Do Teenagers Exhibit Rational Expectations Regarding Mortality, Fertility and Education Outcomes?

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Abstract

Microeconomic models often use the Rational Expectation Hypothesis (REH) instead of including expectation data. This paper examines the validity of the REH using subjective probability questions about mortality, fertility and education outcomes from panel data. First, I ask whether expectations are accurate and homogenous at the individual level; I find substantial forecast biases that depend on the nature of the outcome and decrease with ability and elimination of focal responses. I then propose a Bayesian learning framework to explain biases and find evidence of partial learning, suggesting probabilities become more accurate over time. Finally, I find subjective probabilities have predictive power over and above objective estimates, suggesting they contain private information about anticipated events.

I Introduction

For years microeconomic research has predicted behavior through revealed preference analysis: an individual's utility function is derived by observing the consumption bundles he chooses when faced with different budget constraints[1]. A downside to this approach is that choices under uncertainty can match multiple combinations of underlying preferences and expectations. In order to correctly infer expectations from realizations, one must specify the expectation process a priori. Researchers commonly assume *rational expectations*:

1) expectations are homogenously formed: when forecasting future outcomes and utility, agents incorporate all available information in the same manner; 2) agents understand the stochastic processes that determine outcomes; Hence, on average, there should be no systematic bias and their subjective beliefs should coincide with objectively predictable realizations[2].

Studies using the rational expectations hypothesis (REH) usually lack evidence that their assumption is correct, placing the credibility of their empirical findings at stake[3]. Their proposed models of behavior under uncertainty would be substantially improved if they included self-stated expectations (subjective probabilities) from survey data rather than assume expectations match outcomes (Manski 2004). Until recently, economics has made limited use of survey data, because methods used to elicit expectations are looked upon with skepticism[4]. Nonetheless, a growing number of studies have used subjective probability questions from recent large panels, confirming survey responses can proxy reasonably well for actual expectations (Smith et al 2001, Hurd and McGarry 2002, Benitez-Silva 2006, Delavande 2008, Stinebrickenr and Stinebrickner 2009 among others). It remains a question,

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[1] Revealed preferences are first presented in Samuelson (1948)
[2] See Appendix 1 for more information on the Rational Expectations Hypothesis
[3] See Manski (2004), Walker (2003), Delavande (2008), Stinebrickenr and Stinebrickner (2009) for examples of how misspecification of expectations can lead to biased estimates of preference parameters
[4] See Juster (1966), Doministz and Manski (1997), Manski (2004), Fischhoff et al (2009) for an overview of survey methodology issues and problems in interpreting probability elicitations;.

however, whether and why agents are systematically biased and whether subjective probabilities contain information that can be inferred from more traditional sources.

Drawing on Manski's (2004) suggestion that there is a "critical need for basic research on expectations formation", this paper examines the accuracy, updating and information content of individual subjective probabilities. I focus on young people between the ages of 15 and 20, a relatively understudied group. I use responses to expectation questions about mortality, fertility and education outcomes from the 1997 National Longitudinal Survey of Youth (NLSY 97). First, I ask if subjective probabilities are accurate and homogenously formed as implied by the REH. I then see if the bias can be explained by rational learning framework and if there is private information in self-reported probabilities that would make them superior predictors of behavior in a variety of modeling situations.

The aim of this paper is to examine the validity of the REH assumptions, namely to see how accurately teenagers can forecast important outcomes, and to propose explanations for any group-level biases. Specifically, I attempt to answer the following questions in the following ways:

1) Do subjective probabilities for mortality, education and fertility outcomes exhibit a systematic divergence from objectively estimated values? I will match individual subjective probabilities for the probabilities of dying, getting into college and being pregnant five years into the future with the relevant objective measures, derived by logit estimation; the difference between objective and subjective will yield individual forecast errors.

2) Is there group-level variation in the accuracy of beliefs conditional on certain characteristics/behaviors? To analyze the issue, I regress the forecast errors from (1) on certain characteristics and behaviors.

3) Can the forecast errors be attributed to costly information and learning rather than irrationality? I adopt a Bayesian-updating framework to see if there is partial learning, e.g. if

new information, related to more life experience in general, or to specific changes in behavior (any circumstances that factor in the objective risk) impacts the evolution of subjective probabilities.

4) To what extent can subjective beliefs “outpredict” the constructed objective probabilities? To see if there is private information, I regress individual outcomes on estimated objective risk and on subjective probabilities. A significant coefficient on the latter would support the usefulness of subjective data in behavioral analysis.

The existing literature on expectations has taken several approaches to analyze one or more of the above-mentioned issues for different populations. While there are studies that focus on teenage behavior, most of the empirical work on expectations is centered on the 50-70 age group, especially regarding mortality expectations. Inferred beliefs about longevity have been compared to historical life-table values (Hammermesh 1985, Hurd and McGarry 1995, Schoenbaum 1997, Benitez-Silva 2006, Elder 2007), or to within-sample realizations (Smith et al 2001, Hurd and McGarry 2002, Walker 2003, Fischhoff et al 2009, Khwaja et al 2007). An alternative, often applied for cross-sectional data on youth, is to look at realizations of comparable populations by matching individuals from different cross-sections on their observable characteristics (Viscusi 1990, 1991, Fischhoff et al 2000, Andersson and Lundborg 2007).

A substantial deficiency in the first and last group of studies is that the probability distribution of outcomes is drawn from a different population. This introduces a heterogeneity problem, where unobserved underlying differences between the two populations could confound the comparisons (especially when comparing different cohorts). When historical data is used (e.g. comparing mortality expectations with lifetable values), the econometrician needs to take account not only of the individual heterogeneity between sample observations, but also the overall change in hazard that has affected the entire populations over time (e.g. technological progress or extending the life expectancy of different generations) [5].

This paper contributes to the literature in the following ways:

First, I improve on many of the approaches in the general expectation literature by using longitudinal data. This allows me to observe beliefs and actual realizations for the same individuals, thus avoiding the aforementioned heterogeneity issues of some previous studies; only an individual-specific comparison of subjective and objective probabilities would allow an insight into whether private information is held in responses to expectation questions. Studies that most closely match my intended format (i.e. panel data studies of accuracy and updating) have found subjective beliefs match outcomes on average, but there is substantial heterogeneity in the accuracy of the predictions conditional on characteristics (age, income etc) and behaviors such as smoking (Smith et al 2001, Hurd and McGarry 2002, Khwaja et al 2007). All cited examples use longitudinal data on senior populations, and thus their conclusions may be inapplicable to teenagers.

