provide a coarse ranking of individuals by their risk preference.

I analyze 18,625 gamble responses on the 1992, 1994, 1998, 2000, and 2002 waves of the HRS from 12,003 individuals in the 1931 to 1947 birth cohorts.[5] The panel of gamble responses is unbalanced due to survey attrition, expansion of the survey in 1998, and targeted delivery of the gamble questions in the survey. In particular, the survey usually asks the gambles to new respondents and a random sub-sample of returning respondents. Nonetheless 45% of the individuals answer the battery of income gambles in multiple waves and 8% answer the gambles in three or more waves.

The distribution of gamble responses in Table 2a shows that most individuals are unwilling to take income risks even when the expected value of the gamble is substantially larger than their current lifetime income. In 1992, more than two-thirds of individuals reject the risky

[4]See Kimball et al. (2008) for more details on the minor differences in the gamble question sequence across the five HRS waves. Most notably, in the 1992 and 1994 HRS, the risky job was described as "new" job and there are only two follow-up questions in the 1992 HRS; however, the objective risks in the gambles are the same in all waves.

[5]In 1992 the HRS has a representative sample of individuals age 51 to 61, that is, the 1931 to 1941 birth cohorts, plus their spouses. The spouses are not necessarily representative of their birth cohort. The HRS periodically updates its sample to maintain a snapshot of Americans over age 50. Starting in 1998, the HRS has a representative sample of individuals in the 1942 to 1947 birth cohorts that includes some of the spouses surveyed in earlier waves of the HRS. I use all of the survey responses from individuals in the 1931 to 1947 cohorts across the first six waves. I exclude the gamble responses of spouses outside these birth cohorts, as well as the representative sample of individuals in the 1921 to 1929 cohorts, since they are mostly retired at their initial survey and some express difficulty with the job-related gambles. To insure that the gamble is defined over non-trivial amounts of income, I also exclude individuals with total income less than $6,500 in 2002 dollars (or roughly the fifth percentile of income) at the time of their gamble responses or as an average across the six survey waves. The sample selection criteria have qualitatively little effect on the results.

job that offers a 50–50 chance to double lifetime income or cut it by one-fifth. The expected value of the income from this risky job is 140% of current lifetime income. And less than 13% of individuals accept the risky job with a downside risk of one-half which has an expected value of 125% of current lifetime income. The distribution of the gamble response categories is fairly stable across waves, though individuals in 1998 are willing to accept somewhat more income risk.

This study of changes in risk tolerance utilizes the fact that some individuals answer the gambles in multiple waves. Table 2b summarizes the distribution of response categories across the 6,622 pairs of gambles. The lowest response category 1–2 is the most prevalent, regardless of the response category in the first response. Nonetheless, the rank correlation between the categories in a pair of responses from an individual is 0.18. While this is far from a perfect correlation, it is statistically different from zero at the 1% level. The substantial changes in the gamble response categories across waves might appear to suggest a large degree of change in risk tolerance; however, I will argue that after filtering out the noise, there are only modest systematic changes in risk tolerance.

The placement of these gambles on a large panel study provides an ideal opportunity to study systematic changes in risk tolerance, and the decade in which the gambles are fielded coincides with significant changes in individual circumstances and macroeconomic conditions. Table 3 summarizes the primary set of individual attributes and events that I use to quantify systematic changes in risk tolerance. First the considerable diversity in the sample of gamble respondents in the HRS is noteworthy. Of the 18,625 gamble responses, 43% are from men, 15% are from blacks, and 8% are from Hispanics.[6] About one-fifth of the responses are from individuals with less than twelve years of education versus one-fifth from individuals with sixteen or more years of education.

Over the panel, several individuals have experiences that plausibly alter their expected lifetime income. I focus particularly on job displacements and serious health conditions. While an individual's past behavior may influence the occurrence of these events, they are not perfectly predictable and should represent some shock to an individual. Prior to their gamble response, 25% of the respondents had experienced a job displacement, that is, a job ending with a firm closure or layoff, and 22% had received a diagnosis of heart disease, a stroke, cancer, or lung disease. Most importantly, 13% of the gamble responses were followed later in the survey by a first job displacement for the individual and 17% by a first diagnosis of a serious health condition. This within-person variation is what allows me to identify the direct effect of these events on an individual's risk tolerance. Table 3 also shows that there are meaningful changes in income and wealth during the panel period.[7] On average, the household income and wealth of the respondents at the time of their gamble response is below the average levels of their total income and wealth across the 1992 to

[6]The HRS over-samples blacks, Hispanics, and residents of Florida. The tabulations and estimation in the paper place equal weight on each gamble respondent and do not reflect the distribution of attributes in the population.

[7]Wealth is the total household net worth including housing wealth and excluding pension and Social Security wealth. Income is the total income of a respondent and spouse from all earnings, transfers, and other sources of income. Wealth and income are from the RAND HRS data set and include imputed values.

2002 survey waves. But there is substantial variation across respondents in both the average level and changes in income and wealth.

The gamble responses also coincide with significant changes in the macroeconomy. Performance of the U.S. stock market particularly defined the survey period of April 1992 to February 2003. Figure 1 depicts the large increase and then sharp decline in the annual real returns on the S&P 500 Index. The shaded areas on the figure denote months in which the HRS asked the income gamble questions. The gambles appear on five waves of the HRS and each wave spans 8 to 15 months. This yields meaningful variation both across and within survey waves. Figure 1 also highlights positive association between consumer sentiment and stock market returns. I use the Index of Consumer Sentiment (ICS) in the month of an individual's interview to measure the general economic condition at the time of a gamble response.[8] There is considerable variation in general economic outlook both across and within survey waves. From October 1992 to February 2000 the index rose sharply from 70.3 to 111.3 and over the course of the 2002 HRS the index dropped sharply from 96.9 in May 2002 to 79.9 in February 2003.

3 MODEL OF RISK TOLERANCE

In this section, I discuss how I use the gamble responses on the HRS to quantify changes in an individual's risk tolerance over time, as well as differences across individuals at a point in time. I adopt the expected utility interpretation of the gambles and the general estimation strategy developed by Barsky et al. (1997) and later used in Kimball et al. (2008). I extend the model to use a rich set of covariates to investigate systematic changes in risk tolerance. My model incorporates the potential correlation between the time-constant component of risk tolerance and other time-varying attributes. The estimates from a panel of gamble responses and attributes allow me to determine whether a change in individual circumstances leads to a change in risk tolerance or simply signals an individual's risk tolerance type.

3.1 Mapping Gambles to Preferences

Expected utility theory offers a translation of an individual's gamble responses to a standard metric of risk preference—the coefficient of relative risk tolerance. Specifically, choices in the gambles establish a range for an individual's risk tolerance. Consider a general utility function U and a level of permanent consumption c. Offered a 50–50 chance of doubling lifetime income or cutting it by a fraction π, an individual accepts a risky job when its expected utility exceeds the utility from the certain job, that is, if

$$0.5U(2c)+0.5U((1-\pi)c) \geq U(c). \quad (1)$$

[8]The index is based on a representative sample of U.S. households in the Reuters/University of Michigan Surveys of Consumers and includes their assessment of personal finances and general economic conditions. A description of the index is available at http://www.sca.isr.umich.edu. Howrey (2001) demonstrates that the index has predictive power for economic recessions. Other indicators of the macroeconomic conditions, such as the unemployment rate or real return on the S&P 500 display a qualitatively similar association with the gamble responses.

The greater the curvature of U, the smaller the downside risk π an individual accepts. This interpretation of the gamble responses links lifetime income to permanent consumption and ignores the potential effect of wealth.[9] To quantify risk preference, I assume that relative risk aversion (and its reciprocal relative risk tolerance) are constant in the range of the gambles, suchthat

$$U(c)=\frac{c^{1-1/\theta}}{1-1/\theta} \quad (2)$$

The coefficient of relative risk tolerance, $\theta = -U'/cU''$ (Pratt 1964), in this specification of utility may differ across individuals. It is assumed to be constant for all values of permanent consumption for a given individual. The estimated model of risk tolerance in Section 4, which includes measures of income and wealth, is consistent with this assumption of constant relative risk aversion utility. In this framework, the gamble responses define a range for an individual's risk tolerance θ. The third and fourth columns of Table 1 provides the range of risk tolerance for each of the gamble response categories. As alternate way to quantify risk attitudes, the final column shows the amount of consumption an individual in the response category is willing to sacrifice to avoid the gamble.

3.2 Model of Risk Tolerance

The statistical model of risk tolerance θ_{it} encompasses systematic changes in preferences and a persistent attitude toward risk, such that,

$$\log\theta_{it}=x_{it}\beta+a_i \quad (3)$$

where $x_{it}\beta$ is the time-varying component and a_i is the time-constant component of the logarithm of risk tolerance. The logarithmic specification of risk tolerance captures the fact that most individuals exhibit a low tolerance of risks in the gambles, but some are willing to take large income risks. The parameter β measures the percent change in risk tolerance associated with a change in the attributes x_{it}.

