Does Risk Tolerance Change?

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Abstract

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Whether risk tolerance changes is central to how economists model and study behavior. This paper uses a large panel of responses to hypothetical gambles to quantify changes in an individual's risk tolerance over time and differences in preference across individuals at a point in time. The statistical model combines the gamble responses with a rich set of covariates to measure an individual's coefficient of relative risk tolerance and its association with other attributes, such as wealth and age. The model also allows for a correlation between the time-constant component of risk tolerance and time-varying attributes, as well as transitory variation in the gamble responses due to survey response error.

The maximum-likelihood estimation of a correlated random effects probit uses a panel of responses from over 12,000 individuals in the 1992 to 2002 waves of the Health and Retirement Study. The results confirm substantial heterogeneity across individuals in their willingness to take risk and identify important aspects of stability in risk preferences. For example, changes in wealth and income have no effect on risk tolerance, which supports the standard specification of utility with constant relative risk aversion. The experience of a job displacement also does not alter an individual's risk tolerance, but instead reveals a more risk tolerant type and suggests past selection into a risky career due to preferences. While there are some systematic changes in risk tolerance, such as decline with age and a positive co-movement with macroeconomic conditions, the persistent differences across individuals account for more than 80% of the variation in measured risk tolerance. The individual measure of risk tolerance developed from the gamble responses also strongly relates to actual stock ownership. Altogether the results suggest a well-defined and relatively stable risk preference.

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1 INTRODUCTION

Do individuals have stable and well-defined preferences as standard economic models assume? Or are preferences context-dependent and malleable as some research in behavioral economics suggests? The answer to these empirical questions is central to how we model and study individual behavior. In particular, attitudes toward risk inform the large class of decisions that individuals face in which the outcome of the choices is uncertain, such as asset allocation, career choice, and insurance. Despite its importance, there is little research on whether an individual's risk tolerance evolves over the life-cycle or reacts to changes in personal circumstances.

I use a large panel of responses to hypothetical gambles to investigate these open empirical questions. These gambles over lifetime income were developed and analyzed by Barsky et al. (1997) on the first two waves of the Health and Retirement Study (HRS).[1] I adopt their mapping of the gamble responses to the coefficient of relative risk tolerance and extend their treatment of survey response error. Unlike any previous analysis, I use the panel of gambles to quantify changes in an individual's risk tolerance. I model risk tolerance with a time-varying component and time-constant component. In this framework, I also measure the association between risk tolerance and observable attributes, such as demographics and wealth. The panel of gamble responses and individual attributes allows me to separate the variation in preferences across individuals at a point in time from the variation over time for a particular individual. Specifically, I estimate a correlated random effects probit with almost 20,000 gamble responses from over 12,000 individuals in the 1992 HRS to 2002 HRS. The model also incorporates detailed individual and household information, as well as measures of macroeconomic conditions.

The estimation reveals considerable information on how an individual's risk tolerance evolves over time, as well as the degree to which preferences vary across individuals. There is a moderate decline in an individual's risk tolerance with age, and an improvement in macroeconomic conditions is associated with an increase in risk tolerance. But changes

[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.

in wealth and income do not significantly alter an individual's willingness to take risk. In addition, personal events that plausibly reduce an individual's expected lifetime income have little impact on risk tolerance. The results support the standard specification of utility with constant relative risk aversion and offer no evidence of reference-dependent preferences. In contrast, I find large stable differences across individuals in their risk tolerance type. 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 allows me to highlight the relationship between individuals' earlier decisions, such as career choice, and their risk tolerance type.

The measure of individual risk tolerance that I develop from the gamble responses is also strongly related to actual stock ownership. This demonstrates that a small set of hypothetical questions can capture important between- and within-person variation in preferences that applies to actual risky decisions. As theory predicts, more risk tolerant individuals are more likely to own stocks. Across individuals, a one-standard-deviation increase in average risk tolerance is a associated with a 6 percentage point higher probability of owning stocks – one-sixth of the ownership rate. An increase in an individual's risk tolerance also raises the probability of stock ownership. The measure of risk tolerance is developed from hypothetical job choices — a very different setting from an actual decision to own stocks, so context alone does not determine the willingness to take risk. The measure of risk tolerance also refines standard inference on the determinants of stock ownership. The differences in risk tolerance explain the higher rate of stock ownership among men, but wealth and education remain important predictors of stock ownership even with the preference measure. These findings suggest that differences in transaction costs and risk perceptions may also affect stock ownership. Altogether the application clearly supports the existence of a stable risk attitude and our ability to measure it with the income gambles.

Two other recent papers study changes in risk preferences with very different types of data. My results stand in contrast to the analysis by Post et al. (2006) of 84 contestants on "Deal or No Deal?" which finds that previous outcomes in the game strongly influence a contestant's subsequent risk taking. Their finding of path-dependent preferences agrees with other game shows studies, such as Gertner (1993), and Thaler and Johnson's (1990) experiments with student subjects. In contrast, my study of over 12,000 gamble respondents in the HRS shows that major life events, such as a job displacement or the diagnosis of a serious health condition, do not discernibly alter the willingness to take further risks. An individual's risk tolerance is also unaffected by changes in wealth and income even though "lifetime income" is the explicit reference point in the gamble question. Likewise Brunnermeier and Nagel (2005) find that transitory increases in wealth do not increase risk taking. Their work fits in a large literature initiated by Friend and Blume (1975) that uses actual asset allocation decisions to infer individual preferences. Unlike estimates from the simple and well-defined hypothetical gambles on the HRS, preference estimates from actual risky behavior may be biased due to unobserved confounding factors, such as differences in return expectations. Together the two sources of data — hypothetical income gambles and actual portfolio choices — in more common decision settings support the standard specification of utility with constant relative risk aversion.

The plan of the paper is as follows. Section 2 presents the hypothetical gambles in the HRS. Section 3 uses expected utility theory to map the gamble responses to the coefficient of relative risk tolerance. The section then develops a statistical model of risk tolerance based on the gamble responses. Section 4 presents the results from maximum-likelihood estimation of the model. Section 5 uses the estimates of risk tolerance to study the household's actual decision to own stocks. The final section offers conclusions.

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 1992 HRS, individuals consider the following scenario:

> Suppose that you are the only income earner in the family, and you have a good job guaranteed to give you your current (family) income every year for life.

> You are given the opportunity to take a new and equally good job, with a 50-50 chance it will double your (family) income and a 50-50 chance that it will cut your (family) income by a third. Would you take the new job?

Individuals who accept the risky job then consider another job with a larger downside risk of one-half. Those who reject the first risky job are asked about a job with a smaller downside risk of one-fifth. Starting with the 1994 HRS, individuals who reject their first two risky jobs consider a third job that could cut their lifetime income by one-tenth. Likewise individuals who accept their first two risky jobs consider a third job that could cut their lifetime income by three-quarters. 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 increase in an individual's willingness to accept income risk, so the gamble responses provide a coarse ranking of individuals by their risk preference.

Barsky et al. (1997) designed the gambles and analyzed the responses on the first two waves of the HRS. They acknowledged the potential for a status quo bias in the gamble responses due to the question wording, since individuals may have an aversion to a *new* job unrelated to its income risk. The 1998 HRS revised the hypothetical scenario so that individuals now choose between two new jobs:

> 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?

The objective attributes of the two jobs are identical in the original and revised versions of the question. Furthermore the 1998, 2000, and 2002 HRS use the same sequence of downside risks for the second job as the 1994 HRS uses for the new job. Over 30% of the individuals respond to both versions of the question which allows me to directly investigate the degree of status quo bias from the original wording.

In this paper, I analyze 19,690 gamble responses on the 1992, 1994, 1998, 2000, and 2002 waves of the HRS from 12,574 individuals in the 1931 to 1947 birth cohorts.[2] The panel 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 46% 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 2 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 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.