Second, I extend the existing literature on adolescent behavior. To my knowledge, there have been very few teenage studies focusing on expectations that take advantage of recent large longitudinal panel sets to compare subjective and objective probabilities. Many important lifelong decisions regarding education and family planning are taken during adolescence. Hence it is important to know whether assumptions about the rationality of adult populations can be extended to the 15-17 year olds, a group that lays on the boundary of legally recognized adulthood. Empirical studies that specifically focus on teenage expectation formation and updating have been contradictory. On the one side, Keane and Wolpin (2002), Benitez-Silva et al (2006), Lochner (2007) and Delavande (2008a) find teenagers exhibit forward looking behavior regarding, respectively, welfare program participation, education

[5] Khwaja et al (2007) elaborate on the problems of using lifetable values: 1) the hazards across cohorts differ due to technology; 2) there is a lot of individual heterogeneity in survival; 3) the sample used for life-table values may be different;

attainment, criminal activity and birth control methods[6]. On the other hand, studies including teenage populations like Viscusi (1991), Lundborg and Lindgren (2004) and Fischoff et al (2000, 2009) report beliefs inconsistent with the REH. The first two examples report a substantial overestimation of lung-cancer risk, which is explained using a partial learning framework. The latter two finds NLSY97 participant to be moderately inaccurate about some outcomes and significantly pessimistic about their probability of dying in the near future, and offer no empirically tested explanations.

Thirdly, I attempt to make a comparison of the nature and evolution of subjective beliefs across different domains. Most of the mentioned studies on teenagers focus exclusively on mortality, education and fertility[7]. However, they reach no conclusion as to how accuracy varies with the nature of the question, e.g. when respondents have more control over the outcome.

The implications of my results extend to the general use of expectations data in behavioral choice models, as well as to specific policy issues. There has been speculation in the psychology literature that teens perceive risks more irrationally and are prone to an invulnerability bias (Quadrel, Fischhoff and Davis 1993, Slovic 2001). If teens indeed exhibit a systematic bias in their expectations relative to outcomes, this implies assuming rational expectations to predict their choice behavior is not appropriate. Assuming subjective beliefs can be correctly elicited and used in models instead of using the REH, incorporating the private information content of subjective probability responses could increase the predictive

[6] None of these studies uses NLSY97 data with the exception of Lochner (2007); Keane and Wolpin (2007) use data of AFDC and Food Stamps receipts from 6 states; Benite-Silva et al (2006) use the HRS and NLSY79; Delavande (2008) conducts her own survey;

[7] Fischoff et al (2000, 2009) is the only teenager study that surveys mortality, crime, education, fertility, however without analyzing the causes of their findings; Studies of teenagers' non-mortality related expectations: Benitez-Silva (2006) conducts a test of the RE hypothesis, with extensive instrumentation for measurement error, using HRS mortality data and NLSY79 education expectations; Cowan (2008) looks at how behaviors impact college expectations from NLSY97; Dominitz and Manski (1996) elicit expectations of future earnings conditional on education, using their own survey; Lochner (2007) focuses on expectations about crime and victimization; Walker (2003), Quesnel-Vallée and Philip-Morgan (2003) look at teenage pregnancy expectations and realizations from NLSY97;

power of behavioral choice models. Biases in mortality expectations could play a crucial role in consumption choices of harmful substances such as alcohol, cigarettes and drugs, or engagement in other life-threatening activities (crime, seat belt use etc). Beliefs about education attainment and fertility play a crucial role in models of human capital accumulation and labor market choices, or family planning. In terms of policy, regrettable choices in these domains could be avoided if groups that exhibit a significant bias in their expectations are given more information to help evaluate the future implications of their actions.

The remainder of this paper proceeds as follows: II reviews the literature on subjective beliefs, organizing it by the domain of the expectation question studied; III discusses the data; IV sets forth the methodology; V presents results and proposes explanations and VI concludes.

II Literature Review

Studies on subjective probabilities and mortality

Expectations have long been a part of the macroeconomics literature. Under rational expectations, forecasts of market variables are assumed to affect the evolution of the economy, which in turn affects the formation of expectations which match outcomes (Muth 1961, Lucas1972). The hypothesis has been extensively tested with regard to macro variables (see Lovell 1986 for an overview), but the importance of subjective beliefs for individual-specific outcomes has been less emphasized (Manski 2004), especially on a scale involving large panel datasets (Schwandt 2009).

Hamermesh (1985) is a seminal study that motivated further analysis of subjective beliefs. He uses two small, non-representative samples, one of male economists and the other of randomly selected male respondents, asking subjects about their subjective probability to live until 60 and 80. The surveying form, despite sampling limitations, had several advantages that made expectation measures more reliable: first, it uses a numeric scale for probability, making responses quantifiable; second, the sample of professional economists can serve as a control to see if cognitive limitations in interpreting probabilities creates a measurement error in eliciting subjective beliefs.

The study finds that longevity forecasts have an age distribution consistent in shape with survivability functions taken from life tables. Subjects extrapolate current life tables into the future, taking into account the increasing life expectancy. This suggests subjective beliefs have an expectational component that cannot be captured if current life-table values are used in behavioral models. In addition Hamermesh (1985) finds subjective probabilities are not entirely based on objective actuarial information, with individuals placing a disproportional amount of attention to their parents' longevity when forming their own mortality expectations.

Viscusi (1991) finds the same conditionality of expectation bias on behavior, applying a similar cross-sectional approach, only in the context of how perception of lung cancer risks varies with age. He elicited subjective probabilities by asking "how many of 100 smokers will be diagnosed with long cancer?" and compared them to objective risks taken from Surgeon General reports [8]. Whereas in the 16-21 group youths substantially overestimated the probability of lung cancer (which is attributed to the highly publicized nature of smoking risks in general), smokers were less biased.

In line with some of Viscusi's earlier work (1985), the described pattern of risk perception is explained with a model of Bayesian learning: as new information is acquired, the prior subjective probability is updated to values that reflect reality more accurately. When information is partial, the posterior probability of low-probability events remains higher than the objective probability. For events that have a small true probability, there would be such an

[8] This survey approach has come under substantial criticism due to framing effects. Slovic (2001) points out that first person questions are not the best proxy for true subjective beliefs since people may maintain a personal optimism bias and believe their risk is significantly different than that of the general population. Khwaja et al (2009) however find that there is no significant difference in the accuracy of responses conditional on the method of elicitation.

overestimation because people are prone to overpredict very small risks (Viscusi 1991, Slovic 2001, Andersson and Lundborg 2004 among others). As experience increases and information accumulates, subjective and objective probabilities should converge. The smaller bias of older smokers in Viscusi (1991) conformed with that prediction.

Smith et al (2001) also analyze belief updating in the context of smoking behavior in order to see if subjective probabilities are an adequate proxy for expectations. However, they use a sample of HRS respondents between ages of 51-61 and how their stated probability to live until 75 is updated, conditional on smoking status and following exogenous health shocks. The use of longitudinal data that includes two waves (1992 and 1994) of the expectation questions and detailed, individual-level data on unexpected onset of diseases allows for deeper insights into belief updating.

The results of Smith et al (2001) support the idea that subjective probabilities reflect experience and incorporate relevant information as soon as it becomes available. Smokers rationally expect lower chances of survival to 75, and adjust their probabilities downward upon the onset of a smoking-related condition such as a heart attack or lung cancer. However, the adjustment of heavier smokers was insufficient relative to the objective increase in mortality risk that group faces, suggesting learning is partial.