The time-constant component of risk tolerance a_i may be correlated with the individual circumstances x_{it} that can change risk tolerance. If the model did not include a time-constant, individual-specific effect, then the relationship between observables and risk tolerance would be ambiguous. For example, the experience of a job displacement might directly reduce an individual's willingness to take further risks, that is, $\beta < 0$. Or a job loss could simply reveal information on an individual's (time-constant) risk tolerance type. The latter case could arise if more risk tolerant individuals tend to select career paths with a higher risk of job displacement. To accommodate the possibility of both direct and type effects, I model a relationship between the time-constant component a_i and observable attributes as

[9]As a sensitivity check, I model wealth explicitly in the argument of the utility function, such that $c \propto y + \varphi w$, where y is the current total household income and w is 5% of total household net worth (or an approximate annuity income value of wealth). The estimated weight on wealth φ is 0.019 and is not statistically different from zero at the 5% level. Annuitization based on a life table and the respondent's age has no qualitative effect on the estimated weight. Thus the simplifying assumption of approximating consumption with income is appropriate when interpreting the gamble responses.

$$a_i = \overline{x}_i \lambda + u_i \quad (4)$$

where $\overline{x}_i$ is the panel average of $x_{i1}, \ldots, x_{iT}$ for individual i and the type effect λ measures the persistent systematic differences across individuals in risk tolerance.[10] Continuing the example from above, if more risk tolerant types are more likely to lose their jobs (due to selecting risky jobs), then ever having lost a job (an attribute in $\overline{x}_i$) would be associate with higher risk tolerance, that is, $\lambda > 0$. The term u_i captures the portion of constant risk tolerance a_i that is unrelated to the attributes in $\overline{x}_i$. This mean-zero residual u_i is constant for a given individual over time and is independently distributed across individuals conditional on observables, such that, $u_i | \overline{x}_i \sim \mathrm{N}(0, \sigma_u^2)$. The model of the correlated random effects in equation (4) follows from Mundlak (1978).[11]

My estimation strategy also recognizes the limitations of using a small set of hypothetical gamble responses to infer individual preferences. First, the gamble responses establish an interval, not a point estimate, for risk tolerance, so I do not have the data to simply estimate the linear model. Second, the income gamble questions likely generate substantial survey response error as is common with hypothetical and cognitively difficult questions. Nearly half of the individuals switch their gamble responses across waves—one sign of random noise. Comments made by individuals during the survey also highlight difficulties respondents had in answering the hypothetical income gamble questions.[12] Survey response errors can arise on the gambles when individuals misinterpret the hypothetical scenario or make computational mistakes in their comparison of the jobs.

To incorporate these additional features of the data, I model the latent signal ξ_{it} from the individual's gamble responses as a combination of risk tolerance θ_{it} and a survey response error e_{it}, such that

$$\xi_{it} = \log \theta_{it} + e_{it} = x_{it} \beta + \overline{x}_i \lambda + u_i + e_{it} \quad (5)$$

$$c_{it} = j, \quad \text{if } \log \underline{\theta}_j < \xi_{it} < \log \overline{\theta}_j \quad (i=1, \ldots, N; t=1, \ldots T) \quad (6)$$

[10]The panel is unbalanced, so the average is $\overline{x}_i = (1/T_i \sum_{j=1}^{T} w_{it} x_{it})$, where T_i is the number of survey waves for individual i and w_{it} is an indicator for participation in wave t. I include information on an individual's circumstances from the first six waves of the HRS, not just the waves in which an individual answers the income gambles. To make the estimated effects of an event easier to interpret, I define x_{it} as an event prior to time t and $\overline{x}_i$ as an event before the end of the panel.

[11]Chamberlain (1984) summarizes this modeling strategy and presents a more general specification of the type effects. Specifically, his approach controls for the full set of an individual's covariates $x_{i1}, \ldots, x_{iT}$, not just the panel average, which yields estimates of the type effects that can vary over time or λ_t. One limitation of the general specification is the need for a balanced panel of the observables x_{it}. This restriction would have reduced my sample of gamble respondents by 46%, so I use the more parsimonious form of the correlated random effects with the panel average of observables. The results are comparable for the sub-sample that has a balanced panel of covariates.

[12]Examples from the 1998 HRS interviewer records include: "I'd take the one with more money," "It's too hard for me over the phone," and "I don't have experience. Anything without experience I can't answer." The interviewer records comments made by the respondent at each question. In the 1998 HRS, there were comments to the gambles from less than 8% of individuals and many entries only noted a repetition of the question. This para-data is restricted access and its availability varies across waves. For further information contact hrsquest@isr.umich.edu.

where c_{it} is the gamble response category that is observed in the data. An individual in response category j has a noisy signal of risk tolerance that lies in the interval $(\log\underline{\theta}_j, \log\overline{\theta}_j)$, where the cutoffs are the logarithm of the values in Table 1. The odds and outcomes are explicit in the gamble questions, so with the assumption of constant relative risk aversion utility, the intervals of risk tolerance are known values and do not vary across individuals or across waves. The model of the latent signal incorporates two sources of variation in the gamble responses over time: systematic changes in risk tolerance and survey response error.[13]

The treatment of the measurement error is important in this model. For identification, I assume that all the changes in the gamble responses that are unrelated to observables are survey response error, such that $\mathrm{N}(0, \sigma_{eit}^2)$.[14] The assumptions that all the unexplained variation over time is noise and that all the unexplained, time-constant variation is preferences (in equation 4) are likely both too strong, but necessary without direct information on measurement error or true preferences. Nonetheless, I do explore the properties of the transitory error by allowing the observed attributes to affect the dispersion of the response error. Specifically, the variance in response errors is $\sigma_{eit}=\exp[(x_{it}, \overline{x}_i)\sigma_e]$, where σ_e is a parameter vector that relates individual attributes to the variation in response errors. Thus individuals with a particular attribute, such as less education, do not (by assumption) systematically understate (or overstate) their risk tolerance in their gamble responses; however, I do allow the variance of the response errors to differ across individuals with different attributes.

A restatement of the reduced-form model draws particular attention to the variation in the preference signal within and between individuals. Specifically,

$$\xi_{it}=(x_{it}-\overline{x}_i)\beta+\overline{x}_i(\lambda+\beta)+u_i+e_{it} \quad (7)$$

where the first term $(x_{it}-\overline{x}_i)\beta$ captures a change in risk tolerance for a given individual and the second term $\overline{x}_i(\lambda+\beta)$ captures the differences in risk tolerance across individuals that are associated with observed attributes. The separate identification of the direct effect β and the type effect λ depends crucially on variation in x_{it} over the panel period and variation in $\overline{x}_i$ across the individuals. For time-constant attributes, such as gender and race, or choices made before the survey period, such as years of education, I can only identify the composite term of (β+λ), not the direct effect β. In contrast, the type effect λ of a covariate is not identified when its panel average $\overline{x}_i$ is the same for all individuals. For example, the gamble respondents all experienced the same macroeconomy of the 1990s, so any association between the average economic conditions in the panel and the persistent component of risk tolerance is absorbed in the estimate of the constant.

[13]Earlier studies of the income gambles by Barsky et al. (1997) and Kimball et al. (2008) on the HRS also model the time variation in gamble responses due to response error. Yet, My analysis is the first to investigate changes in risk tolerance that are both systematically associated with observed changes in circumstances and due to the random variation from response errors. For identification, I assign all the changes in the latent signal that are unrelated to these covariates to the survey response error.

[14]The survey response error also includes an indicator for a gamble response to the original (“new job”) version of the question (asked in the 1992 and 1994 HRS). For ease of exposition this control q_{it} is omitted from the description of the model.

3.3 Log-Likelihood of Gamble Responses

I use maximum-likelihood methods to estimate the parameters (β, λ, σ_u, σ_e) of the reduced-form model in equation (5) with the panel of income gamble responses and covariates. I compute the probability of observing an individual's set of gamble responses over the survey period with a truncated normal distribution function, where the order of the function corresponds to the number of waves (up to five) in which an individual answers the income gambles. For an individual who answers the gambles in only one wave, the likelihood of being in gamble response category *j* at time *t* is:

$$\begin{aligned} \mathrm{P}(c_{it}=j|x_{it},\overline{x}_i)=&\mathrm{P}(\log\underline{\theta}_j<\xi_{it}<\log\overline{\theta}_j|x_{it},\overline{x}_i) \\ =&\Phi\left(\frac{\log\overline{\theta}_j-x_{it}\beta-\overline{x}_i\lambda}{\sigma_{\xi it}}\right)-\Phi\left(\frac{\log\underline{\theta}_j-x_{it}\beta-\overline{x}_i\lambda}{\sigma_{\xi it}}\right) \end{aligned} \quad (8)$$

where $\sigma^2_{\xi it}=\mathrm{Var}(\xi_{it}|x_{it},\overline{x}_i)=\sigma^2_u+\sigma^2_{eit}$ and $\Phi(\cdot)$ is the univariate normal cumulative distribution function. I extend the likelihood function accordingly for the individuals who answer the gamble questions in multiple survey waves.[15] Since the lower bound log $\underline{\theta}$ and upper bound log $\overline{\theta}$ for the latent signal in each response category are known, the mean effects of β, and λ are identified separately from the variance terms and are interpretable as if the latent signal ξ_{it} were directly observed.[16] Given the model of preferences, the estimate of β is the percent change in risk tolerance for a given individual due to a change in x_{it} and λ is the percent difference in risk tolerance across individuals due to a difference in $\overline{x}_i$. The parameter estimates are those that maximize the conditional log-likelihood of the sample.[17]