The placement of these gambles on a large panel study provides an ideal opportunity to study systematic changes in an individual's risk tolerance. The eleven-year period in which the gambles are fielded coincides with many significant changes in individual circumstances and macroeconomic conditions. Table 3 summarizes the primary set of individual attributes and events that I use to quantify changes in risk tolerance. First the considerable diversity in the sample of gamble respondents on the HRS is worth noting. Among the 12,574 individuals, 43% are male, 17% are black, and 9% are Hispanic.[3] About one-quarter of the individuals

[2]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. But the spouses are not necessarily representative of their 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 this cohort group, as well as the representative sample of individuals in the 1921 to 1929 cohort, since they are mostly retired at their initial survey in 1998 and some express difficulty with the job-related gambles. The sample selection criteria have qualitatively little effect on the results.

[3]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.

did not complete high school versus almost one-fifth who have a college degree.

Over the panel, several individual 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. By the end of the panel, 34% of the gamble respondents have experienced a job displacement, that is, a job ending with a firm closure or layoff, and 37% have received a diagnosis of heart disease, a stroke, cancer, or lung disease. Most importantly, over a third of the displacements and half of the health conditions occur after an individual's first gamble response but before the end of the panel. 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 wealth and income during the panel period.[4] For the median respondent, household wealth is increasing across the survey waves and household income is decreasing, but there is considerable dispersion across respondents in the average level and changes in wealth and income. Overall these patterns reflect the fact that many of the individuals retire during the panel. Paired with the gamble responses, this longitudinal variation in an individual's wealth and income allows me to test the standard utility assumption of constant relative risk aversion.

The collection of the income gamble responses also coincides 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 outlook at the

[4]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 and transfers. Wealth and income are from the RAND HRS data set and include imputed values.

time of a gamble response.[5] 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.

Detailed information on the respondents allows me to investigate potential concerns about the quality of the gamble responses. In particular, I use the gambles to quantify an individual's coefficient of relative risk tolerance, that is, his inverse elasticity of marginal utility with respect to consumption, but the gambles refer explicitly to lifetime income — not lifetime consumption. The focus on "income" in the question reflects a compromise between conceptual accuracy and respondent comprehension. The choice between two hypothetical jobs places the gambles in a familiar setting and makes large movements in income feasible. As Rabin (2000) demonstrates, only large stakes — not the small payoffs that are typical in experiments — can inform us about an individual's diminishing marginal utility. Nonetheless the question on the HRS does not clearly specify how individuals should treat their non-labor income and wealth when evaluating the gambles. It is possible that an individual with considerable wealth relative to his expected income may accept greater job risks than another individual with less wealth even when the two have the same level of risk tolerance.

Table 4 shows no such bias in the responses due to large values of wealth relative to income. In 1992 individuals with wealth-to-income ratios above the median value of 2.2 are actually less (not more) willing to take income risks. In the 1998 and 2002 HRS, there is no significant difference between the gamble responses of individuals with high wealth-to-income ratios and those with low ratios. The ratio of current wealth to current income even overstates the relative importance of outside wealth. The gambles are defined over lifetime income, which should be several times larger than current annual income, even among a sample nearing retirement. Nonetheless the comments from a handful of individuals do suggest a confounding wealth effect.[6] Some variation in the question interpretation is inevitable, but

[5] A description of the index is available at the Survey of Consumers (www.sca.isr.umich.edu). Howrey (2001) demonstrates that the index has predictive power for economic recessions.

[6] Of the roughly 400 comments made by respondents during the income gamble sequence on the 1998 HRS, only three individuals discuss outside wealth and income: "Assume I can take everything I own with me?" "I could never lose since I have a pension, take high risk." "Do I still have retirement from government — security blanket?" The interviewer records any comments or questions made by the respondent. The

most individuals appear to use the intended permanent consumption concept of "total family income for life" or ignore their outside wealth when they evaluate the gamble.

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. (2005). Unlike the earlier analysis of the gamble responses in the HRS, I use a rich set of covariates in my model of risk tolerance to investigate systematic changes in risk tolerance. The model also allows for 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 circumstance leads to a change in risk tolerance.

3.1 Mapping Gambles to Preferences

Expected utility theory links the gamble responses to a cardinal measure of risk preferences — the coefficient of relative risk tolerance. Specifically, I use an individual's responses on the gambles to establish a range for his risk tolerance. Offered a 50-50 chance of doubling lifetime income W or cutting it by a fraction π, an individual accepts the risky job if its expected utility exceeds the utility from the certain job — that is, if

$$0.5U(2W) + 0.5U((1-\pi)W) \geq U(W). \tag{1}$$

The greater the curvature of U, the smaller the downside risk π an individual accepts. To further quantify risk preferences, I assume that relative risk aversion over lifetime income

HRS comment data are restricted-access and their availability varies across waves.

and its reciprocal relative risk tolerance are constant, such that

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

The coefficient of relative risk tolerance, $\theta = -U'/WU''$ (Pratt 1964), in this common specification of utility may differ across individuals but is constant for all values of lifetime income for a given individual. The estimation of this model tests the maintained hypothesis of constant relative risk aversion utility.

With a specific utility form, the gamble responses then imply a quantitative range for an individual's risk tolerance θ. Consider an individual, in gamble response category 3, who accepts the job with a one-fifth downside risk and rejects the job with a one-third downside risk. These choices imply a coefficient of relative risk tolerance between 0.27 and 0.50, since

$$\underline{\theta}_3 = 0.27 \iff 0.5\frac{2^{1-1/\underline{\theta}_3}}{1-1/\underline{\theta}_3} + 0.5\frac{(1-1/5)^{1-1/\underline{\theta}_3}}{1-1/\underline{\theta}_3} = \frac{1^{1-1/\underline{\theta}_3}}{1-1/\underline{\theta}_3} \tag{3}$$

$$\overline{\theta}_3 = 0.50 \iff 0.5\frac{2^{1-1/\overline{\theta}_3}}{1-1/\overline{\theta}_3} + 0.5\frac{(1-1/3)^{1-1/\overline{\theta}_3}}{1-1/\overline{\theta}_3} = \frac{1^{1-1/\overline{\theta}_3}}{1-1/\overline{\theta}_3}\,. \tag{4}$$

The highest downside risk an individual accepts and the smallest risk he rejects determine the upper and lower bounds on his risk tolerance. Table 5 provides these boundaries for each of the gamble response categories. The gamble responses provide a cardinal, albeit interval-coded, signal of an individual's coefficient of relative risk tolerance.

3.2 Model of Measured Log Risk Tolerance

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

$$\log \theta_{it} \quad = \quad x_{it}\beta + a_i \tag{5}$$

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 individuals are willing to take large income risks. The parameter β measures the percent change in risk tolerance associated with a change in the observed attributes x_{it}.

The time-constant component (or the pre-survey level) of risk tolerance a_i may be correlated with the individual circumstances x_{it} that can change risk tolerance. For example, experiencing a job displacement may reduce an individual's willingness to take further risks, that is, $\beta < 0$. Or the event could primarily reveal an individual's risk tolerance type if more risk tolerant individuals tended to select career paths with a higher risk of displacement. To accommodate such selection effects, I model a relationship between the time-constant component a_i and observable attributes as

$$a_i = \overline{x}_i \lambda + u_i \tag{6}$$

where $\overline{x}_i$ is the panel average of $x_{i1}, ..., x_{iT}$ for individual i and the type effect λ measures the persistent systematic differences across individuals in their risk tolerance.[7] The term u_i captures the portion of constant risk tolerance a_i that is unrelated to the attributes in $\overline{x}_i$, a vector that includes a constant. This mean-zero residual 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 (6) follows from Mundlak (1978). Chamberlain (1984) summarizes this modeling strategy and presents a more general specification of the type effects.[8]

My primary goal is to estimate the model of risk tolerance, but responses to the income gambles on the HRS provide an incomplete signal of preferences. The gamble responses establish an interval, not a point estimate, for an individual's implied risk tolerance, so I do

[7]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.