Hurd and McGarry (2002) also investigate the evolution of survival probabilities using HRS data and a two-year interval between waves. However, they also focus on the unobserved expectational content of beliefs. Health shocks affect probabilities, but so do health-unrelated events like the death of relatives, or even genetically-unrelated family members. This implies there could be a heuristic mechanism to expectation formation: information that is seemingly unrelated to mortality (but less costly) is used to forecast death. The authors ask whether that additional information content in subjective responses has objective predictive power and find that, even when controlling for health changes, private information is a significant determinant of outcomes.

Hurd and McGarry (2002) conclude subjective probabilities are superior predictors than observable factors after comparing the self-reported probabilities with within-sample mortality rates for the 1992-1994 period. Khwaja et al (2007) take the analysis a step further by using the HRS follow-up survey to compare subjective and objective hazards 10 years after the baseline interview. They assess the accuracy of subjective beliefs and what factors drive a divergence between them and objective measures by using hazard functions. Then they ask if there is private information (specifically of future anticipated actions) in subjective beliefs over and above that of estimated objective hazard.

The comparison of subjective and objective hazards shows no bias on average. However, there is heterogeneity and smokers tend to be more pessimistic and never smokers more optimistic than their objective risk would suggest. The updating analysis confirms Smith et al (2001). More interestingly, subjective probabilities for individuals that intend to quit, as revealed by looking at their smoking history over the 10 years, were lower than those who remained smokers, implying their intention to quit was mapped into their response at baseline. Khwaja et al (2007) regress outcomes on both subjective and objective hazards to see if there is any significant predictive power of subjective beliefs that was not contained in the estimated objective hazard already. As would be expected from the analysis on updating, the coefficient for subjective probabilities was positive and statistically significant.

Domain-specific studies for education and fertility outcomes of teenagers

Walker (2003) analyzes NLSY97 data of teenage birth risk perception, asking whether subjective probability measures provide evidence of bounded rationality. He proposes two competing explanations for teenage pregnancies: 1) either teens underestimate their conception risk and unintentionally underuse contraception, or 2) they have difficulty assessing the negative repercussions of childbirth on their future earnings and human capital formation, resulting in earlier sexual initiation and intentionally lower contraceptive effort [9]. The first hypothesis implies a departure from rational expectations, the second views actions as a rational response to incorrectly perceived incentives. In order to evaluate the hypotheses, Walker (2003) compares the subjective pregnancy risk of 15-17 year olds from the first two waves of the NLSY97 with objective risk. Objective probabilities are computed using a biological model of conception that takes account of coital frequency and contraceptive effort.

While perception of risk is accurate on average, Walker (2003) finds that it varies considerably conditional on poverty status. His results support both explanations of unintended pregnancies. Consistent with the second hypothesis, poverty is significantly related to lower initiation age, which in turn causes higher objective and subjective risks[10]. Regarding the first hypothesis of bounded rationality, poor teens, especially those who start having sex earlier, had subjective beliefs that were elevated, but were still significantly lower than objective risks relative to non-poor teens. This implies expectations become less "rational" (pregnancies become more unintended) with poverty and age/experience levels.

Haveman et al (1997) also examine the determinants of the teen childbearing choice and its rationality, emphasizing the importance of economic tradeoffs (the second hypothesis in Walker (2003)). They use the Panel Study of Income Dynamics and construct a structural model to test whether the decision to bear a child relates to the foregone income possibilities of early parenthood (quantified as difference of income predictions conditional on having/not having a child). Other determinants they include are family/demographic characteristics (including religiosity, family structure, income), education, neighborhood characteristics

[9] Policy implications for the two potential explanations are fundamentally different; the first one would imply more information provision, e.g. sex ed classes; the second one would support increasing the economic return to not giving birth, e.g. decreased AFDC generosity.
[10] Since expected incomes in pregnancy/non-pregnancy scenario are not calculated, there is not enough evidence to conclude this is rational

(incidence of unemployment an single parenthood, education level etc.), policy variables (availability of abortion, and generosity of social assistance etc), sexual behavior.

Consistent with previous studies, the difference in expected income always had a significant effect on the choice. Adding family background and neighborhood parameters made a significant difference to the probit model; State welfare benefits and family planning expenditures have a small, but statistically significant effect, however not when interacted with income. Unexpected to the authors, local labor market characteristics have no significant effect. Their results are robust to several specifications, but the authors acknowledge a weakness of the choice model is not including any information on the sexual partners of sample women.

Relevant to my research, the conclusions of the abovementioned study and Walker (2003) support the idea fertility choices are not fully irrational since they respond to economic incentives and expectations are accurate on average; However, the bias in subjective expectations of certain groups (those of low socio-economic status) motivates more investigation into what determines the degree of rationality different types of individuals apply when planning for pregnancy.

Reynolds and Pemberton (2001) analyze subjective probabilities of college education and their evolution across generations using the 1979 and 1997 NLSY cohorts. They note that if observed actual attainment of 1979 participants can be taken as a predictor, teenagers in 1997 seemed wildly optimistic about their prospects of obtaining a college degree. Based on a review of the education literature, they identify some non-trivial determinants of college prospects like family structure (single-parent household, number of siblings, education attainment of parents), resources (parent income and employment status), local economic prospects (county-level unemployment and level of education), student performance and teacher and peer attitudes[11].

The Reynolds and Pemberton (2001) analysis is of interest for several reasons: first, it identifies what variables in the NLSY at the individual and family level could serve as determinants of the objective probabilities of college enrollment. They find that some individual and local labor market differences had a diminishing effect on expectations over time: responses in 1979 were significantly less related to county-level education attainment and unemployment, and the magnitude of the effect of being female and non-white diminished. More interestingly, family structure became more important in 1997, with one-parent respondents being significantly more pessimistic. In addition, the study does not control for ability, even though measures are readily available for both cohorts.

Second, even though this is not the research objective of Reynolds and Pemberton (2001), their paper raises questions about the predictive power of subjective probabilities. While the increase in college expectations between generations is consistent with the overall increase in enrollment over the period, the follow-up statistics of the NLSY79 show that of the 1,440 15 year olds that intended to complete college in 1979, only 416 had done so by 1994. This evidence of optimism motivates further research into how the subjective probabilities of the same individuals have varied over different waves to incorporate more objective information.

Belley and Lochner (2007) also analyze the determinants of the schooling decision and their evolution across the two NLSY cohorts. They include roughly the same explanatory variables as Reynolds and Pemberton (2001) and confirm their importance: among other things, parent education attainment and family structure are significant. Unlike the previously reviewed study, this one includes ability and unsurprisingly finds it to have the most

[11] The last three categories are only available in the 1997 data

important role in determining educational outcomes after controlling for demographic characteristics.