4 ESTIMATES OF RISK TOLERANCE

The contribution of this paper is its analysis of the systematic changes in risk tolerance. Nonetheless, it is useful to start by summarizing the distribution of risk tolerance in the pooled cross-section. Similar to earlier studies with the HRS hypothetical gambles, the results from the maximum-likelihood estimation reveal a low degree of risk tolerance on average, although there is considerable preference heterogeneity across individuals. The mean of relative risk aversion in the sample is 9.6 and its standard deviation is also 9.6.[18] This implies that an average respondent would be willing to pay 28% of lifetime income to avoid a gamble with the 50–50 chance of doubling lifetime income or cutting it by one-third. It is possible that some feature in the framing, fielding, or modeling of the gambles may bias the estimated level of risk preference. Yet even with a persistent misstatement in the gamble

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[15]The individual-specific random effect u_i is constant over time, such that the $\mathrm{Cov}(\xi_{is},\xi_{it}|x_{is},x_{it},\overline{x}_i)=\sigma^2_u$ for $s \neq t$. To simplify the computation of the higher order probabilities, I integrate the product of the univariate densities conditional on u_i over the distribution of u_i. See Cameron and Trivedi (2005) for a further discussion of this standard method. For the integration, I use Matlab codes for Gaussian quadrature from Miranda and Fackler (2002). I use correlated random effects for the probit model of gamble responses, since there is no consistent fixed-effects estimator, see Chamberlain (1984) for a discussion.

[16]In contrast, a standard ordered probit model also estimates the cutoffs, so only the ratio of the mean effects to the unobserved standard deviation is identified. Even with known cutoffs, the identification of σ_u and σ_e requires that at least some individuals respond to the gambles in more than one wave.

[17]For the estimator, I use the modified method of scoring, a Newton-Raphson algorithm in which the sample average of the outer product from the score function approximates the information matrix. I calculate the score with numerical differentiation code from Miranda and Fackler (2002) and implement the maximum-likelihood estimator in Matlab The estimates of the asymptotic standard errors are also derived from this estimator of the information matrix.

[18]See Kimball et al. (2008) for more details on the distribution of risk preference estimated with a similar sample of HRS gamble responses.

responses, this panel of answers to the same question over a decade still provides valid information on the stability of individuals' preferences.

In this panel of older individuals, the gamble responses reveal few sources of systematic and long-lasting shifts in risk tolerance. I find a moderate decline in risk tolerance with age and a co-movement of individual risk tolerance and the macroeconomic conditions. But changes in the individual's total household income or wealth do not significantly alter an individual's willingness to take risk. In addition, a job displacement and diagnosis of a serious health condition, two personal events that plausibly reduce expected lifetime income, have little impact on risk tolerance. These results support the standard utility specification of constant relative risk aversion for within-person changes in consumption. I also find large stable differences across individuals in risk tolerance type that relate to commonly observed attributes. The estimated effects of time-constant observed attributes, such as gender and race, broadly conform to the results in earlier cross-sectional studies of risk attitudes. The panel structure of the HRS also reveals a relationship between individuals' earlier decisions, such as career choice, and their risk tolerance type. The rest of this section discusses the results from the maximum-likelihood estimation. The full model has 55 parameters, including direct effects, type effects, and error variance effects related to 20 observed attributes, so I have chosen to present the results in pieces. Each subsection discusses a portion of the coefficient estimates from the baseline model and a portion of the estimates from alternate models. Appendix Table 1 contains the full set of covariates and estimates.

4.1 Household Income and Wealth

The outcomes in the hypothetical gambles are defined as fractions of "your current family income every year for life," so the changes in income that individuals experience over the panel of gamble responses provide the power to test the utility specification of constant relative risk aversion. The gamble responses reveal no discernible change in risk tolerance when an individual's current income or wealth deviates from its average level in the panel.[19] The first column of Table 4 shows that a 10% increase in current income relative to the individual's average income is associated with only a 0.3% increase in risk tolerance. With a standard error of 0.3% the direct effect of a within-person change in income on risk tolerance is a precisely estimated zero effect. Likewise changes in an individual's current wealth have no discernible effect on risk tolerance. These results are consistent with the assumption of constant relative risk aversion utility.[20]

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[19]The net value of total household wealth is the sum of all wealth minus all debts. Wealth components include value of primary residence, net value of other real estate, net value of vehicles, net value of businesses, and net value of financial assets (IRAs, stocks, CDs, bonds, cash, and other assets). Debts include value of all mortgages, value of other home loans, and value of other debts. Total household income includes earnings, employer pensions, Supplemental Security Income, Social Security disability and retirement, unemployment and workers compensation, and other government transfers for the husband and wife plus household capital income and other income. This analysis uses RAND HRS (Version F) data and imputations for wealth and income. Qualitatively similar results are obtained from the balanced sample of respondents in all five HRS waves.

[20]The absence of an effect from changes in wealth could either signal a non-integration of wealth in the evaluation of the income gamble or provide support for CRRA. The hypothetical nature of the question may also play a role in the results. In an experimental study with actual and hypothetical stakes, Holt and Laury (2002) find that changes in the magnitude of the stakes lead to changes in an individual risk aversion only when the stakes are real, but not when they are hypothetical. The largest possible payoff to a single gamble in their experiment is $346.50 and the largest change is the payoffs across their treatments is $342.65. In contrast, the stakes in the HRS gambles are defined over lifetime income where the median level of current income is $54,176 and the median deviation in current income from average income is $2,167. The large difference in the scale of the risks between their study and mine complicates a direct comparison of the results.

The gamble responses, however, do not imply that risk aversion is constant across individuals with different levels of lifetime income. There are modest and statistically significant differences in risk tolerance across individuals related to their level of average income and average wealth in the panel. A 10% higher level of average income is associated with a 0.9% higher relative risk tolerance – a pattern that might imply more risk tolerant types select higher risk, higher return sources of income. This effect is modest in size but is statistically different from zero at the 5% level. Similarly, individuals with greater indebtedness reveal a higher level of risk tolerance in their gamble responses, with a 10% more negative average wealth associated with a 0.5% higher relative risk tolerance. There is no discernible pattern in risk tolerance across individuals with different, positive levels of average wealth. This could result from a cancelling of two effects: less risk tolerant individuals accumulate precautionary saving and more risk tolerant individuals select riskier, higher return assets.

These results from the HRS are comparable to previous multivariate, cross-sectional studies of hypothetical choice data that find an association between the willingness to take risk and the level of income and wealth, including Donkers et al. (2001) and Dohmen et al. (2006).[21] With different survey questions and modelling approaches in their cross-section studies, their point estimates are not directly comparable to my results. In general, the association between risk preferences and income or wealth in all of these studies is consistently small relative to demographics, such as gender and age.[22]

The second column of Table 4 investigates the robustness of the baseline estimates of income and wealth effects. The question frame of a hypothetical job choice may impede non-workers from revealing their true preferences and obscure an effect of income or wealth on risk tolerance. This issue could be particularly severe in the HRS where one-third of the individuals are not working at the time of their gamble response and over 40% experience a change in their work status during the panel. The estimates in the second column of Table 4 demonstrate that the risk tolerance of working household heads is no more sensitive to changes in income or wealth than the risk tolerance of all respondents. The direct effects of income and wealth in this sub-sample are not substantially altered and remain statistically indistinguishable from zero at the 5% level. The positive association between the logarithm of average income and risk tolerance does increases to 0.14 from 0.09. The type effect of negative wealth decreases to 0.01 from 0.05 and is no longer distinguishable from zero.

4.2 Major Life Events

I also examine the association between risk tolerance and two major life events, a job displacement and a the diagnosis of a serious health condition, that likely affect an

[21]In their univariate analysis, Barsky et al. (1997) find that the average imputed risk tolerance is flat across the middle three quintiles of both income and wealth, but is somewhat higher in the bottom and top quintiles. Their results are not directly comparable, since they do not control for other observables that might be correlated with income or wealth and risk tolerance. In addition, they do not correct for heteroskedasticity in the response errors.