[8]Specifically, Chamberlain controls for the full set of an individual's covariates $x_{i1}, ..., x_{iT}$, 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.

not have the data to simply estimate the linear model. In addition, 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 income gamble questions.[9] 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 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 ϵ_{it}, such that

$$\xi_{it} = \log \theta_{it} + \epsilon_{it} \tag{7}$$

$$c_{it} = j, \quad \text{if} \quad \log \underline{\theta}_j < \xi_{it} < \log \overline{\theta}_j \quad (i = 1, ..., N; t = 1, ...T) \tag{8}$$

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 5. With the odds and outcomes explicitly stated in the gamble questions and constant relative risk aversion utility, the cutoffs are known values and do not vary across individuals or across waves. The model of the latent signal incorporates two sources of variation in gamble responses over time: systematic changes in risk tolerance and survey response error. Earlier studies of the income gambles on the HRS also include the time variation in gamble responses due to response error, but my analysis is the first to investigate changes in risk tolerance that are associated with observed changes in circumstances. I assign all the changes in the latent signal that are unrelated to these covariates to the survey response error. This modeling assumption likely understates any high frequency shifts in risk tolerance, but it is consistent with my attempt to measure a well-defined preference that would apply to other risky decisions made by the individual.

The specification of the survey response error also allows me to investigate the average

[9] Examples from the 1998 HRS 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."

effect of the question wording on individual's gamble responses, as well as quantify the relationship between the dispersion in the response error and observed attributes. The survey response error ϵ_{it} has the form

$$\epsilon_{it} \quad = \quad q_{it}\delta + e_{it} \tag{9}$$

where q_{it} is an indicator for a gamble response to the original ("new job") version of the question, so δ measures the degree of status quo bias in responses to the gamble question on the 1992 and 1994 HRS.[10] The term e_{it} is a survey response error that is unrelated to the question type and is independently distributed $\mathrm{N}(0, \sigma^2_{eit})$ across individuals and over time. I allow the observed attributes in the model of risk tolerance and the question type to also affect the dispersion of the response error. Specifically, the dispersion in response errors is $\sigma_{eit} = \exp[(x_{it}, \overline{x}_i, q_{it})\sigma_e]$, 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 systematically understate (or overstate) their risk tolerance in their gamble responses, but the response errors in this group may be larger in absolute value than those made by individuals with more education. The term e_{it} soaks up changes in an individual's gamble responses that are not associated with the observed attributes, as well as the unsystematic transitory variation in the gamble responses across individuals. The heteroscedastic variance of e_{it} permits the precision in the gamble responses — or the degree of wave-to-wave switches — to vary with individual attributes and question type. The gambles are complicated hypothetical questions on a lengthy survey and answers to the gambles have no real consequences, so a careful treatment of the survey response error is essential to infer risk tolerance from the gamble responses.[11]

[10] Features of the gamble delivery, such as a face-to-face or a telephone interview, or differences in respondent's survey behavior, such as time to complete the interview and frequency of item non-response, could also be included in q_{it}. For covariates that systematically affect both preferences and response errors, it would not be possible to separately estimate β and δ.

[11] Previous research also finds that the use of hypothetical questions leads to more variance in responses — not a systematic bias in the responses. In their survey of experimental studies, Camerer and Hogarth (1999) find that the size of financial incentives does not affect the average performance on judgment tasks. But smaller financial incentives are associated with greater variance or noise in the responses. Similarly Dohmen et al. (2006) establish a strong but imperfect correlation between the responses to hypothetical gambles on a large survey and gambles in an experiment with actual payoffs.

Combing the models of risk tolerance and survey response error yields a reduced-form description of the latent signal from the gamble responses:

$$\begin{aligned} \xi_{it} &= x_{it}\beta + a_i + q_{it}\delta + e_{it} && (10) \\ &= x_{it}\beta + \overline{x}_i\lambda + q_{it}\delta + u_i + e_{it} && (11) \end{aligned}$$

This is the underlying model that I estimate with the data. A restatement of the model draws particular attention to the variation in the preference signal within and between individuals. Specifically,

$$\xi_{it} = (x_{it} - \overline{x}_i)\beta + \overline{x}_i(\lambda + \beta) + q_{it}\delta + u_i + e_{it} \tag{12}$$

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 $(\beta + \lambda)$, 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 outlook in the panel and the persistent component of risk tolerance is absorbed in the estimate of the constant.

3.3 Log-Likelihood of Gamble Responses

I use maximum-likelihood methods to estimate the parameters $(\beta, \lambda, \delta, \sigma_u, \sigma_e)$ of the reduced-form model in equation (11) 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. Consider, for example, an individual who answers the gambles in only one wave of the HRS, but participates in multiple waves of the survey. The attributes x_{it} that are observed with a response to version q_{it} of the income gambles and the average of these attributes across the entire panel $\overline{x}_i$ yield the following likelihood that the individual is in gamble response category j at time t:

$$\begin{aligned} \mathrm{P}(c_{it} = j | x_{it}, \overline{x}_i, q_{it}) &= \mathrm{P}(\log \underline{\theta}_j < \xi_{it} < \log \overline{\theta}_j | x_{it}, \overline{x}_i, q_{it}) \\ &= \Phi\left(\frac{\log \overline{\theta}_j - x_{it}\beta - \overline{x}_i\lambda - q_{it}\delta}{\sigma_{\xi it}}\right) - \Phi\left(\frac{\log \underline{\theta}_j - x_{it}\beta - \overline{x}_i\lambda - q_{it}\delta}{\sigma_{\xi it}}\right) \end{aligned} \quad (13)$$

where $\sigma^2_{\xi it} = \mathrm{Var}(\xi_{it}|x_{it}, \overline{x}_i, q_{it}) = \sigma^2_u + \sigma^2_{eit}$ and $\Phi(\cdot)$ is the univariate normal cumulative distribution function. I adjust the likelihood function accordingly for the individuals who answer the gamble questions in multiple survey waves.[12] 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, λ, and δ are identified separately from the variance terms and are interpretable as if the latent signal ξ_{it} were directly observed.[13] 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 maximum-likelihood estimator finds the values of the parameters that maximize the conditional log-likelihood $\mathcal{L}$ of the sample:

$$\mathcal{L}(\beta, \lambda, \delta, \sigma_u, \sigma_e | c_i, x_{it}, \overline{x}_i, q_{it}) = \sum_{i \in N} \sum_{j \in J} 1[c_i = j] \log \mathrm{P}(c_i = j | x_{it}, \overline{x}_i, q_{it}) \quad (14)$$

where $c_i = (c_{i1}, ... c_{iT})$ is the set of an individual's gamble responses on the HRS and J

[12]The individual-specific random effect u_i is constant over time, such that the $\mathrm{Cov}(\xi_{is}, \xi_{it} | x_{is}, x_{it}, \overline{x}_i, q_{is}, q_{it}) = \sigma^2_u$ 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 method. For the integration, I use Matlab codes for Gaussian quadrature from Miranda and Fackler (2002). My use of correlated random effects also follows from the probit model of gamble responses, since no consistent fixed-effects estimator exists for this non-linear model, see Chamberlain (1984) for a discussion.

[13]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.

contains all possible sets of response categories. For the estimator, I use the modified method of scoring, a Newton-Raphson algorithm in which the inner product of the score function provides the Hessian of the likelihood function.[14] The estimates of the asymptotic standard errors are also derived from this estimator of the information matrix.