Even after controlling for ability, income is a strong determinant of attainment. This is perplexing since under an assumption that capital markets are perfect and ability is highly correlated with income, all able individuals should attain education in view of high expected earnings. The literature on education proposes two explanations of why income is significant even after ability is controlled for: 1) education is viewed as a normal good that brings utility aside from future earnings or 2) there are borrowing constraints. To reconcile their findings with either hypothesis, Belley and Lochner (2007) construct a choice model of education and conclude the second explanation is more likely.

Stinebrickner and Stinebrickner (2009) examine how learning about ability affects the college drop-out decision of low-income students. They use the Berea Panel Study (BPS), which traces the expectations of 420 entering students over four years regarding their future grade performance. The BPS is a unique data set because Berea College has zero cost of attendance, hence the panel allows to separately test the hypothesis that dropping out is caused by optimistically biased beliefs of one's academic ability rather than just credit constraints.

First, Stinebrickner and Stinebrickner (2009) find future freshman tend to be overly optimistic about their future grade performance. Using future elicitations of self-reported expectations, they explain the bias using a partial learning framework: individuals update their beliefs at the end of the semester using both prior expectations, and relevant new information about their ability. That new information about ability is proxied for by the grades the student receives during the semester. Further, the authors estimate simplified behavioral models of the drop-out decision that incorporate the subjective beliefs about future performance. Their conclusion is that learning about ability plays a crucial role in the drop-out decision of BPS participants.

III Data

A. The NLSY97

Data on subjective and objective beliefs comes entirely from the National Longitudinal Survey of Youth (NLSY). The NLSY is a series of surveys conducted by the Bureau of Labor Statistics with the purpose of documenting the transition to adulthood of a nationally representative sample, including institutionalized population and foreign-born citizens. Hour-long interviews are held annually, however some sections (such as the aptitude tests and the Parents Questionnaire and the ASVAB) have been administered once.

The original sample of the 1997 NLSY included 8,984 youths, screening more than 75,000 households to select the sample, which is representative of US residents born between 1980 and 1984. There is a supplemental sample that overrepresents blacks and Hispanics, and some of the youths in the sample reside in multi-respondent households. The interviewers were conducted annually, using an automated computer system that minimizes the probability of inconsistent responses to conduct in-person interviews. Areas of the youth survey that are potentially sensitive, such as sexual activity, substance use and criminal behavior, are asked in a self-administered portion of the survey in which the respondent answers in private using a computer (the audio computer assisted self-interviews, ACASI). A total of 8 data waves are available, conducted between February 1997 and July 2005, with a little more than a thousand observations lost due to attrition.

The *Youth questionnaire* portion of the survey contains very detailed information on schooling and employment, and additional data on financial characteristics, family background, relationships, social behavior and health. Some questions are asked only in certain waves. The *Household roster* portion contains demographic, educational, martial status and employment information on all residents of the household. The *Parent questionnaire*, only administered in 1997, asks about family's employment and education history in more detail, as well as some behavior and expectation questions from the parents' point of view. Another portion, the *Armed Services Vocational Aptitude Battery (CAT-ASVAB)* is a 12 section standardized test measure of ability[12] that was administered to all respondents in fall 1997-winter1998. Finally, *high school transcript* data with rich data on education history was collected in 2000 and subsequent years for 6,232 adolescents, or 69% of the sample.

The NLSY97 has asked expectation questions in 1997, 2000, 2001 and 2002; there are a total of 82 variables that measure subjective probability. In Wave 1, the sample was limited to those 15 and over (3,544 adolescents). The questions from that wave asked what situations does the respondent (R) expect to find himself in the next year, by age 20 and by age 30; by next year and in the next 5 years for Wave 4 questions; various times in Waves 5 and 6.

B. Strengths and limitations

The response mode to expectation questions prompted respondents to choose an integer between 0 and 100. This makes the NLSY97 data a superior source for analyzing expectations in comparison to traditional sources in social psychology and opinion polling that use qualitative measures. There is substantial evidence in the literature on measuring expectations that quantitative elicitation of expectations is essential to making interpersonal comparisons and model estimation (Juster 1966, Manski 1990, Manski 2004, Dominitz and Manski 1999, Walker 2003)

A major issue with self-reported probabilities is whether they can serve as reliable, unbiased estimates of the true subjective belief. The NLSY97 data has been investigated across several dimensions, including the frequency of non-responses, incidence of "don't knows", validity across waves and heaping of responses around certain values (0, 50, 100, numbers ending in 0 and 5). Overall, there is evidence that respondents interpret the questions

[12] the ASVAB is a multiple choice test prepared by the US armed Force to determine qualification for enlistment and covering areas as diverse as mathematical reasoning/knowledge, verbal expression/comprehension, general science, automobile and electronics knowledge; the AFQT score is computed as the percentile of the ASVAB

reasonably well: they use the entire range without tendencies for higher or lower responses; the elicitations are internally consistent across waves (e.g. probability of becoming pregnant within next year is stated as lower than probability of becoming pregnant by age 20 for 90% of respondents); they are correlated with related measures (race, gender, individual characteristics, other expectation measures and outcomes) and accurate when compared with population averages (Fischhoff et al 2000, Parker and Fischhoff 2001). The high occurrence of 50-50 responses should not pose a challenge: even though focal values may reflect epistemic uncertainty (i.e. respondents are not aware of the causation mechanism behind the outcome) or implausible estimates, they still hold an information content that is pertinent to the analysis [13](Walker 2003, Khwaja et al 2007). This is why I have been cautious in excluding focal observations for parts of my analysis, particularly when the focal value is close to the mean of the distribution.

Another source of measurement concern is the high degree of pessimism regarding death probability, with means approaching an unrealistic 20%. Judging by the accuracy of estimates in other domains, it is more likely that the bias is due to a cognitive tendency to overestimate small probabilities[14] rather than an inability to answer the question (Fischhoff et al 2009, Viscusi 1991). Analysis of correlations found that mortality expectations were highly responsive to perceived threats of crime, violent events, crime and health conditions, meaning the variable captures teenagers' relative feelings of vulnerability (Fischhoff et al 2009). Hence even if there is some measurement error, this will affect the exact magnitude of the difference between subjective and objective probabilities, but the conclusions about the conditionality of believes on different characteristics should not be affected.

[13] For instance, Khwaja et al (2007) find that individuals reporting 0 or 1 probability of survival have a correspondingly lower or higher objective death risk (the difference being statistically significant only for the 1st group). They also replicate their study with a sample excluding focal responses and reach the same qualitative conclusions

[14] For an overview of the literature on cognitive biases in perceiving small probabilities, see Slovic (2001)

A final limitation is the accuracy of responses to questions regarding some sensitive behaviors. Relative to outside statistics from another national survey, Walker (2003) found sexual activity reports match averages, but pregnancy history data implies underreporting: pregnancy frequency was 20%-25% lower for NLSY respondents than for the comparison sample. I feel it is reasonable to dismiss this concern, given that the NLSY97 uses the ACASI administration system and that there is no guarantee the results used for the comparison are not more biased.