[22]In their index of risk aversion, Donkers et al. (2001) find that being 10 years younger has the same marginal effect as having 81% more income. On a qualitative general risk question and a hypothetical lottery question, Dohmen et al. (2006) find even smaller marginal effects, such that a one year difference in age is equivalent to more than a 75% difference in income or wealth. By my estimates, the decline in risk tolerance from a one year increase in age is equivalent to the decline in risk tolerance from current income 59% below average income or current wealth 49% below average wealth.

individual's expected lifetime income.[23] The gambles on the HRS are defined over current lifetime income, so a shift in this reference point could alter an individual's attitude toward risk. For example, individuals may accept more income risk after a negative personal shock if that gamble could restore their original level of lifetime income. Or individuals who have received one draw of bad luck may simply be less willing to "spin the wheel" again.[24] Rather than a change in risk tolerance, these events—which do not occur purely at random —could also signal an individual's risk tolerance type. For example, high risk tolerant types may have selected riskier career paths with a higher chance of displacement, so they comprise a large fraction of the workers who actually experience displacements. Or more risk tolerant individuals may have forgone preventative health care or engaged in risky health behaviors and thus are more likely to be struck by a serious health condition later in life. A panel of gamble responses and events is essential for separating these mechanisms.

In Table 5 both a job displacement and the onset of a health condition are associated with a decline in risk tolerance of 6% and 9% respectively. These direct effects are imprecisely estimated and not statistically different from zero at the 5% level.[25] More striking is the evidence of selection into risky careers based on individual preferences. Among individuals with no prior job displacement at the time of their gamble response, those who will experience a displacement later in the panel are 19% more risk tolerant than those who will never experience a displacement. The estimate of the type effect is both economically and statistically significant, and suggests that high risk tolerance types have systematically chosen riskier careers with a higher chance of displacement.[26] The estimated type effect of a serious health condition is only 2% and is not statistically different from zero at the 5% level.

I use the gamble responses that individuals provide before and after major life events to identify the impact of these events on risk tolerance. In an unbalanced panel, attrition could be systematically related to these events and thus to changes in risk tolerance. The second column of Table 5 presents the results from the model estimated with individuals who respond in all six waves of the HRS.[27] The balanced panel produces similar estimates of the type effects, but different estimates of the direct effects. The estimated direct effects imply a larger declines in risk tolerance of 11% after a job displacement and of 15% after the onset of a health condition. The direct effect of a health condition is now statistically significant. The bottom panel of Table 5 shows that the estimated type effects in the unbalanced and balanced panels are similar. In the balanced panel, individuals who will experience a job displacement later in the panel are 20% more risk tolerant and those who will experience the

[23]Several studies find that a job displacement lowers current and future earnings (Ruhm 1991), as well as reduces long-run consumption (Stephens 2001). Likewise Smith (2003) finds that a severe health event affects household income and wealth.

[24]Alternatively, a decrease in an individual's risk tolerance following a negative income shock could also follow from a model of internal habit formation.

[25]I define a job displacement as a job ending with a business closure or a layoff. The HRS provides information on up to two jobs prior to the initial interview, the job at each interview, and jobs between interviews. I define a serious health condition as heart disease, stroke, cancer, or lung disease. The HRS asks separately about these and other conditions.

[26]The positive correlation between risk tolerance and job displacement highlights the need to directly measure individual preferences. For example, studies of household wealth accumulation that do not address the variation in preferences related to income risk may underestimate the amount of precautionary savings.

[27]Note that this is a balanced panel of information on job displacements, health conditions, and other demographics, but not on the income gambles. The income gambles are only asked in five of the six survey waves and not to all respondents.

onset of a health condition are 6% more risk tolerant than individuals who will not experience the event before the end of the panel. As in the unbalanced panel, the across-person difference in risk tolerance that is revealed by a job displacement is statistically significant.

4.3 Life Cycle and Business Cycle

The ten-year panel of gamble responses from 1992 to 2002 also provides a unique opportunity to examine systematic changes in risk tolerance with age and with changes in the macroeconomic conditions. Yet, even with multiple observations from the same individuals, I face the standard challenge of separating the effects of age, birth cohort and time.[28] I model the time effects with a measure of macroeconomic conditions at the time of the gamble response. I use a linear specification for the age effects and indicator variables that span five to six birth years for the cohort effects. The first column of Table 6 presents the estimates of the model. I find that each year of age is associated with a 1.7% decline in an individual's risk tolerance. This implies almost a 20% decrease in risk tolerance over the survey period associated with aging.[29] Individuals in the 1937–41 birth cohorts are also 16% more risk tolerant than individuals in the 1931–1936 cohorts. The effects of birth cohort are suggestive of individuals closer to the Great Depression being less willing to take risk.[30]

There is a strong positive relationship between risk tolerance and the business cycle, as measured by the Index of Consumer Sentiment (ICS) in the month of the gamble response. A ten-point increase in the sentiment index is associated with a 9% increase in risk tolerance, holding all other observables constant.[31] During the panel period, there are substantial movements in this measure of economic conditions which imply quantitatively important changes in average risk tolerance. For example, the estimates suggest that the steady rise in sentiment from October 1992 to February 2000 accompanied a 36% increase risk tolerance (all else equal) and then the sharp decline in sentiment from May 2002 to February 2003 accompanied a predicted 15% decrease in risk tolerance. The movements in risk tolerance over the business cycle are substantial in magnitude; however, they do not signal a permanent shift in an individual's risk tolerance. To explore the duration of the macroeconomic effects, the second column of Table 6 adds a measure of consumer sentiment at six months and one year prior to the gamble response. The strongest association

[28]Age, birth cohort, and time form a perfect relationship, that is, age = year – birth year, so the separation of the effects requires further assumptions. See Hall et al. (2007) for a discussion of various identification strategies and other references. Sample attrition that is related to an individual's risk tolerance, such as engaging in risky health behaviors that raise the chance of death, could also bias the estimates.

[29]In comments during the gamble sequences, some individuals explicitly recognize the effect of aging on risk tolerance: "Depends on how old you are. If you are 25, you gamble, but not now." and "If I were younger, I would take a chance." Other studies, including Barsky et al. (1997), Donkers et al. (2001), Dohmen et al. (2006), Cohen and Einav (2007), and Kimball et al. (2009) also find that older individuals are less willing to take risks. But my analysis is the first to use within person variation in gamble responses to identify the effect of aging. Even though this analysis uses a rich set of covariates, there are several events that are correlated with aging and are not included in this model of risk tolerance. The current results show an negative association, but not a causal link, between aging and risk tolerance. The age range of the HRS is limited and cannot address how risk tolerance might change earlier in the life cycle.

[30]Using measures of financial risk-taking in the Survey of Consumer Finance, Mullemendier and Nagel (2009) similarly find that exposure to a period of high stock returns may lead a cohort of individuals to persistently take more risk.

[31]The monthly ICS has a standard deviation of 12.7 in the period of January 1978 to May 2009 and is 20.4 points lower in NBER-dated recession months than in non-recession months. The estimates suggest that individuals are 18% (0.009 * −20.4 = −0.18) more risk averse during a recession in this reference period.

of 0.006 (t-statistic of 2.2) is between current macroeconomic conditions and risk tolerance. The estimated effect declines to 0.004 (t-statistic of 1.6) and −0.001 (t-statistic of −0.4) for macroeconomic conditions at six months and one year prior to the gamble response respectively. These results suggest the effect of changes in the macroeconomic conditions on risk tolerance is short-lived. Applying these estimates to the current downturn, the out-of-sample prediction is that, on average, risk tolerance fell by 20% in 2008.[32]

The last two columns of Table 6 use an alternate specification of the year effects that includes indicator variables for the survey wave. In the third column, the model controls for the survey wave of a gamble response, but not for consumer sentiment. All of the year effects are economically and statistically significant. This alternate specification has only a modest impact on the point estimate for age and birth cohort. In the last column, the model includes both the indicators of the survey wave and the measure of consumer sentiment. Here the effect of macroeconomic conditions is identified entirely from within-wave variation. Nonetheless the estimate of 0.007 is only 17% lower than the estimate of 0.009 in the baseline model and is still statistically different from zero at the 5% level. In addition, the Index of Consumer Sentiment soaks up much the wave-to-wave differences in gamble responses. Only in the 1994 HRS do the gamble respondents remain significantly more risk tolerant than the gamble respondents in the 1992 HRS.[33] Again the estimated effects of age and birth cohort are not altered by different specification of the time effects. The comparison of the results in Table 6 demonstrates that my parsimonious model of age, cohort, and time in the first column captures the systematic change in individuals' risk tolerance with age and macroeconomic conditions.

4.4 Demographics and Cognition

While there are modest changes in risk tolerance, 73% of the systematic variation in preferences in this sample is driven by the time-constant differences across individuals. The estimates in the first column of Table 7 reveal substantial differences in risk tolerance by gender, race, and years of education. The relative risk tolerance of men is 14% higher than of women. There is an even larger disparity in the willingness to take risk by race with blacks 28% less risk tolerant than whites. The income gambles on the HRS also reveal a strong positive association between education and risk tolerance, such that those with more than post-graduate education are 32% more risk tolerant than high school graduates.[34]

Table 7 also provides the estimated effects of marital status on risk tolerance. Entering a marriage is associated with an 11% increase in risk tolerance, though the estimate is not

[32]This calculation holds all else equal and compares average monthly sentiment in 2007 (85.6) with the average monthly sentiment in 2008 (63.8) or a decline of 21.8 index points, such that 0.009* −21.8 = −0.20

[33]The gambles on the 1994 HRS are asked in a module at the end of the survey. In the four other waves, the gambles appear near the end of the Cognition or Expectations Section of the core survey. This section is generally in the middle-end of the survey. Individuals are randomly selected to participate in the module in 1994, and they are explicitly given an opportunity to skip this extra section. The group of gamble respondents—and the environment of the question collection—in 1994 may not be entirely comparable to gamble responses on other waves.