4 ESTIMATES OF RISK TOLERANCE

The results from the estimation reveal considerable information on how an individual's risk tolerance evolves over time, as well as the degree to which preferences vary across individuals. There is a moderate decline in an individual's risk tolerance with age and an improvement in macroeconomic conditions is associated with an increase in risk tolerance. But changes in wealth and income do not significantly alter an individual's willingness to take risk. In addition, personal events that plausibly reduce an individual's expected lifetime income have little impact on risk tolerance. The results strongly support the standard specification of utility with constant relative risk aversion and offer no evidence of reference-dependent preferences. In contrast, I find large stable differences across individuals in their risk tolerance type. 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 allows me to investigate the 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. Appendix Table 1 contains the full set of covariates and estimates.

4.1 Individual Attributes

The estimated model of risk tolerance shows substantial differences across individuals by gender, race, and education. Table 6 reports that the risk tolerance of men is 15% higher

[14] I calculate the score with numerical differentiation code from Miranda and Fackler (2002) and implement the maximum-likelihood estimator in Matlab.

than of women — a finding consistent with a vast literature on gender differences in risk taking; see Byrnes et al. (1999) for a meta-analysis of the studies in psychology. 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. 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 but my analysis is one of the few attempts to quantify these differences in terms of the coefficient of relative risk tolerance.[15]

The bottom part of Table 6 presents the first estimates of systematic change in risk tolerance. In particular, I find that entering a marriage is associated with an 18% increase in risk tolerance. Yet less risk tolerant types are more likely to be consistently married in the panel. All else equal, an individual who is married at each survey is 18% less risk tolerant than an individual who is never married.[16]

I also find a strong relationship between responses to the income gamble questions and the subjective probability questions on the HRS. Specifically, individuals who tend to provide precise probability answers also accept more hypothetical income risk and exhibit less random variation in their gamble responses. 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

[15]In their study of the income gambles on the HRS, Barsky et al. (1997) compare their measure of an individual's risk tolerance — estimated from only the gamble responses — across several groups. Their findings are qualitatively similar to mine, but my comparisons occur in a multivariate maximum-likelihood model. The model of heteroscedasticity in the survey response error also refines the estimated relationships between observed attributes and risk preference. For example, the standard deviation of men's survey response error is 11% larger than women, so if I instead force the error to be homoscedastic in this nonlinear model, the estimated difference in risk tolerance by gender increases to 22% from 15%.

[16]This calculation adds the estimated direct effect of 18% with the type effect of -35%. 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."

argue that individuals with less precise probability beliefs should be less risk tolerant.[17] The results in Table 6 are consistent with their hypothesis, such that a one-standard deviation higher average FEP is associated with a 19% higher level of risk tolerance. A change in an individual's FEP relative to his average FEP over the panel also has a large and significant effect on his measured risk tolerance.

4.2 Job Displacement and Health Condition

A job displacement and a serious health condition are two major life events that likely affect an individual's expected lifetime income.[18] The gambles on the HRS are defined over lifetime income, so a shift in this reference point could alter an individual's attitude toward risk. For example, an individual may accept more income risk after a negative personal shock if that gamble could restore his original level of lifetime income. Or an individual who has received one draw of bad luck may simply be less willing to "spin the wheel" again. Rather than a change in risk tolerance, these events — which do not occur purely at random — could signal an individual's risk tolerance type. For example, high risk tolerant types may have selected risky 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, and thus accepted a higher risk of a serious health condition. A panel of gamble responses and events is essential for separating these mechanisms.

Both a job displacement and the onset of a health condition are associated with a decline in risk tolerance of 6% and 9% respectively, but these direct effects are imprecisely estimated and not statistically different from zero.[19] More striking is the evidence of selection into risky

[17] 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.

[18] 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.

[19] 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.

careers based on individual preferences. Among individuals with no prior job displacement, those who will experience a displacement later in the panel are 20% more risk tolerant than those who will never experience a displacement. The estimate of the type effect is both economically and statistically significant, as it suggests that high risk tolerance types have systematically chosen riskier careers with a higher chance of displacement. The positive correlation between risk tolerance and income risk underscores the need for a direct measure of individual preferences. For example, studies of household wealth that do not address this systematic variation in preferences would underestimate the amount of precautionary savings.[20]

4.3 Age, Cohort, and Time

Changes in attitudes toward risk over the life cycle are of particular interest. Even with panel data, the fixed set of birth cohorts and the concurrent changes in aggregate conditions complicate any effort to identify the direct effect of age.[21] In my model of risk tolerance, I adopt a linear specification of an individual's age at the time of the gamble response, an indicator variable for being in one of three cohort groups that each span 5 or 6 birth years, and a measure of the macroeconomic conditions in the interview month. The first column of Table 8 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 11-year survey period due to aging.[22] Individuals in the 1937-41 birth cohorts are also 17% more risk tolerant than individuals in the 1931-1936 cohorts. The effects of birth cohort are generally consistent with individuals closer to the Great Depression

[20]In a comparison of savings in the former East and West Germany after reunification, Fuchs-Schündeln and Schündeln (2005) also find evidence of job selection due to risk preferences. They also show that ignoring this selection would underestimate precautionary wealth by 40% among German households.

[21]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. (2005) 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.

[22]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), and Dohmen et al. (2006), 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.

being less willing to take risk. Finally there is a strong positive relationship between risk tolerance and macroeconomic conditions, as measured by the Index of Consumer Sentiment (ICS). A ten-point increase in the sentiment index is associated with a 9% increase in an risk tolerance. And there are large swings in this measure of current and anticipated economic conditions which implies that average risk tolerance rose 36% from October 1992 to February 2000 and later dropped sharply by 15% from May 2002 to February 2003.

The second two columns of Table 8 use alternate specifications of the year effects to check the robustness of my baseline estimates. In column two, the model controls for the survey wave of a gamble response, but not consumer sentiment.[23] All of the year effects are economically and statistically significant, but this alternate specification has little impact on the point estimate on age and cohort. In the third 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 0.006 is only somewhat lower than the estimate of 0.009 in the baseline model and has a t-statistic of 1.88. In addition, the Index of Consumer Sentiment soaks up much the wave-to-wave differences in gamble responses. Only gamble respondents to the 1994 HRS remain significantly more risk tolerant than those to the 1992 HRS.[24] Again the estimates of the age and cohort effects are unaffected. The comparison of the model results in Table 8 demonstrates that my parsimonious model of age, cohort, and time in the first column adequately captures the important features of individuals' risk tolerance.

4.4 Household Wealth and Income

Whether a change in financial resources leads to changes in tolerance is a question that directly informs how economists specify utility in their models of behavior. I find no evidence

[23]In addition, I cannot control separately for the question version, since all the gamble respondents in the 1992 HRS and 1994 HRS answer the "new job" version of the question.

[24]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, but they are explicitly given an opportunity to skip this extra section. Thus the actual group of respondents — and the environment of the question collection — in 1994 may not be entirely comparable to gamble responses on other waves.

of a systematic relationship between an individual's risk tolerance and his total household wealth or income.[25] The first column of Table 9 shows that a 10% increase in current wealth relative to the individual's average wealth is associated with only a 0.1% increase in risk tolerance. With a standard error of 0.2% the direct effect of wealth is a precisely estimated zero. Likewise changes in an individual's current income have no effect on risk tolerance. The differences in risk tolerance across individuals who have different levels of average wealth and income in the survey period are also minimal. An individual with a 10% higher average wealth is 0.1% more risk tolerant, and a 10% higher average income is associated with 0.7% higher risk tolerance. These effects are all small in magnitude and not statistically distinguishable from zero.