IV. Methodology

A. Subjective probabilities

The initial step of my analysis is to look at the observable portion of the data and derive pairs of subjective probability elicitations asked in different waves. Pairs are necessary to conduct my updating analysis. An underlying assumption is that these expressed subjective probabilities are the closest observable measure of teens' expectations for future events, given their information set at the time the questions are asked. I have chosen the following pairs of expectation questions as proxies for subjective probabilities:

Mortality:

1) In 1997 (baseline): *What is the percent chance that you will die (from any cause -- crime, illness, accident, and so on) between now and when you turn 20?*
2) In 2002: *What is the percent chance that you will die from any cause -- crime, illness, accident, and so on, in the next year?*

The first question was asked to 3431 individuals aged 15 and over, the sample size for the 2002 question was limited to 1330.

Fertility:

1) In 2000 (baseline): *What is the percent chance you will become pregnant within 5 years?*

2) In 2001: *What is the percent chance you will become become pregnant in the next 5 years?*

Aside from the trivial difference in the phrasing (*in* instead of *within*), the first question was asked to 3922 female repondents, whereas second one was asked to a much limited sample of 630 individuals. This considerably limits my sample size for the analysis of updating and could present a problem.

<u>Education</u>

1) In 2000 (baseline): *What is the percent chance you will be a student in a regular school 5 years from now*[15]*?*
2) In 2001: same

As with the fertility question, the first question was asked to the entire sample of 8025 available respondents, whereas the second sample was randomly limited to 1950 respondents.

B. Sample realizations and objective probabilities

In order to analyze the predictive power of subjective probabilities, I compare them with the objective risk that a researcher can derive without having any expectation data at hand. The probabilities I construct are predicted based on within-sample, individual-specific realizations, hence they avoid a lot of person-to-person heterogeneity that stems from using outside actuarial data.

The objective probabilities represent the researcher's best a-posteriori estimate of the actual risk the individual was facing at baseline, given the observable information of the individual's background and behavior *at the time of the interview*. In effect, using only baseline characteristics excludes changes in time-variant covariates makes the forecast myopic, as it would not incorporate outcome-determining changes in behavior that occur after

[15] Regular school is one that offers an academic diploma or degree: e.g., elementary school, high school, college, graduate school, law school, or nursing program leading to an rn degree. Not included as regular school are: training at a technical institute, license trade programs, etc., unless the credits obtained are transferrable to a regular school and could count toward an academic diploma or degree.

baseline interviewing. The longitudinal format allows me to include variables from all years to account for behavioral changes between baseline and outcome and thus deliver a more accurate prediction. However, this would not be consistent with my research goal, namely to compare the predictive power of subjective probabilities against the forecast a researcher can make without having data on future periods.

While the longitudinal format allows for a more complex survival analysis of the objective probability, a comparison of objective and subjective hazards is not possible. I could derive objective hazards and account for any duration dependence because I have multiple points over time when the individual was observed, hence I can derive a survival function. However, I cannot do the same with subjective hazards because subjective expectations were not observed multiple times for the same event.

In order to produce a forecast, I first use a logit model to see how outcomes vary conditional on individual characteristics and behaviors. Objective probabilities are then predicted for a wider sample using the estimated coefficients. The specific determinants for each of the three domains are discussed bellow.

Mortality

-Outcome

Y_i = 1 if individual was reported deceased at the most recent interview;

-Determinants: mental and physical health

Based on the reviewed studies on objective mortality risk in the HRS sample (Smith et al, 2001, Khwaja et al 2007), I expect health measures to be highly relevant. I include controls for self-reported health status at baseline (*health_1997*) ranging from 0 (poor) to 5 (excellent), and parent-reported presence of chronic conditions (*health_chronic*)[16].

[16] Chronic conditions include asthma, anemia, heart disease, diabetes, cancer, epilepsy, kidney condition, infectious disease and other

I also control for psychological conditions by including a mental health index[17]. The variable captures general feelings of optimism or pessimism, and despite the evidence that there is a strong pessimistic bias that drives subjective responses (Fischhoff et al 2000, Walker 2003), self-reported perceptions could capture a portion of the objective risk that is contained in the omitted health characteristics. For instance, more depressed individuals would be more likely to commit suicide, or be generally less cautious in their behavior since they perceive life as less valuable/enjoyable.

Finally, I account for the access youths have to medical care by controlling for insurance coverage (*health_ins_1997*), as reported by the parent.

Considering that I am dealing with young people, it is likely that many deaths in my sample are due to accidental or violent causes rather than health conditions (Andersson and Lundborg 2007). I control for the likelihood individuals participate in activities that could result in their untimely death:

<u>-Determinants: crime and substance abuse:</u>

I control for youth's direct involvement in crime by including a control for gang membership (*gang_ever*_1997). This control may not be as effective: due to the wording of the gang questions, a lot of respondents may not actually belong to a gang in the criminal sense of the word[18]. I use some alternative indicator variables: whether the individual sells illegal drugs (*sell_drugs_1997*) or has stolen anything valued above $50 (*stole_ever_1997*).

In order to capture general risk attitude, I account whether the person has ever smoked (*cigs_ever*) or drank alcohol (*alc_ever*). Since smoking, drug-use and drinking are risky choices, the substance status and frequency of use could tell us something about the proneness

[17] "The NLSY 97's measure of behavioral and emotional problems utilizes a set of sixitems developed as an indicator of children's mental health for the National HealthInterview Survey (NHIS). The items have also been used in the National Survey of America's Families (NSAF). The items for the indicator were selected from the Child Behavior Checklist (CBCL), a standardized questionnaire used to obtain parent's ratings of their children's problems and competencies" (BLS 2009)

[18] In the text of the question, gang is defined as "a group that hangs out together, wears gang clothes or colors, has set clear boundaries of its territory or turf, and protects its members or turf against rival gangs through fighting or threats. "

of the individual to engage in other behaviors that pose a more immediate threat to life, such as driving without a seatbelt (Andersson and Lundborg 2007). In addition, substance abuse variables could capture deleterious health effects that were not otherwise measured.

-Determinants: perceived threats and environment:

Fischhoff et al (2009) find subjective risk correlates more with perceived victimization risk than with perceived health threats. The importance placed on that type of threat suggests neighborhood characteristics could be significant predictors. Direct or indirect involvement in crime and victimization as a result of living in a dangerous neighborhood could be the cause of death for some participants. Because self-reported feelings about risk could be biased, I include indirectly measured threat information that is reported by the interviewer or parent. To capture environment threats, I control for presence of gangs in neighborhood (*gangs_hood*) and whether the respondent has seen anyone get shot (*shoot_witness*).

Finally, I expect general demographic characteristics like income and education of parents to have explanatory power. More affluent and educated households could be less likely to be involved in an accident because they are able to purchase safer goods or are more knowledgeable of how to avoid danger (Andersson and Lundborg 2007).