[34]Other work that analyzes hypothetical risky choices and qualitative measures of risk taking on large-scale surveys, such as Dohmen et al. (2006) and Donkers et al. (2001), has found similar patterns for all three variables. Byrnes et al. (1999) surveys the vast psychology literature that finds gender differences in risk taking. However, my analysis is one of the few attempts to quantify these differences in terms of the coefficient of relative risk tolerance. And Barsky et al. (1997) only provide a univariate analysis of risk tolerance across demographic groups.

statistically different from zero at the 5% level. Yet less risk tolerant individuals are more likely to be consistently married in the panel. All else equal, an individual who is married at each survey is 16% less risk tolerant than an individual who is never married and the selection effect is statistically significant.[35]

Finally there is a strong relationship between the measures of risk tolerance and probabilistic thinking skills in the HRS. Individuals who provide more precise answers to the subjective probability questions in the survey are also willing to take more risk on the hypothetical income gambles and exhibit less random variation in their gamble responses across survey waves. In my model of risk tolerance, I use the measure of probability precision developed by Lillard and Willis (2001), that is, the fraction of the subjective probability questions to which the individual provides an exact answer (not 0, 50, 100). There are roughly 20 such questions in each survey wave that cover future personal and general events. On average respondents only give exact answers to about 40% of the probability questions. Lillard and Willis (2001) use a model of uncertainty aversion to argue that individuals with less precise probability beliefs should be less willing to take risk.[36] The results in Table 7 are consistent with their hypothesis, such that an individual whose average fraction of exact probabilities (FEP) in the panel is one standard above the sample average FEP is 20% more risk tolerant.[37] An increase in an individual's current FEP relative to their panel average FEP is also associated with a substantial increase in risk tolerance.

This paper focuses on within-person changes and across-person differences in risk tolerance that are systematically related to other observed attributes. Yet, the gamble responses also imply a large amount of residual variation. The model of risk tolerance allows for an individual-specific, time-constant component of risk tolerance that is uncorrelated with the observables. In Table 7 the estimated standard deviation of this random individual effect is 0.72 which is large both in absolute terms and relative to the other estimated mean effects. As a comparison, the standard deviation of log risk tolerance that is systematically associated with the rich set of covariates is 0.41. There is even more transitory variation in the gamble responses that is unrelated to the observables. The estimated standard deviation of the response errors is 1.55 and is more than twice the standard deviation of the individual effect. These transitory errors may subsume unobserved shifters in true preferences; however, in support of the response error view, I find that individuals without a high school degree, more focal probability responses, and lower income and wealth exhibit more random variation in their gamble responses across waves.[38] (See Appendix Table 1.) Nonetheless, the magnitude of these residuals highlights the scope for further investigation of time-constant survey response errors and transitory preference shocks.

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[35]This calculation adds the estimated direct effect of 11% with the type effect of −27%. The comment data also provide evidence of how a family mitigates the desire to take risks, such as "If just I, gamble, but for family go with the first."

[36]A common survey response strategy on subjective questions could provide an alternate source of covariation between an individual's gamble and probability responses. To minimize survey time and effort, some individuals may choose the "easy" answer to both questions, that is, 0–50–100 on the probabilities and reject the risky (and computationally intensive) job on the gambles.

[37]Kézdi and Willis (2003) also establish a positive association between actual stock ownership and more precise probability beliefs. The statistical model of risk tolerance that I estimate is observationally equivalent to uncertainty aversion model of Lillard and Willis (2001), but I do not explicitly test their mechanism.

[38]In their comparison of experimental and survey-based elicitations of risk tolerance on a student sample, Anderson and Mellor (Forthcoming) note that the degree of consistency across and within methods differs across individuals. Their findings are also suggestive of large, heteroskedastic response errors to the hypothetical gambles.

As the first two columns of Table 7 reveal, the modelling of the response error variance affects the estimates of risk tolerance. The baseline model in the first column allows the estimated standard deviation of the transitory response errors to vary with the model covariates. The model in the second column instead imposes homoscedasticity. While the qualitative patterns in risk tolerance are largely the same, in many cases, the point estimates on the direct and type effects differ substantial across the two models of response error variance. For example, the standard deviation of men's response error is 12% larger than women's response error, so in the homoscedastic model, the estimated difference in risk tolerance by gender increases to 22% from 14% in the heteroscedastic model.[39] These shifts in the point estimates also reflect the nonlinearity of the maximum-likelihood model.

The degree of non-systematic variation (or measurement error) also suggests caution when using the gamble responses to "control" for individual preferences in the other studies of risky behaviors. The results in this section point to heterogeneity in and selection on risk preferences and underscore the need for an individual-specific control; however, when using the gambles responses as a covariate, the measurement error should be addressed. As Kimball et al. (2008) discuss in more detail, there are two types of measurement error that are relevant when using the gambles as a covariate. First, the random noise in the responses implies that the individual-specific proxy of risk tolerance must remove the classical measurement error or the coefficient estimate on the proxy will suffer from attenuation bias. Second, a proxy based on only the gamble responses (even one that removes measurement error) as in Barsy et al. (1997) is still imperfect. The gamble responses are a useful, but crude ordering of individuals by risk preference, thus they may not soak up all of the systematic variation in risk preferences. The variation in risk preferences that is not captured by the gamble responses may be correlated with other covariates that matter for the risky behavior, such as gender and education. In this case, the coefficients on those other covariates will still include an indirect effect of risk tolerance on the behavior of interest even after the risk tolerance proxy is included in the regression. Kimball et al. (2008) develop an GMM estimator to address this second type of measurement error (under some additional assumptions). The more general implication of the measurement error is that researchers should not simply treat the gamble responses as a perfect control for preferences and careful inference is required when using the gamble responses to study risky behaviors.

5 DISCUSSION

Despite the apparent noise in the gamble responses, there are three main justifications for using this data to study changes in preferences. First, I estimate the systematic changes with a risky choice that is consistently defined over time. While extraneous details in the gambles, such as the sequence of the risks, may affect the responses and bias the estimated level of risk tolerance, I focus on the changes in risk preferences which are unaffected by time-constant question effects. Unlike panels of actual risky behavior, with the well-defined gambles, I can better separate preference changes from changes in expectations or

[39]The estimated effects of age and income, not reported here, are also greatly affected by the error variance assumptions. The homoscedastic model estimates a 47% smaller decrease in risk tolerance with age than the baseline model (a direct effect of −1.2% under versus −1.7%). The difference in risk tolerance associated with differences in average income is 50% smaller (0.06% versus 0.09%) and no longer statistically different from zero.

institutions. Second, the stakes of the gambles over lifetime income are large, as Rabin (2000) argues is necessary for measuring risk preference. In large, representative samples in the U.S., this criterion limits the question to a hypothetical situation and relies on the intrinsic motivation of the survey respondents to evaluate the gambles. The tradeoff of hypothetical data is a likely increase in the noise and the survey response errors. (See Camerer and Hogarth (1999) for a review of several experiment with varying financial incentives.) Accordingly, my statistical model of risk tolerance excludes the random variation in the gamble responses and I focus on systematic changes in preferences. Third, individuals' responses to hypothetical gambles are correlated with their actual risky behavior. Consistent with Barsky et al. (1997), in the appendix, I show that more risk tolerant individuals (according to the gambles) are more likely to own stocks and an increase in an individual's risk tolerance increases the probability of stock ownership. The experimental validation by Dohmen et al. (2008) of a hypothetical lottery question also supports the use of hypothetical choice data. Despite their limitations, the gamble responses in the HRS offer valuable information on the magnitude and sources of change in risk preferences.

My work with the HRS gambles contributes to a diverse empirical literature on changes in risk preferences. Three comparable papers highlight the range of choice data and time horizons that have been used. In an experiment with small-scale monetary stakes, Harrison et al. (2005) find no significant shift in risk preferences over a six month period with 31 subjects.[40] My results with a panel of 12,003 individuals over a decade also point to relatively stable risk preference. The analysis by Post et al. (2008) of 84 contestants on the game show "Deal or No Deal?" finds that recent events in the game strongly influence a contestant's subsequent risk taking.[41] In contrast, my study shows that major life events, such as a job displacement or the diagnosis of a serious health condition, do not permanently alter the willingness to take further risks. An individual's risk tolerance is also unaffected by changes in income and wealth even though lifetime income is the explicit reference point in the gamble question. More similar to my results, Brunnermeier and Nagel (2008) also find that transitory increases in wealth do not increase risk taking in household asset allocation. They use asset allocation to infer preferences; however, the portion of portfolio changes that reflect an active decision by households is difficult to measure and thus complicates their inference. Nonetheless, my analysis of the hypothetical gambles also finds support for constant relative risk aversion. Altogether, this literature points to both a time-varying and a permanent component in risk taking. The contribution of my paper is to quantify the relative magnitude of these components and investigate specific observable sources of variation.