These results support the standard specification of utility with constant relative risk aversion. Yet this is one case where my findings depart from previous cross-sectional analysis of other surveys. Both Donkers et al. (2001) and Dohmen et al. (2006) report a positive and statistically significant association between the level of wealth and income and the willingness to take risk. Their point estimates rely on different survey questions and are not expressed in terms of the coefficient of relative risk tolerance, so I cannot quantify the magnitude of the discrepancy. But the estimated marginal effects of wealth and income in the previous studies are also small relative to other demographics, such as age and gender.[26]

Table 9 also shows that the definition of wealth has little impact on the estimates. The baseline model in the first column uses the net value of total household wealth and the model in the second column uses the net value of non-housing financial assets. The direct effects of financial wealth on risk tolerance are even smaller than total wealth and these estimates are

[25] 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.

[26] 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 risk question and a hypothetical lottery question, Dohmen et al. (2006) find even smaller marginal effects, such that a one year change in age is comparable to a 100% change in wealth. And these cross-sectional studies combine the direct and type effects in a single parameter estimate.

not statistically different from zero. Individuals with 10% higher average financial debt over the panel are 0.5% more risk tolerant and this estimate is now statistically significant at the 5% level. The panel of gamble responses is one difference in my analysis of risk preference, but even when I restrict the data to a single response from each individual, the marginal effect of wealth and income is qualitatively unchanged. Likewise the model of survey response error and controlling for precision in individuals' answers to other hypothetical questions does not alter the effect of wealth and income on risk tolerance. There is no evidence that the coefficient of relative risk tolerance moves with wealth and income.

4.5 Measure of Individual Risk Tolerance

Using the model estimates, I now form a measure of an individual's risk tolerance. Specifically, I calculate the expected value of log risk tolerance conditional on the observed attributes and gamble responses of an individual in the panel, that is,

$$\mathrm{E}(\log\theta_{it}|x_{it},\overline{x}_i,c_i) \quad = \quad x_{it}\widehat{\beta}+\overline{x}_i\widehat{\lambda}+\mathrm{E}(u_i|x_{it},\overline{x}_i,c_{it},...c_{iT}) \tag{15}$$

where c_{it} is an individual's gamble response category in a particular wave. The mean of the random effect u_i conditional on attributes $\overline{x}_i$ is zero, but an individual's set of gamble responses $c_i = (c_{it},...c_{iT})$ does provide some information on the level of this component.[27] The decomposition of the preference measure into permanent and transitory components is again useful with

$$\mathrm{E}(\log\theta_{it}|x_{it},\overline{x}_i,c_i) \quad = \quad (x_{it}-\overline{x}_i)\widehat{\beta}+\overline{x}_i(\widehat{\beta}+\widehat{\lambda})+\mathrm{E}(u_i|x_{it},\overline{x}_i,c_i) \tag{16}$$

where the first term on the right is a transitory component related to changes in observed attributes of an individual, the second is a permanent component related to differences across individuals in their observed attributes, and the third is a permanent component related only to the difference across individuals in their gamble responses.

[27]The variance of the conditional expectation of u_i in the sample is much smaller than its unconditional variance. See Kimball et al. (2005) for a further discussion of how this diminished variability impacts the use of a measure based on the conditional expectation.

Table 10 shows more than 80% of the variation in this measure of preferences stems from persistent differences across individuals. In each wave, the systematic between-person differences account for more than half of the variation in the measure of risk tolerance. The variation related to changes in individuals' circumstances in the panel is only about 11% of the total variance. The bottom row of Table 10 shows that there is a large amount of random, heteroscedastic noise in the gamble responses. The variance of the survey response error is an order of magnitude larger than the variance in the measure of risk tolerance. Nonetheless the gambles do provide information on the systematic differences across individuals in preferences and on changes in an individual's risk tolerance over time. And this measure of risk tolerance developed from the gambles also predicts actual risky choices made by individuals.

5 STOCK OWNERSHIP

Economic theory assigns a central role to risk preference in the decision to hold risky assets, so stock ownership represents a natural application for my measure of individual risk tolerance. I find that increases in an individual's risk tolerance, as well as a persistently more risk tolerant type predict actual stock ownership in the panel. The measure of risk tolerance also refines the standard inferences on the determinants of stock ownership, including the effects of gender, education, and wealth.

Assets are held jointly in a household, but many attributes, such as risk tolerance, are defined for an individual. So I analyze the stock ownership decisions of 5,997 individuals, who were the financial respondents in original households, over the first six waves of the HRS. A financial respondent is the member of the household who is the most knowledgeable about the household's finances and this individual answers the questions on the survey about the household's wealth and income. Years in which the individual's household has no financial wealth, negative net worth, or zero income are excluded, which leaves an unbalanced panel with over 26,000 person-year observations. Pooling across households and survey waves, 36% of the observations own stocks directly.[28] The rate of stock ownership also varies across

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

waves from 33% of households in the 1992 HRS to 37% of households in the 2000 HRS. And almost one-third of the individuals report movements into or out of stocks over the panel.

The first column of Table 11 presents the estimated marginal effects of individual and household attributes on the probability of owning stocks. This model includes no measure of an individual's attitude toward risk. Education, wealth, and income are strong predictors of stock ownership — similar to the results in numerous studies of household portfolios, for example, see Guiso et al. (2002). African Americans and Hispanics are much less likely to hold stocks than whites, and being married is also associated with a lower rate of stock ownership.[29] As the results in Section 4 show, there is considerable variation across individuals in their risk attitudes, and some of these observed attributes are also correlated with risk tolerance. So a direct measure of risk tolerance is needed to separate the effects of preferences on stock ownership from the other effects that may be related to these observables, such as transaction costs and risk perceptions.

The estimation in Section 4 with the hypothetical gambles provides an individual-specific measure of risk tolerance over the panel period. The second column of Table 11 provides the estimates from a model that controls for an individual's average log risk tolerance in the panel, as well as the difference between the individual's current log risk tolerance and his panel average level. Across individuals, a 10% higher level of average risk tolerance is associated with a 1.4 percentage point higher probability of owning stocks. This estimate is both statistically and economically significant, since a one-standard-deviation difference in average risk tolerance corresponds to a 6.4 percentage point difference in the predicted probability of stock ownership — over one-sixth of the actual stock ownership rate.[30] My results from a panel of stock ownership decisions are consistent with the cross-sectional analysis of Barsky et al. (1997) who find a positive association between risk tolerance and the allocation of financial assets to stocks. Table 11 also shows that the measured changes

[29] The marginal effects in Table 11 are calculated in Stata with estimates from a random effects panel probit model, evaluated at the sample median of the variables with the random effect set to zero. For discrete variables, the marginal effect reflects a change from 0 to 1.

[30] Asymptotic standard errors are reported in the second column Table 11. The measure of individual risk tolerance is developed from a maximum likelihood estimation, so the asymptotic standard errors in the stock ownership model overstate the estimate precision. Bootstrap replications on a related, but computationally less intensive model in Kimball et al. (2005) yield only modest increases in the standard errors. Furthermore, the asymptotic t-statistic on the panel average of log risk tolerance is 5.6

in risk tolerance are related to actual stock ownership. An individual whose risk tolerance is currently 10% above his average level in the panel is 0.6 percentage points more likely to own stocks.

A direct measure of risk tolerance also refines the association between stock ownership and commonly observed attributes. For example, the variation in risk tolerance absorbs much of the higher probability of stock ownership among men in the baseline model. In contrast, it appears that the effect of education on stock ownership is only partially related to risk tolerance. With a direct preference measure, the marginal effects of a college and post-graduate education drop by 4 and 6 percentage points respectively. Yet, the individuals with higher education are still over 10 percentage points more likely to own stocks than individuals with only a high school degree. Individuals without a high school degree are 15 percentage points less likely to own stocks and this pattern is not affected by the risk tolerance measure. These results suggest that the commonly observed association between education and stock ownership combines differences across education groups in risk attitudes, transaction costs of investing in stocks, and perceived risk of stocks. I also find that the marginal effects of wealth and income on stock ownership are unrelated to differences in risk preference. This suggests that alternate explanations, such as a fixed cost of buying stocks, are needed to explain the strong association between wealth and stock ownership, as 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. This analysis of stock ownership also clearly demonstrates that the hypothetical gambles do capture meaningful differences in preferences.