Fertility:

-Outcome:

Y_i=1 for any pregnancies I experienced between 2000 and 2005.

- Determinants

Objective pregnancy probabilities at baseline should be directly affected by sexual behavior at that time (frequency and contraceptive methods reported at year 2000) and indirectly related to demographic characteristics, social and family environment.

Based on the Schwartz et al (1980) model of conception presented in Walker (2003), I expect the frequency of the coital act (*sex_freq_2000*) and the contraceptive effort (*sex_BC_freq*) to be the most important instruments in my forecast[19]. I also expect those who had lower initiation age (*sex_init_age_2000*) and higher count of sexual partners (*sex_partners_2000*) to have a higher probability based on Delavande (2008) and Walker (2003).

In terms of family and income characteristics, I expect income/poverty level to increase the pregnancy risk (Walker 2003). Growing up in a single parent home (*family_father*), a less religious household (*family_relig*), or having mother that gave birth as a teenager (*family_teen_mom*) could negatively affect the effort of teens to apply contraceptive effort by setting a lifestyle example (Manlove et al 2006).

I also control for student's enrollment status (*enroll_2000*), anticipating those not enrolled in school will have a higher probability of getting pregnant. This may be so because they have dropped out and place a higher value on conception (intentional or unintentional), or because they have graduated from highschool/college and the opportunity cost of childbearing is less.

Finally, respondents who were cohabitating with a partner on a permanent basis in 2000 (*marr_stat_2000*) should be expected to face a higher pregnancy probability. This could be either because the frequency of coital activity would be higher, or because of intentional family planning. I will construct a variable for whether the youth is cohabitating with a partner or spouse.

Education

-Outcome:

Y_i=1 if the respondent is enrolled in high school, a 2 or 4 year college or a graduate program for the 2005 academic year. There are several possible "sub-outcomes" for those

[19] The available measures for contraceptive effort like *TIMES R USED BIRTH CONTROL SINCE DLI* are absolute numbers, e.g. (*how many of those times [that you had sex]did you or your sexual partner or partners use any method of birth control*). I construct a measure of the frequency of times R used birth control, FREQ_BC_USE = (*…TIMES R USED BIRTH CONTROL…) / (…TIMES R HAD SEX…)*

enrolled in a regular school: they could be in high-school[20], a 2 year college, a 4 year college or a graduate program. More importantly for forecasting accuracy, there are also several possible baseline perspectives from which the respondent could be looking 5 years into the future (in high school, graduated HS, in 2 or 4 year college/grad school). Based on the perspective (enrollment status) at baseline, I stratify the sample into two broad categories: an unrestricted one with the full sample, and a restricted one with high school juniors, assuming they are predicting their prospects of being in college when looking 5 years into the future.

-Key determinants

After controlling for demographic characteristics, ability should play the most important part in determining the probability of high school completion and college attendance (Belley and Lochner 2007). I use the ASVAB combined math and verbal score (*ASVAB_perc*) as a cumulative measure of ability[21] which is created by the NLS staff to most closely math AFQT scores. The AFQT is widely used as a reliable measure of ability in the literature (Belley and Lochner 2007).

Intuitively, academic performance is another important predictor of education prospects. For the restricted sample, I include measures of the respondent's cumulative GPA for 2000. While ability will be highly correlated with academic performance, I expect some students with low ability may attain better education because they work hard, and vice versa.

Income by itself is another intuitive regressor, and I include the relative poverty measure (*HHPR_2005*). If education is viewed as a good that brings utility aside from the increased returns, wealthier families should purchase more of it. Although income and ability are highly correlated, I expect a positive income-attendance relationship even after including ASVAB scores, based on the Belley and Lochner (2007) conclusion that borrowing

[20] In the general case, youths born between 1980-84 should not be enrolled in high school 5 years from 2000 either because they drop out or have graduated. In fact, only 33 of the 7319 youths who answered the 2005 enrollment status question were still enrolled in high school.

[21] See section 3 for more info on the ASVAB

constraints discourage attendance by increasing its marginal cost. In addition, Stinebrickner and Stinebrickner (2009) show that even in the absence of borrowing constraints, lower-income students are much more likely to drop out of college.

I include several variables on family characteristics and peer effects. The highest grade attained by parents (*educ_mom*, *educ_dad*), aside from being a proxy for income or genetic transfer of ability, could operate if parents are seen as role models (Reynolds and Pemberton 2001). Under the same logic, I control for the percent of peers who intended to go to college in 1997 (*peers_coll_1997*).

Engagement in risky health behaviors is proxied for by the Substance Use Index (*SUI_2000*) that accounts whether the youth smoked cigarettes, drank more than 1 drink or used drugs. Substance users may be les likely to exert effort because of different discount factors. The literature on education supports a correlation between education attainment and health: there is a possibility that engagement in risky behaviors, which negatively affects health, reduces college prospects (Fuchs 2004).

C. Analysis of forecast errors

The next step of my analysis is to derive the mean actual and absolute prediction errors for each domain, respectively denoted as $\bar{\varepsilon}$ and $|\bar{\varepsilon}|$ and measured as the average difference between individual subjective responses and predicted objective probability. The actual error measures the relative degree of optimism/pessimism, whereas the absolute value of the error concerns the accuracy of the forecast. The aim of the analysis is to see whether probabilities are formed correctly and offer some explanations for the biases.

The REH predicts mean errors equal to zero (expectations are unbiased) and statistically independent of demographic characteristics (all individuals incorporate all the available information) (Schwandt 2009). I plan to use the objective estimates from the previous subsection to run the following tests:

First, I plot the error distributions, derive average forecast errors and, jointly and separately test the hypotheses that $\bar{\varepsilon} = 0$ and $|\bar{\varepsilon}| = 0$. While I expect mean actual errors to be close to zero for education and fertility and significantly positive and large for mortality, the mean absolute errors should be larger in magnitude and significantly different from 0 as there will be no offsetting between individual over- and under-predictions.

Second, I run OLS regressions of errors by individual characteristics and jointly and individually test whether coefficients are different from zero to see if forecast biases are operating at a group level, where groups are defined by demographics, cognitive ability, mental health and substance use behaviors. While the coefficients, specifically the time-variant ones, should not be interpreted as causal, they provide sufficient ground to dispute the REH (Schwandt 2009, Benitez-Silva et al 2006) [22]. I expect women to overpredict errors across domains (Andersson and Lundborg 2007)[23]; younger individuals to be more biased in absolute terms because of less life experience in predicting future outcomes (Viscusi 1991); lower-income teens to be more likely to under-predict their pregnancy risk or be over-optimistic about graduating from college (Walker 2003, Reynolds and Pemberton 2001). I include the mental health index to gauge whether individuals with more emotional problems (a lower mental health score) are more prone to pessimism. Finally, I expect there to be no differences in error levels that can be explained by race.