6 CONCLUSION

Risk tolerance differs systematically both across individuals and over time. Most of these differences stem from characteristics, such as gender and ethnicity, that are constant over time for a particular individual; however, there are some sources of systematic change in an

[40]In addition to using real monetary incentives, the related experimental studies, including Anderson, Harrison, Lau and Rutstrom (2008), tend to relax the expected utility assumptions and explore more flexible functional forms.

[41]This strong path dependency of preferences agrees with other game shows studies, such as Gertner (1993) and Bombardini and Trebbi (2005), and Thaler and Johnson's (1990) experiments with student subjects.

individual's risk tolerance, such as aging and changes in macroeconomic conditions. Other changes in individual circumstances, including the loss of a job or the end of a marriage, appear to reveal information about individuals' risk tolerance type, rather than a change in their willingness to take future risks.

The finding that risk tolerance differs greatly across individuals, but much of the systematic variation is associated with time-constant attributes (in this older sample of adults) has important consequences for studying risky behavior. The large differences in risk preference across individuals underscore the need for a direct measure of these differences. The relative persistence in preferences and the correspondence between this survey measure of risk tolerance and actual risky behavior supports our ability to measure risk preference at the individual level. Yet, the apparent noisiness of the hypothetical gamble responses needs to be further explored with higher frequency data and other survey questions, since the "survey response error" may be absorbing short-lived, but behaviorally important preference shocks. In addition, the gamble responses from individuals ages 45 to 70 in the HRS provide little insight on the formation of preferences, in particular on the direction of causality in the positive association between education and risk tolerance. The estimation techniques in this paper could be applied directly to this interesting question if the gambles were asked to the same individuals at different points in their life. Among individuals in their formative years, the systematic time-variation in risk preference is likely to be larger than among the older individuals in the HRS. Nonetheless, the results of this paper make clear that economic studies of behavior need to take into account the stable component of risk preference that differs systematically across individuals.

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APPENDIX 1: STOCK OWNERSHIP

The primary reason to study preferences is to better understand behavior, so in this appendix I calculate and then use an individual-specific measure of risk tolerance from the gamble responses to analyze stock ownership of households over the 1990s. As economic theory predicts, there is a strong positive association between the measure of risk tolerance and the holding of risky financial assets. I also find that a temporary increase in risk tolerance, as well as a persistently higher level of risk tolerance raise the marginal probability of actual stock ownership. The measure of risk tolerance also refines the common inference on other determinants of stock ownership, including the effects of gender, education, and wealth. Finally this analysis of stock ownership highlights the usefulness and validity of the risk tolerance proxy.

Appendix 1.1 Measure of Individual Risk Tolerance

First I use the estimates Section 4 to form a proxy for an individual's risk tolerance at a particular point in time. Specifically, I calculate the expected value of log risk tolerance conditional on the individual's observed attributes x_{it} and $\overline{x}_i$ and gamble responses c_i in the panel, such that,

$$\mathrm{E}(\log\theta_{it}|x_{it},\overline{x}_i,c_i) = x_{it}\beta+\overline{x}_i\lambda+\mathrm{E}(u_i|x_{it},\overline{x}_i,c_{it},\ldots c_{iT}). \quad (9)$$

The mean of the random effect u_i conditional on attributes $\overline{x}_i$ is zero, yet an individual's set of gamble responses $c_i = (c_{it}, \ldots c_{iT})$ does provide some information on the expected level of this component.[42]

The decomposition of the preference measure into permanent and transitory components is again useful with

$$\mathrm{E}(\log\theta_{it}|x_{it},\overline{x}_i,c_i) = (x_{it}-\overline{x}_i)\beta+\overline{x}_i(\beta+\lambda)+\mathrm{E}(u_i|x_{it},\overline{x}_i,c_i) \quad (10)$$

where the first term on the right is a transitory component related to changes in the observed attributes of an individual, the second term is a permanent component related to differences across individuals in their observed attributes, and the third term is a permanent component related only to the difference across individuals in their gamble responses. The variance of the systematic within-person changes in risk tolerance (the first term) accounts for only 11% of the total variance in the individual measure of risk tolerance, whereas the variance of the systematic across-person differences (the second term) accounts for 45% of the total variance. Both changes in risk tolerance over time and differences in risk tolerance across individuals contribute to the systematic heterogeneity in measured preferences, though the stable differences across individuals are empirically more important. A substantial portion of the between-person variation in the risk tolerance proxy is not related to the observables in the model.

Appendix 1.2 Stock Ownership

To study stock ownership, I use a balanced panel of HRS households over the first six waves from 1992 to 2002.[43] In the pooled sample, 46% of the financial respondents own stocks directly.[44] The cross-sectional rate of stock ownership varies in the panel period. Stock ownership increases from 41% of households in the 1992 HRS to 47% of households in the 2000 HRS and then decreases slightly to 45% in the 2002 HRS. Following the same respondents over the panel, 28% never hold stocks, 20% always hold stocks, and 52% change ownership status at least once.

[42]The variance of the conditional expectation of log θ_{it} is much smaller than its unconditional variance. See Kimball et al. (2008) for a further discussion of how this diminished variability impacts the use of a proxy based on the conditional expectation.

[43]Individual-level variables in the analysis, such as risk tolerance, are those of the household's financial respondent. The financial respondents is the individual who is most knowledgeable about the finances of the household and who reports on the income and wealth in the survey. I exclude financial respondents who are in households with no financial assets, negative net worth, or no income at any of the six survey waves. I follow a financial respondent even if his or her original household dissolves. This yields a balanced panel of 2,464 financial respondents with 14,784 household-wave observations.

[44]The definition of stocks includes financial assets in corporate stocks, mutual funds, or investment funds and excludes stocks held indirectly in IRAs or DC-pensions.

The first column of Appendix Table 2 presents the estimated marginal effects on the probability of owning stocks for a subset of the model covariates.[45] The results in the first column are similar to the results in numerous studies of household portfolios, for examples, see Guiso et al. (2002). Men are 3 percentage points more likely to own stocks than women, though the effect is not precisely estimated. Higher levels of education and wealth are particularly strong predictors of stock ownership. College graduates are 19 percentage points more likely to own stocks than high school graduates. A 10% higher average wealth across individuals is associated with a 2.9 percentage point higher probability of stock ownership, and a 10% increase in wealth for a particular individual increases the probability of stock ownership by 1.4 percentage points.

The results in the second column of Appendix Table 2 show how a direct measure of risk tolerance refines the inferences on stock ownership. This model adds two measures of individual's risk tolerance: the average of log risk tolerance across the six survey waves and the deviation between current log risk tolerance and the panel average level. As economic theory predicts, both measures of risk tolerance are positively associated with stock ownership.[46] A 10% higher level of average risk tolerance across individuals is associated with a 1.0 percentage point higher probability of stock ownership. And a 10% increase in an individual's risk tolerance raises the probability of stock ownership by 0.9 percentage points. Both of these effects are statistically and economically significant.[47] The model of risk tolerance estimated in Section 4 reveals considerable heterogeneity, so a one-standard difference in risk tolerance corresponds to a 8.2 percentage point difference in the predicted probability of stock ownership—almost one-fifth of the actual ownership rate.

The measure of risk tolerance also refines the association between stock ownership and the other covariates. (See Kimball et al. (2008) for a more thorough analysis of this argument.) For example, the variation in risk tolerance absorbs much of the higher probability of stock ownership among men that is estimated in the first model. Likewise the effect of education on stock ownership is partially reduced when the model includes a measure of risk tolerance. Specifically, the estimated marginal effects of a college education and post-graduate education drop by 17% and 35% respectively. These results suggest that differences in risk preference can account for some of the commonly observed association between education and stock ownership. In contrast, Appendix Table 2 shows that the marginal effect of wealth on stock ownership is unrelated to differences in risk preference. Alternate explanations, such as transaction costs, are needed to explain the strong association between wealth and stock ownership, since there is no evidence of decreasing relative risk aversion. A direct measure of risk tolerance provides an opportunity to explore the mechanisms behind the large differences in stock ownership across households and over time. The strong

[45]The correlated random effects probit of stock ownership estimated in Stata includes all the covariates from the model of risk tolerance (see Appendix Table 1), except for the fraction of exact probability responses, job displacements and health conditions, and adds indicator variables for the survey waves. The key exclusion restriction is that FEP does not affect stockholding directly. Its effect on stock ownership is mediated through risk tolerance. The marginal effects are computed at the sample median of the variables with the random effect set to zero.

[46]Other measures of stock ownership, such as the dollar value of stock holding and the share of financial assets held in stocks, produce qualitatively similar results. My results in the panel are consistent with the results of Barsky et al. (1997) in the cross-section.

[47]The asymptotic standard errors in the second column Table 2 do not account for the sampling variation in the risk tolerance measures which are generated from the first-step maximum-likelihood estimates. Bootstrap replications on a related, but computationally less intensive model in Kimball et al. (2008) yield only modest increases in the standard errors.

association between the measure of risk tolerance and actual stock ownership also demonstrates that the hypothetical gambles capture meaningful differences in preferences.