6 CONCLUSION

Individuals exhibit a stable risk preference that shapes behavior across different decision contexts and circumstances. There are modest changes in individuals' risk tolerance with age and macroeconomic conditions. More commonly a change in an individual's circumstance, such as a job displacement, reveals information about a risk tolerance type, not a change in the willingness to take risk. My results are broadly consistent with the treatment of preferences in standard economic models, in particular the specification of utility with constant relative risk aversion.

But how sensitive are the results to the specific features of the hypothetical gambles that I analyze? In particular, how does the question frame — a choice between two jobs — affect the resulting measure of risk tolerance when over one-third of the respondents are not working at the time of their gamble response and over 40% experience a change in their work status during the survey period? It is important to stress that my paper focuses on the variation in risk tolerance over time for a given individual and across individuals at a particular point in time, not the average level of the preference parameter. Respondents in all of the waves are asked about the same set of hypothetical income risks. This is a degree of objective conformity rarely achieved in the study of actual decisions. Response error alone — either a question effect common to all respondents or confusion with the question that only affects certain groups of respondents — would not alter the interpretation of my results. Instead a bias in the gamble responses would have to be systematically related to the observed covariates in my model. The results, in particular the analysis of actual asset allocation decisions, provide the strongest defense of the methods.

Altogether I find no evidence that changes in individual's circumstances have a long-lasting impact on risk preference. I investigate the typical candidates for reference dependency — movements in wealth and income — with changes in the reported values and with the study of major life events. Shocks to individuals' actual or expected financial resources have no effect on their measured risk tolerance. Yet responses to the income gambles could be consistent with transitory movements in preference due to the decision environment. For example, there is a positive association between the general economic outlook at the time of a gamble response and an individual's willingness to take risks. Attitudes toward risk may move over the business cycle, but there is no evidence this translates into a permanent shift in risk tolerance. Furthermore my model assigns much of the transitory variation in gamble responses to the residual of "survey response error." It is possible that data collected at a higher frequency could provide more insight on the initial magnitude and dissipation of any short-lived reference effects. In the end, the research question must inform the modeling of preferences. Studies, as in behavioral economics, that seek to understand how context can produce choices at odds with an individual's general risk attitude will require a formal treatment of transitory reference effects. My results imply that the standard preferences used in economic models can capture the central tendencies of behavior, either in a cross-section of individuals facing a similar risky choice or for one individual facing a series of risky decisions over a lifetime.

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Table 1: Risk Tolerance Categories by Downside Risks

Response	Downside Risk	
Category	Accept	Reject
1	None	1/10
2	1/10	1/5
3	1/5	1/3
4	1/3	1/2
5	1/2	3/4
6	3/4	None

NOTE: In a series of questions, respondents choose between a certain job and a risky job. With equal chances, the risky job will double lifetime income or cut lifetime income by a specific fraction (downside risk). The largest downside risk accepted and smallest risk rejected across the income gambles define an individual's response category. In 1992 there are four categories 1-2, 3, 4, and 5-6. In 1994 and later surveys, response categories range from 1 to 6. The downside risks associated with these six categories are in the table. Risk tolerance increases in the category number. In 1992, persons in the combined category 1-2 decline risky jobs with one-third and one-fifth downside risks. Persons in category 5-6 accept risky jobs with one-third and one-half downside risks.

Table 2: Responses to Lifetime Income Gambles

	HRS Survey Wave				
% in Category	1992	1994	1998	2000	2002
1: Reject All	64.5	44.3	39.9	45.2	43.7
2: Accept 1/10		17.0	18.4	19.3	18.7
3: Accept 1/5	11.7	13.5	16.2	14.4	15.3
4: Accept 1/3	10.9	15.0	9.3	8.6	9.8
5: Accept 1/2	12.8	6.3	9.2	7.0	6.4
6: Accept 3/4		3.9	7.0	5.6	6.1
Respondents	10,230	635	2,618	987	5,220
% Non-Response	2.5	10.3	6.0	11.1	8.7

NOTE: Author's tabulations from HRS public access data files. The sample includes 12,574 individuals in the 1931 to 1947 birth cohorts. The tabulations here are unweighted. Gamble response categories are summarized by the highest downside risk accepted. Table 1 provides details on the category definition. In 1992 and 1998, the survey mainly asks the gambles to new respondents in face-to-face interviews. In the other survey waves, the gambles are mainly asked to returning respondents in telephone interviews. These differences likely drive the variation in the gamble non-response rate across waves.

Table 3: Attributes of Gamble Respondents, 1992 - 2002

	HRS Survey with Gamble Responses				
Percent	1992	1994	1998	2000	2002
Male	41.8	40.3	48.6	42.0	40.2
Black	16.8	15.3	14.5	13.7	15.1
Hispanic	9.0	4.1	7.0	7.9	7.9
High School Drop Out	27.6	20.9	17.2	23.3	19.8
H.S. Grad / Some College	55.1	61.6	57.1	55.5	57.6
College / Post Graduate	17.3	17.5	25.6	21.2	22.7
Job Displacement					
Previous	20.9	23.0	22.0	32.6	32.9
Ever	34.2	32.9	28.7	35.1	32.9
Health Condition					
Previous	19.2	21.1	18.8	28.8	29.6
Ever	38.5	37.0	28.2	33.4	29.6
Married					
Currently	75.3	75.6	71.6	66.0	71.1
Change in Panel	12.8	12.0	8.3	14.0	12.8
Mean (Standard Deviation)					
Current Age	55.2	56.9	55.6	62.0	60.3
	(3.9)	(3.9)	(4.2)	(4.3)	(3.0)
Fraction Exact Probability					
Current Level	0.46	0.38	0.39	0.40	0.47
	(0.23)	(0.22)	(0.24)	(0.24)	(0.22)
Current - Panel Average	0.07	-0.02	-0.03	0.00	0.03
	(0.17)	(0.14)	(0.14)	(0.15)	(0.14)
Median (Interquartile Range)					
Log of Wealth					
Current Level	11.8	12.0	11.9	12.1	12.1
	(1.7)	(1.6)	(1.8)	(1.9)	(1.8)
Current - Panel Average	-0.13	-0.07	-0.06	0.03	0.08
	(0.67)	(0.61)	(0.53)	(0.56)	(0.59)
Log of Income					
Current Level	10.8	10.9	10.9	10.7	10.8
	(1.1)	(1.1)	(1.2)	(1.3)	(1.2)
Current - Panel Average	0.01	-0.01	-0.01	-0.05	-0.08
	(0.47)	(0.47)	(0.35)	(0.49)	(0.53)
Respondents	10,230	635	2,618	987	5,220

NOTE: Author's unweighted tabulations are from HRS public access data files and Rand HRS (Version F) data set. 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 including housing wealth and excluding pension and Social Security wealth. Income is the total income of a respondent and spouse from all earnings and transfers. Wealth and income are from the RAND HRS data set and include imputations. The median value for wealth above is only for individuals with positive wealth. The estimation controls separately for negative wealth.