Regarding behaviors and attitudes, young smokers may be more pessimistic about their survival chances based on findings that teenagers overestimate the well-publicized risks of smoking such as lung cancer (Viscusi 1991, 1990, Lundborg and Lindgren 2004). While my regression cannot ascertain the direction of the causal relationship, it is also possible that relative pessimism about death causes teens to engage in risky behaviors like smoking. Even

[22] Theoretically, if individuals use all available information when they form expectations and forecast errors are only due to random exogenous shocks (rather than a group-level bias), these errors should be independent form information available at time t and from time-invariant characteristics;

[23] Andersson and Lundborg (2007) cite numerous references from the economics and psychology literature suggesting females tend to be overly cautious and perceive comparable health and environmental risks as greater

though I mostly expect a positive correlation between error and smoking status, there is competing evidence that smokers are relatively optimistic about their survival due to misperceptions of the smoking risk (Schoenbaum 1997, Slovic 2001, Khwaja et al 2007)[24]. However, these studies focus on the 50-70 age group. At these ages, even though smokers have rationally increased their subjective death probability in response to information, the adjustment is insufficient as their objective death risk is also considerably higher than that of non-smokers. For the teenager population, it is highly unlikely that the objective death risk is as significantly impacted by smoking since the effects of the habit manifest themselves later in life.

Finally, absolute errors could stem from limitations in expressing probability concepts. To test this notion, I include a measure of cognitive ability measured by the ASVAB percentile score. I expect the regression of the absolute error to be more reliable in measuring the effect of cognitive limitations. If people are unable to express probabilities the coefficient of the absolute error should be positive and significant. I expect insignificant coefficients for both specifications since there is consensus in the literature people are able to interpret probability questions (Manski 2004, Elder 2007, Delavande 2008).

D. Updating

The next step in my analysis is to look at the evolution of subjective beliefs and attempt to reconcile any systematic forecast errors with a rational learning hypothesis. Teenagers could be inaccurate when predicting their pregnancy, fertility and especially mortality risk owning to a documented psychological tendency of agents to overestimate small probabilities and underestimate large ones. Under a partial learning framework this is not irrational, but rather the consequence of incomplete learning due to high information costs or limitations in processing information (Khwaja et al 2007). I apply a Bayesian updating

[24] Explanations for relative optimism vary from partial learning (Khwaja et al 2007) to cognitive dissonance, framing effects and other psychological limitations in risk perception (Slovic 2001)

model to each of the three outcomes to see if relevant information from life events that transpire between the two waves of subjective probability elicitations is incorporated in the revision of these probabilities. The goal is two-fold: 1) Determine whether probabilities converge over time, i.e. are adolescent expectations intertemporally consistent; 2) Find how the updating process varies across groups and for different domains.

In the Bayesian updating model developed by Viscusi (1985, 1991) the updated subjective probability is assumed to follow a beta distribution. The updating process can be represented with the following equation[25]:

$$P_{t+1} = \frac{\theta P_t + \gamma r_t}{\theta + \gamma} \tag{4}$$

The posterior risk P_{t+1} is viewed as a weighted function of the prior probability P_t and the probabilistic value of the relevant information that the even will occur, received between the two periods (further known as the unobserved risk equivalent) $r_{t.}$ To each of these arguments agents assign precision parameters, respectively θ and γ. The unobserved risk equivalent r_t can be represented as a function of two factors: fixed demographic characteristics (*D*) and a vector of change variables that reflect information acquired between period t and t+1 (ΔZ):

$$r_t = f\,(D, \Delta Z) \tag{5}$$

Viscusi (1985) shows that under such treatment, beliefs will converge: lower risk events that tend to be overestimated will be revised upward, the converse holding for higher risk events that are underestimated. My hypothesis is that new information is rationally incorporated in the revision of probabilities, eventually leading to their convergence. Based on Viscusi (1985), I expect negative parameter estimates of the product of the risk equivalent r_t and the weight of the risk equivalent $\Psi = \gamma/\theta$ for overestimated priors like mortality and

[25] The beta distribution has two shape parameters, and does not impose symmetry requirements unlike the normal distribution. Most using an updating framework assume beta distribution over a normal one as it is more flexible (Delavande 2008b)

education attainment, and positive for underestimated ones like pregnancy risk. Such evidence of convergent beliefs/partial learning will support the idea that teenagers, while biased in the short run, are eventually able to accurately predict their outcomes and conform to the predictions of the REH. A lack of convergence could signal teenagers use heuristic rules to form probabilities, for example irrationally basing their risk assessment on prior beliefs and ignoring relevant information (conservative heuristic), or conversely placing too much emphasis on irrelevant but more salient information (representative heuristic) (Delavande 2008).

Following Smith et al (2001), I use the following empirical specification to estimate the relative weights placed on the prior and the risk equivalent:

$$P_{(t+1)i} = \alpha P_{ti} + \sum_{j=1}^{k} \beta_j R_{ij} \tag{6}$$

where the vector R_j includes the risk equivalent factors in equation (5) and a regression intercept. Given P_t and P_{t+1} I can estimate the risk equivalent of new information r_t and the weight of the risk equivalent Ψ, the product of which will tell me if there is convergence.

$$\mathrm{r}_t = \frac{\sum_{j=1}^{k} \beta_j R_{ij}}{1-\alpha} = \frac{P_{t+1} - P_t}{1-\alpha} \tag{7}$$

$$\psi = \frac{\gamma}{\theta} = \frac{1}{\alpha} - 1 \tag{8}$$

The following variables will be constructed as factors included in R_j for each domain:

Mortality:

The posterior subjective probability for mortality P_{t+1} from the year 2002 is regressed on the baseline probability P_t from the year 1997; in addition to demographic characteristics like gender, age, race and income, the following change variables are included in the vector R_j:

- Changes in health status

I create an indicator variable, *d_health_worse1* if the individual average values of the self-reported health status between 1998 and 2002 is lower than the 1997 value. I will also account for the presence of a new chronic disease in that period (*d_health_chron)*[26]. I expect positive signs on these coefficients.

- Changes in attitudes, behaviors and substance use

Teens who feel more depressed may intend to engage in riskier activities or even commit suicide because they value life less. I attempt to capture this in my *d_health_unhappy* variable. Because the Mental Health Score, the most thorough measure of emotional wellbeing, was only recorded once, I used the negative change in the answer to the question *How often r has been a happy person in past month*, asked in 2000 and 2002.

Behaviors like substance use offer a reasonable proxy for pessimistic life attitudes. New smokers may feel more likely to die either because they expect negative health effects; or, because they feel more likely to die, they perceive the delayed consequences of tobacco use as less threatening. The variable *d_cigs_ever* indicates the youth smoked at least one cigarette for the first time between 1998 and 2002.

Active or passive crime involvement is another behavior that could induce an upward revision of mortality risk perception. Being the victim or witness of a violent crime should increase subjective mortality beliefs (*d_victim_1997_2002, d_witness_1997_2002*). Variables for whether the youth became a member of a gang between 1998 and 2002 (*d_gang_join, d_gang_left*), started selling drugs (*d_sell_drugs*) or stole something with value more than $50 (*d_stole_ever)* proxy for direct involvement.