Appendix Table 1

Maximum-Likelihood Estimates of Log Risk Tolerance

Latent Variable: Log of Noisy Risk Tolerance: ξ_{it}				
	Mean Effect			
Variable	**Direct**	**Type**	**Composite**	**Std. Dev. Effect**
Constant			**−3.30** (0.74)	**1.46** (0.49)
Male			**0.14** (0.04)	**0.12** (0.02)
Black			**−0.28** (0.06)	**0.18** (0.03)
Hispanic			−0.03 −(0.03)	0.10 (0.05)
1937–1941 Cohorts			**0.16** (0.06)	0.003 (0.04)
1942–1947 Cohorts			0.16 (0.10)	0.03 (0.07)
High School Drop Out			0.02 (0.06)	**0.09** (0.03)
Some College			**0.17** (0.05)	0.03 (0.03)
College Graduate			**0.22** (0.06)	−0.01 (0.04)
Post Graduate			**0.32** (0.06)	0.03 (0.04)
Index Consumer Sentiment / 10	**0.09** (0.02)			**−0.04** (0.02)
Current Age / 10	**−0.17** (0.08)			0.02 (0.05)
Currently Married	0.11 (0.09)			−0.07 (0.06)
Fraction Exact Probability	**0.82** (0.10)			**−0.42** (0.07)
Previous Job Displacement	−0.06 (0.07)			0.01 (0.05)
Previous Health Condition	−0.09 (0.06)			−0.05 (0.05)
Log (Current Income) / 10	0.29 (0.34)			0.14 (0.25)
Log (Current + Wealth) / 10	0.10 (0.17)			**−0.22** (0.11)
Log (| Current − Wealth |) / 10	0.35 (0.21)			−0.10 (0.13)
Proportion of Years Married		**−0.27** (0.10)		−0.05 (0.07)
Panel Average FEP		**0.27** (0.14)		**−0.57** (0.09)
Ever Job Displacement		**0.19** (0.06)		0.02 (0.05)

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Latent Variable: Log of Noisy Risk Tolerance: ξ_{it}				
	Mean Effect			
Variable	**Direct**	**Type**	**Composite**	**Std. Dev. Effect**
Ever Health Condition		0.02 (0.06)		0.02 (0.04)
Log (Average Income) / 10		0.60 (0.45)		**0.68** (0.30)
Log (Average + Wealth) / 10		−0.07 (0.22)		**0.31** (0.14)
Log (| Average − Wealth |) / 10		0.15 (0.30)		**0.51** (0.18)
"New Job" Version			−0.08 (0.09)	−0.07 (0.06)

NOTE: Standard errors are in parentheses. Estimates in bold are statistically significant at the 5% level. The log-likelihood is −23573.5. The sample includes 12,003 individuals. The estimated standard deviation of the unpredictable persistent component of risk tolerance is 0.72. The standard deviation of the transitory component is $\sigma_{eit}=\exp[(x_{it},\overline{x}_i)\sigma_e]$ where σ_e is the parameter vector of the standard deviation effects. The gambles in the 1992 and 1994 HRS ask about a new job, whereas the wording in the later waves removes the status quo bias. See the notes on Table 4–7 and text for details on the variables.

Appendix Table 2

Decision to Own Stocks

Dependent Variable: Indicator of Stock Ownership		
Parameter	**Marginal Effect on Probability**	
Log Risk Tolerance		
Individual Panel Average		**0.10** (0.03)
Current – Panel Average		**0.09** (0.04)
Male	0.03 (0.03)	0.01 (0.03)
High School Drop Out	**−0.15** (0.03)	**−0.15** (0.03)
Some College	0.06 (0.03)	0.04 (0.03)
College Graduate	**0.19** (0.04)	**0.16** (0.04)
Post Graduate	**0.11** (0.04)	0.07 (0.04)
Log of Current Wealth	**0.14** (0.01)	**0.15** (0.01)
Log of Average Wealth	**0.15** (0.02)	**0.16** (0.02)
Predicted Probability	0.31	0.34
Log-Likelihood	−6904.94	−6897.3

NOTE: Asymptotic standard errors are in parentheses. Estimates in bold are statistically significant at the 5% level. The correlated random effects probit is estimated on a balanced panel with 2,464 financial respondents and 14,784 total observations from the 1992 to 2002 HRS. The model of stock ownership includes all the covariates from the model of risk tolerance (see Appendix Table 1) except for the fraction of exact probability responses, job displacements and health conditions. The stock ownership model adds indicator variables for the survey waves. The marginal effect of a variable on the probability to own stocks is computed at the median values of the variables with the random effect equal to 0.

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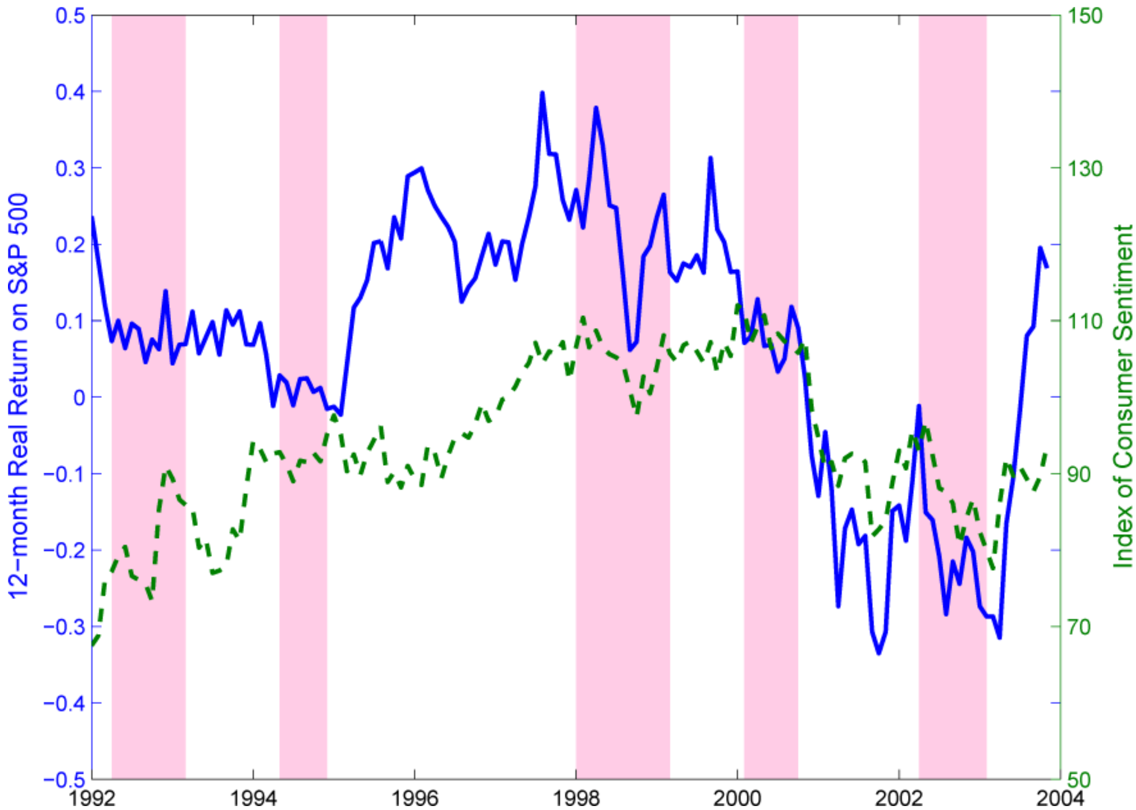

Figure 1.

Stock Market Returns and Consumer Sentiment, 1992 – 2004

NOTE: The solid line is the total annual return from the S&P 500 Total Return Index (including dividends) over the previous 12 months. The monthly value of the S&P 500 Index is the closing value on the last business day of the month. The index from Global Financial Data is adjusted for dividends and splits. The CPI-U removes general price inflation from the return. The dashed line is the current monthly value of the Index of Consumer Sentiment from the University of Michigan Survey of Consumers. The shaded areas denote months in which the HRS fielded the income gambles. These interview months for the five waves are 4/1992 to 3/1993, 5/1994 to 12/1994, 1/1998 to 3/1999, 2/2000 to 11/2000, and 4/2002 to 2/2003.

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Table 1

Risk Tolerance Response Categories

Response Category	Downside Risk of Risky Job		Bounds on Risk Tolerance		% Income Pay to Avoid 1/2 Downside Risk
	Accepted	Rejected	Lower	Upper	
1	None	1/10	0	0.13	46
2	1/10	1/5	0.13	0.27	41
3	1/5	1/3	0.27	0.50	31
4	1/3	1/2	0.50	1.00	20
5	½	3/4	1.00	3.27	8
6	¾	None	3.27	∞	–

NOTE: In a series of questions, respondents choose between a job with a certain income and a job with risky income. With equal chances, the risky job will double lifetime income or cut lifetime income by a specific fraction (downside risk). The largest risk accepted and the smallest risk rejected across gambles define a response category. In 1992 there are four categories 1–2, 3, 4, and 5–6. In 1994 and later surveys, the response categories range from 1 to 6. At the lower bound of risk tolerance for a category, an individual with CRRA utility is indifferent between the certain job and a risky job with the largest downside risk accepted. The upper bound similarly follows from the smallest downside risk rejected. The percent of lifetime income that an individual is willing to pay to avoid the risky job with a 1/2 downside risk is calculated with the upper bound of risk tolerance in the response category.