Table 4: Gamble Responses by Wealth-to-Income Ratio

Wealth-to-Income Ratio	% in Response Category 1-2	3	4	5-6	Pearson χ^2 Statistic	Average Age	Number of Respondents
1992 Above Median	65.5	12.0	10.5	12.0	9.6	55.7	5,038
1992 Below Median	63.5	11.5	11.4	13.6	(0.02)	54.7	5,192
1998 Above Median	57.6	16.4	9.5	16.5	0.5	56.3	1,317
1998 Below Median	59.0	15.9	9.2	15.9	(0.91)	54.9	1,301
2002 Above Median	62.4	14.8	9.6	13.2	3.6	60.5	2,608
2002 Below Median	62.5	15.8	10.0	11.7	(0.31)	60.0	2,612

NOTE: In each row, the percent in the response categories sum to 100. The median values of the wealth-to-income ratios among gamble respondents are 2.3 in the 1992 HRS, 2.2 in the 1998 HRS, and 3.0 in the 2002 HRS. The p-value for the Pearson χ^2 Statistic is in parentheses. The null hypothesis is no association between the respondent group and the gamble responses categories.

Table 5: Bounds for Risk Tolerance

Response Category	Lower Bound	Upper Bound
1	0	0.13
2	0.13	0.27
3	0.27	0.50
4	0.50	1.00
5	1.00	3.27
6	3.27	∞

NOTE: At the lower bound of risk tolerance for a category, an individual with constant relative risk aversion 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. See Table 1 for the downside risks associated with the risk tolerance response categories. For the combined category 1-2 in 1992 the lower bound is 0 and the upper bound is 0.27. Category 5-6 has a lower bound of 1.0 and is not bounded above.

Table 6: Individual Attributes

Latent Variable: Log of Risk Tolerance	
Parameter	Estimate
Composite Effect: $\beta + \lambda$	
Male	**0.15**
	(0.03)
Black	**-0.28**
	(0.06)
Hispanic	-0.04
	(0.08)
High School Drop Out	0.02
	(0.05)
Some College	**0.18**
	(0.05)
College Graduate	**0.23**
	(0.06)
Post Graduate	**0.34**
	(0.05)
Direct Effect: β	
Currently Married	**0.18**
	(0.09)
Fraction Exact Probability	**0.78**
	(0.10)
Type Effect: λ	
Proportion of Waves Married	**-0.35**
	(0.10)
Average FEP Across Waves	**0.32**
	(0.13)
Log-likelihood	-24893.8

NOTE: Asymptotic standard errors are in parentheses. Estimates in bold are statistically significant at the 5% level. The correlated random effects model with known cutoffs is estimated with a panel of gamble responses and observed attributes on the HRS from 12,574 individuals. Appendix Table 1 provides the full set of covariates and estimates. The estimates are interpretable as the elasticity of risk tolerance with respect to an observed attribute with the values of the other covariates held constant. 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). The covariates under the type effects are an individual's average over the panel period, not an average across individuals.

Table 7: Job Displacement and Health Condition

Latent Variable: Log of Risk Tolerance	
Parameter	Estimate
Direct Effect: β	
Previous Job Displacement	-0.06
	(0.06)
Previous Health Condition	-0.09
	(0.06)
Type Effect: λ	
Ever Job Displacement	**0.20**
	(0.06)
Ever Health Condition	0.01
	(0.06)
Log-likelihood	-24893.8

NOTE: Asymptotic standard errors are in parentheses. Estimates in bold are statistically significant at the 5% level. The sample includes 12,574 individuals. Appendix Table 1 provides the full set of covariates and estimates. A job displacement is a job ending with a firm closure or layoff. A health condition is heart disease, stroke, cancer, or lung disease.

Table 8: Age, Cohort, and Time

Latent Variable: Log of Risk Tolerance			
	Estimate		
Parameter	(1)	(2)	(3)
Current Age	**-0.017**	-0.019	-0.019
	(0.008)	(0.010)	(0.010)
1937-1941 Cohorts	**0.17**	**0.15**	**0.15**
	(0.06)	(0.07)	(0.07)
1942-1947 Cohorts	0.16	0.12	0.12
	(0.10)	(0.12)	(0.12)
Consumer Sentiment	**0.009**		0.006
	(0.002)		(0.003)
1994 HRS		**0.27**	**0.20**
		(0.08)	(0.08)
1998 HRS		**0.35**	0.19
		(0.08)	(0.11)
2000 HRS		**0.29**	0.12
		(0.10)	(0.14)
2002 HRS		0.21	0.14
		(0.11)	(0.11)
"New Job" Question	-0.06		
	(0.09)		
Log-likelihood	-24893.8	-24890.6	-24888.5
Parameters	55	59	61

NOTE: Asymptotic standard errors are in parentheses. Estimates in bold are statistically significant at the 5% level. The sample includes 12,574 individuals. The first column is the preferred 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 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 73.3 in October 1992 to 111.3 in February 2000. A gamble response on the 1992 HRS survey is the omitted wave control. The "new job" version of the income gamble question is asked on the 1992 and 1994 waves of the HRS.

Table 9: Household Wealth and Income

Latent Variable: Log of Risk Tolerance		
	Wealth Includes Housing, IRAs, and Non-Financial Assets	
Parameter	Yes	No
Direct Effect: β		
Log of Current Wealth (Positive)	0.011	0.007
	(0.016)	(0.008)
Log of | Current Wealth (Negative) |	0.034	0.017
	(0.019)	(0.009)
Log of Current Income	0.008	0.007
	(0.017)	(0.017)
Type Effect: λ		
Log of Average Wealth (Positive)	-0.002	0.013
	(0.020)	(0.012)
Log of | Average Wealth (Negative) |	0.016	**0.031**
	(0.027)	(0.014)
Log of Average Income	0.060	0.056
	(0.034)	(0.033)
Log-likelihood	-24893.8	-24895.7

NOTE: Asymptotic standard errors are in parentheses. Estimates in bold are statistically significant at the 5% level. The sample includes 12,574 individuals. Appendix Table 1 provides the full set of covariates and estimates. In the first column, wealth is total household wealth (including housing, vehicles, businesses, and IRAs) minus all debts. In the second column wealth is the net value of non-housing financial wealth. Income is total earnings, pensions, government transfers, and capital income received by the husband and wife in the household. With small point estimates for the wealth and income effects, the actual variable used is the estimation is the log(value) divided by 10.

Table 10: Variance Decomposition of the Measure of Risk Tolerance

Variance	HRS Survey Wave					
	1992	1994	1996	1998	2000	2002
Measure of Risk Tolerance	0.21	0.22	0.22	0.25	0.25	0.25
Change in Observables: Within	0.03	0.02	0.02	0.03	0.02	0.03
Differences in Observables: Between	0.12	0.12	0.12	0.13	0.13	0.13
Differences in Gambles: Between	0.06	0.06	0.06	0.08	0.08	0.08
Survey Response Error						
Random, Heteroscedastic Noise	2.86	2.71	3.20	2.84	2.66	3.04
Number of Survey Respondents	10,385	9,175	8,666	10,192	9,510	9,224

NOTE: The measure of risk tolerance, $\mathrm{E}(\log \theta_{it} | x_{it}, \overline{x}_i, c_i)$, is calculated with the maximum-likelihood estimates for each individual whose covariates x_{it} are observed in the survey wave, not just those who provide a gambles in the wave. The first row is the variance of the risk tolerance measure in the wave. The next three rows show the variance of the following components of the measure: $(x_{it} - \overline{x}_i)\widehat{\beta}$, $\overline{x}_i(\widehat{\beta} + \widehat{\lambda})$, and $\mathrm{E}(u_i | x_{it}, \overline{x}_i, c_i)$. The unconditional variance of the response error in the final row is the average value of $\widehat{\sigma}^2_{eit}$ for the respondents in the wave.