Table 2a

Responses to Lifetime Income Gambles

Response Category	% by HRS Survey Wave				
	1992	1994	1998	2000	2002
1	64.7	44.4	39.5	45.0	43.2
2		17.2	18.7	19.4	18.8
3	11.9	13.8	16.2	14.6	15.6
4	10.9	15.0	9.4	8.6	9.9
5	12.5	5.9	9.1	6.8	6.5
6		3.7	7.1	5.6	6.0
Responses	9,647	594	2,502	943	4,939

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Table 2b

Changes in Individuals' Responses Across Waves

First Gamble Response	% in Category on Second Response				Number of Response Pairs
	1–2	3	4	5–6	
1–2	68.2	13.4	8.6	9.9	4,003
3	55.7	23.7	10.1	10.4	969
4	53.8	16.5	14.9	14.8	744
5–6	46.7	15.4	12.5	25.5	906

NOTE: Author's unweighted tabulations from HRS public access data files. The sample includes 12,003 individuals in the 1931 to 1947 birth cohorts. See the text for details on the sample selection. See Table 1 for the definition of the response category. A respondent may contribute more than one pair to the tabulations in Table 2b. Time between the gamble responses ranges from two to ten years. According to the chi-squared statistic, the null hypothesis of no association between the first and second gamble response is rejected at the 1% level.

Table 3

Attributes at Gamble Response 1992 – 2002

Percent	1992–2002
Male	42.9
Black	14.7
Hispanic	7.5
High School Drop Out	22.0
H.S. Grad / Some College	57.2
College / Post Graduate	20.8
Job Displacement	
Prior to Response	24.7
After Response	12.9
Health Condition	
Prior to Response	22.0
After Response	16.8
Married	
Current Status	78.9
Change in Panel	13.5
Mean (Std. Dev.)	
Age	56.9 (4.5)
Fraction Exact Probability	
Individual Panel Average	0.41 (0.18)
Current – Panel Average	0.04 (0.16)
Log of Income	
Individual Panel Average	10.9 (0.8)
Current – Panel Average	−0.04 (0.47)
Log of Wealth (Positive)	
Individual Panel Average	11.5 (2.5)
Current – Panel Average	−0.15 (0.75)
Responses	18,625

NOTE: Author's unweighted tabulations are from HRS public access data files and Rand HRS (Version F) data set. The sample includes 12,003 individuals. A job displacement is a job ending with a firm closure or layoff. A health condition includes heart disease, stroke, cancer, and lung disease. Fraction exact probability is the fraction of subjective probability questions to which the respondent gave a non-focal answer (not 0, 50, or 100). Wealth is the total household net worth and income is the total income of the respondent and spouse. Both variables are from the RAND HRS data and include imputations.

Table 4

Household Income and Wealth

Latent Variable: Log of Risk Tolerance		
Parameter	**All Gamble Respondents**	**Working Household Heads**
Direct Effect: β		
Log of Current Income	0.03 (0.03)	0.03 (0.06)
Log of Positive Current Wealth	0.01 (0.02)	−0.03 (0.03)
Log of | Negative Current Wealth |	0.03 (0.02)	0.01 (0.03)
Direct and Type Effects: $\beta + \lambda$		
Log of Average Income	**0.09** (0.03)	**0.14** (0.06)
Log of Positive Average Wealth	0.003 (0.014)	−0.02 (0.02)
Log of | Negative Average Wealth |	**0.05** (0.03)	0.01 (0.04)
Log-likelihood	−23573.5	−10022.8
Number of Respondents	12,003	5,692

NOTE: Asymptotic standard errors are in parentheses. Estimates in bold are statistically significant at the 5% level. Income is total earnings, pensions, government transfers, and capital income received by the respondent and spouse in the household. Wealth is total household wealth (including housing, vehicles, businesses, and IRAs) minus all debts. The model in the first column is estimated with all the gamble responses. Appendix Table 1 provides the full set of covariates and estimates. The second column only includes gamble responses from household heads who are working.

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Table 5

Job Displacements and Health Conditions

Latent Variable: Log of Risk Tolerance		
Parameter	**All Gamble Respondents**	**Balanced Panel of HRS**
Direct Effect: β		
Previous Job Displacement	−0.06 (0.07)	−0.11 (0.08)
Previous Health Condition	−0.09 (0.06)	**−0.15** (0.07)
Type Effect: λ		
Ever Job Displacement	**0.19** (0.06)	**0.20** (0.07)
Ever Health Condition	0.02 (0.06)	0.06 (0.07)
Log-likelihood	−23573.5	−13426.4
Number of Respondents	12,003	6,591

NOTE: Asymptotic standard errors are in parentheses. Estimates in bold are statistically significant at the 5% level. A job displacement is a job ending with a firm closure or layoff. A health condition is heart disease, stroke, cancer, or lung disease. The model in the first column is estimated with all the gamble respondents. Appendix Table 1 provides the full set of covariates and estimates. The model in the second column only uses the gamble responses of the individuals who respond to all six HRS waves 1992–2002.

Table 6

Age, Cohort, and Time

Latent Variable: Log of Risk Tolerance				
Parameter	**Alternate Specifications of Time Effects**			
Age	**−0.017** 0.008	−0.16 (0.09) (0.00)	**−0.021** 0.010	**−0.021** 0.010
1937–1941 Cohorts	**0.16** (0.06)	**0.17** (0.07)	0.14 (0.07)	0.14 (0.07)
1942–1947 Cohorts	0.16 (0.10)	0.16 (0.11) (0.00)	0.10 (0.12)	0.10 (0.12)
Consumer Sentiment	**0.009** (0.002)	**0.006** (0.003)		**0.007** (0.004)
ICS Six Months Ago		0.004 (0.003)		
ICS One Year Ago		−0.001 (0.003)		
1994 HRS			**0.27** (0.08)	**0.19** (0.09)
1998 HRS			**0.37** (0.08)	0.19 (0.11)
2000 HRS			**0.32** (0.11)	0.12 (0.14)
2002 HRS			**0.24** (0.11)	0.17 (0.11)
Log-likelihood	−23573.5	−23571.5	−23571.2	−23569.0
Parameters	55	59	59	61

NOTE: Asymptotic standard errors are in parentheses. Estimates in bold are statistically significant at the 5% level. The sample includes 12,003 individuals. The first column is the baseline specification of the model, see Appendix Table 1 for the full set of covariates and estimates. The 1931–1936 birth cohort is the omitted cohort group. Consumer Sentiment is the value of the University of Michigan Index of Consumer Sentiment (ICS) in the month of an individual's gamble response. Over the months with HRS gamble responses, the ICS from the Survey of Consumers ranges from a low of 73.3 in October 1992 to high of 111.3 in February 2000. The models in the first two columns include a categorical control for a gamble response in the 1992 or 1994 HRS to capture differences due to the "new" job frame of the question.

Table 7

Individual Attributes

Latent Variable: Log of Risk Tolerance		
	Model Allows for Heteroscedastic Errors	
Parameter	**Yes**	**No**
Direct and Type Effects: $\beta + \lambda$		
Male	**0.14** (0.04)	**0.22** (0.03)
Black	**−0.28** (0.06)	**−0.12** (0.05)
Hispanic	−0.03 (0.08)	0.05 (0.06)
High School Drop Out	0.02 (0.06)	**0.09** (0.04)
Some College	**0.17** (0.05)	**0.19** (0.04)
College Graduate	**0.22** (0.06)	**0.25** (0.06)
Post Graduate	**0.32** (0.06)	**0.40** (0.06)
Direct Effect: β		
Currently Married	0.11 (0.09)	0.10 (0.08)
Fraction Exact Probability	**0.82** (0.10)	**0.52** (0.09)
Type Effect: λ		
Proportion of Years Married	**−0.27** (0.10)	**−0.23** (0.09)
Average FEP Across Waves	**0.27** (0.14)	**−0.05** (0.12)
Std. Dev. of Individual Effect : σ_u	**0.72** (0.03)	**0.77** (0.03)
Std. Dev. of Response Error: σ_e	**1.55** (0.01)	**1.50** (0.02)
Log-likelihood	−23573.5	−23801.3
Parameters	55	29

NOTE: Asymptotic standard errors are in parentheses. Estimates in bold are statistically significant at the 5% level. The sample includes 12,003 individuals. The first column is the baseline specification of the model, see Appendix Table 1 for the full set of covariates and estimates. The model in the second column imposes homoscedasticity on the response errors. Fraction exact probability (FEP) is the fraction of the subjection probability questions in the survey to which an individual gives a non-focal response (not 0, 50, or 100). Covariates under the type effects are for an individual over the panel period.