Table 11: Decision to Own Stocks

Dependent Variable: Indicator of Stock Ownership		
	Marginal Effect on Probability	
Variable	(1)	(2)
Log Risk Tolerance		
Individual Panel Average		**0.14**
		(0.03)
Current - Panel Average		**0.06**
		(0.03)
Current Age / 10	-0.04	-0.01
	(0.04)	(0.05)
1937-1941 Cohorts	-0.03	**-0.06**
	(0.02)	(0.03)
1942-1947 Cohorts	-0.03	-0.04
	(0.04)	(0.05)
Male	0.028	0.009
	(0.014)	(0.016)
Black	**-0.15**	**-0.15**
	(0.01)	(0.02)
Hispanic	**-0.17**	**-0.19**
	(0.02)	(0.02)
Married	**-0.03**	-0.02
	(0.01)	(0.02)
High School Drop Out	**-0.13**	**-0.15**
	(0.02)	(0.02)
Some College	**0.10**	**0.07**
	(0.02)	(0.02)
College Graduate	**0.22**	**0.18**
	(0.03)	(0.03)
Post Graduate	**0.16**	**0.10**
	(0.03)	(0.03)
Log Wealth	**0.16**	**0.18**
	(0.01)	(0.01)
Log Income	**0.06**	**0.06**
	(0.01)	(0.01)
Predicted Probability	0.21	0.25
Log-Likelihood	-11096.7	-11074.2

NOTE: The marginal effect of a variable on the probability of stock ownership uses estimates from a random effects panel probit evaluated at the median values of the covariates and the random effect equal to 0. Asymptotic standard errors are in parentheses. Estimates in bold are statistically significant at the 5% level. Both models also include survey wave controls. The sample includes 5,997 financial respondents from original households in 1992 with 26,035 person-wave observations from 1992 to 2002.

Appendix Table 1: Maximum-Likelihood Estimates of Log Risk Tolerance

Latent Variable: Log of Noisy Risk Tolerance: ξ_{it}				
	Mean Effect			Std. Dev.
Variable	Direct	Type	Composite	Effect
Constant			**-3.16**	**1.68**
			(0.71)	(0.47)
Male			**0.15**	**0.11**
			(0.03)	(0.02)
Black			**-0.28**	**0.19**
			(0.06)	(0.03)
Hispanic			-0.04	**0.14**
			(0.08)	(0.04)
1937-1941 Cohorts			**0.17**	-0.01
			(0.06)	(0.04)
1942-1947 Cohorts			0.16	0.01
			(0.10)	(0.07)
Drop Out			0.02	**0.07**
			(0.05)	(0.03)
Some College			**0.18**	0.03
			(0.05)	(0.03)
College Graduate			**0.23**	-0.01
			(0.06)	(0.04)
Post College			**0.34**	0.03
			(0.05)	(0.04)
Index Consumer Sentiment / 10	**0.09**			**-0.05**
	(0.02)			(0.02)
Current Age / 10	**-0.17**			0.01
	(0.08)			(0.05)
Currently Married	**0.18**			-0.07
	(0.09)			(0.06)
Fraction Exact Probability	**0.78**			**-0.44**
	(0.10)			(0.07)
Previous Job Displacement	-0.06			0.003
	(0.06)			(0.05)
Previous Health Condition	-0.09			-0.05
	(0.06)			(0.05)
Log (Current + Wealth) / 10	0.11			**-0.21**
	(0.16)			(0.10)
Log (| Current − Wealth |) / 10	0.34			-0.11
	(0.19)			(0.12)
Log (Current Income) / 10	0.08			-0.06
	(0.17)			(0.10)

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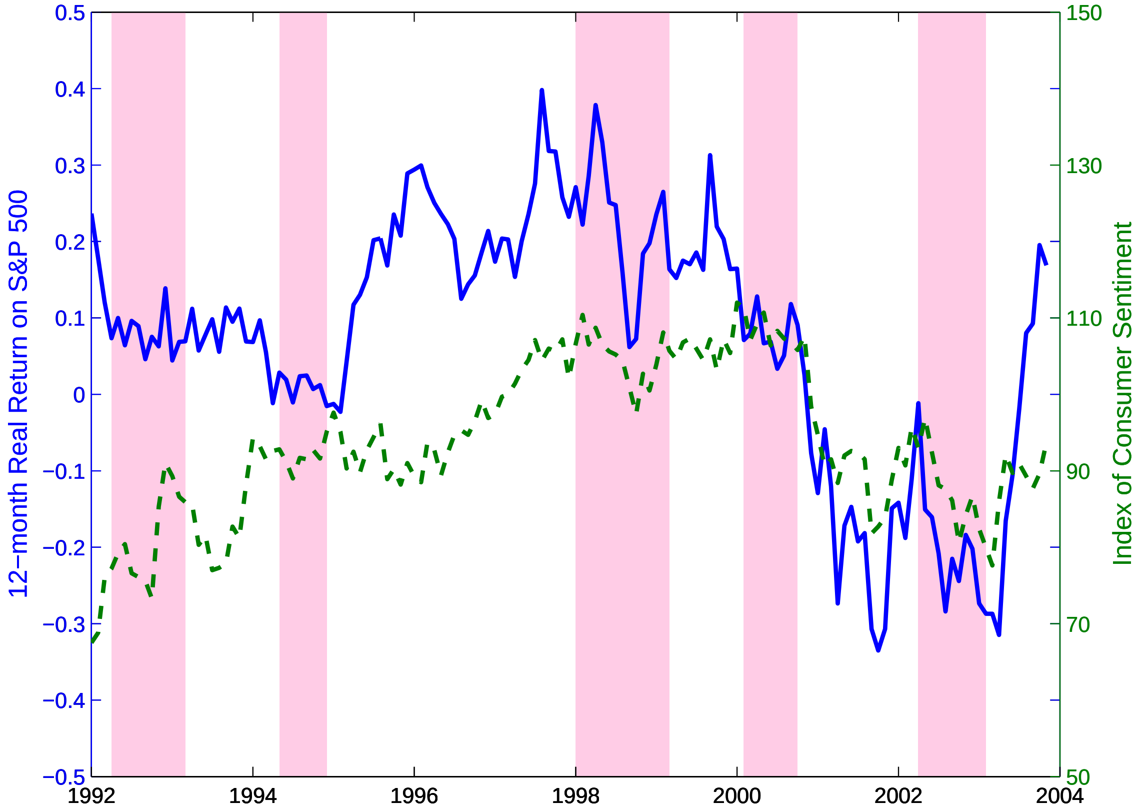
Appendix Table 1 – continued from previous page

Latent Variable: Log of Noisy Risk Tolerance: ξ_{it}				
	Mean Effect			Std. Dev.
Variable	Direct	Type	Composite	Effect
Proportion of Years Married		**-0.35**		0.06
		(0.10)		(0.07)
Panel Average FEP		**0.32**		**-0.57**
		(0.13)		(0.09)
Ever Job Displacement		**0.20**		0.02
		(0.06)		(0.05)
Ever Health Condition		0.01		0.03
		(0.06)		(0.04)
Log (Average + Wealth) / 10		-0.02		**0.28**
		(0.20)		(0.12)
Log (| Average − Wealth |) / 10		0.16		**0.38**
		(0.27)		(0.15)
Log (Average Income) / 10		0.60		**-0.48**
		(0.34)		(0.20)
"New Job" Version			-0.06	-0.09
			(0.09)	(0.06)

NOTE: Standard errors are in parentheses. Estimates in bold are statistically significant at the 5% level. The log-likelihood is -24893.8. The sample includes 12,574 individuals. The estimated standard deviation of the unpredictable persistent component of risk tolerance is 0.72. The standard deviation of the transitory component is $\sigma_{eit} = \exp[(x_{it}, \overline{x}_i, q_{it})\sigma_e]$ 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 6-9 and text for details on the variables.

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.