[26] There is room for measurement error here, as the 1997 presence of chrnic condition was parent-reported and the 2002 reported by the respondent.

-Changes in family and neighborhood environment

Hurd and McGarry (2002) show that a substantial portion of the revision in mortality probabilities is based on the death of genetically related and unrelated household members. Death of a close relative is a salient and traumatic event, which can psychologically lead to a positive bias in one's own perception of death risk (Slovic 2001). I construct variables for whether one of the respondent's parents or siblings has died in the 1998-2002 period (*d_death_unexp*).

Another mortality-related change in environment is the perceived dangerousness of the youth's surroundings. I control for the emergence of new gangs in the respondent's neighborhood (*d_gangs_hood*).

Fertility

The analysis is in principle similar to the mortality one. However, the updating period is shorter by four years as the posterior subjective probability for being pregnant P_{t+1} from the year 2002 is regressed on the baseline probability P_t from the year 2001. A problem of using short horizon is that 1) fewer events occur in a shorter period, and 2)more of the behaviors that lead to events could be anticipated, hence they can have less of a "learning" effect on the prior probability. A person would be more likely to expect an event and its consequences if the time frame is set one year into the future than if it were 5 years, and might incorporate the effect of that event in the prior probability. Hence there could be less relative weight placed on the information from such an event. Also, the different horizon limits the possibility of comparing the updating process across domains. Nevertheless, I expect the weight of new information to be less than in Subsection A due to the shorter period. The following variables will be included in the vector R_j:

-Changes in coital frequency and contraceptive effort:

Sexual activity and contraceptive effort are the strongest correlates of fertility (Delavande 2008, Walker 2003). Intuitively, expect acquiring more sexual experience will have a strong positive effect on the revision of pregnancy risk: *d_sex_freq* accounts for net changes in reported coital frequency. Unfortunately, I cannot control if the youth lost their virginity in the period because only sexually active girls were asked pregnancy questions in 2001.

An increase in the contraceptive effort (*d_sex_BC_freq*) should signal a downward update of P_{t+1}. Because the birth control definition includes methods of varying efficacy, I would like to account for changes in the contraceptive method that imply lesser pregnancy risk. I introduce the dummy *d_sex_BC_withdrawl* if youths switched to withdrawal or any form of contraception that's not pills or condoms[27].

-Changes in family structure and education

Revisions in pregnancy expectations could be the result of changes in marital status (*d_marr_new*). Youths who marry or permanently settle with a partner could decide to have a child. The intention to have a child also depends on the perceived opportunity costs of childbearing in terms of foregone education. I introduce a variable *d_enroll_new* if the respondent either dropped out or graduated from college and expect a positive coefficient. Income shocks (*d_inc_shock)* can also change the perceived costs of childbearing.

Education

Like in the fertility case, the updating interval for enrollment is limited to one year. A major difference from the previous models is that I look at a restricted sample of prospective college students (transitioning from junior to senior year of high school). The following variables will be included in the vector R_j:

[27] Unfortunately, data on this only applies to the last time the respondent had sex rather than the entire 1-year period

-Changes in income/cost of attendance

A widely reported result in the education literature is that low income students are less likely to attend/graduate from college because borrowing constraints increase the marginal cost of attendance (Belley and Lochner 1997, Stinebrickner and Stinebrickner 2009). A negative change in household income (*d_income*) should lead to downward revisions of P_{t+1}. This relationship should be stronger for individuals in the restricted sample, since college education is more costly.

-Changes in academic performance

The literature suggests a strong relationship between academic performance and drop-out rates: prospective students tend to be overoptimistic about their future college performance, but lower their expectations for future attainment after they receive more information about their ability in the form of lower grades (Stinebrickner and Stinebrickner 2009). Changes in GPA trasitioning from junior to senior year or from high school to college (*d_gpa_HS, d_gpa_coll*) will at least in part capture new information students receive of their own ability leading them to reconsider the likelihood of future attainment

-Changes in school and family structure

I expect significant life transitions could have a psychological effect that leads to a change in expectations and education priorities. Aside from adaptation difficulties, moving to a new school (*d_enroll_new*) could lead to positive or negative effects on college prospects depending on school quality. Parent divorce or the death of a family member (*d_family_divorce*, *d_death_unexp*) could place a psychological toll, leading to a downward revision.

E. Private Information

An alternative explanation to the systematic forecast errors from subsection B is that they are due to private information rather than biased expectations. Subjective probabilities could contain information that is relevant to the outcome, but is not captured in the objective estimate because the information set available to the researcher is not complete.

Khwaja et al (2007) illustrate how private information in the form of anticipated future actions explains some of the forecast error in the mortality perceptions of smokers over a 10 year period. Smokers have a general tendency to understate the subjective hazard of dying by age 75. This could be due to the relative optimism of those smokers who intend to quit smoking, who would state a lower mortality hazard in anticipation of health improvements after they quit. The authors look into the quitting history of respondents, stratify their sample and show that smokers who quit 4 years after baseline do in fact face a lower mortality chance and adjust their subjective beliefs in advance. However, without observing this group's future quitting, a researcher would get biased estimates of their objective hazard (they would come out to be strongly optimistic).

In the given example, the unobserved intention to quit is private information: it affects the outcome, but would not be incorporate in the objective probability estimates if the researcher only has data on baseline characteristics and realized outcomes. However, it would be incorporated in the subjective probability, making self-reported probabilities more accurate predictor of the realized outcome than objective estimates. To compare the predictive power of subjective and objective probabilities, I plan to regress realized outcomes R_i on baseline subjective and objective estimates following the logic of Khwaja et al (2007). I plan to use OLS to estimate the following specification:

$$R_i = \alpha + \beta S_i + \gamma O_i + \varepsilon$$

(9)

If there is private information in the subjective beliefs not included in the objective probability, the parameter estimate β should be positive and statistically significant.

V. Results

A. Subjective probabilities

Panel A of Table 1 presents the subjective probability elicitations directly form the *Expectations and Attitudes* portion of the NLSY. Panel B contains the variables I constructed to measure what actually happened to those who responded to the subjective probability questions.

Table 1: Subjective probabilities and their realizations

Question (year) Outcome	Mean	SD	Obs.
A. Subjective Probabilities			
% chance die by age 20 (1997)	0.203	0.225	3431
% chance pregnant in next 5yrs (2000)	0.303	0.312	2979
% chance enrolled in 5yrs (2000)	0.451	0.383	6890
B. Outcomes			
Died 1997-2007	0.013	0.102	3431
Pregnant 2000-2005	0.544	0.498	2979
Enrolled 2005	0.249	0.433	6890

Mortality

In 1997, the 3431 respondents that were asked the mortality expectation question gave an average probability of 0.203 that they will die by the time they turned twenty. In 2002, the average probability to die in the next year was 0.19. Compared to the realizations, the values are remarkably overestimated. The average mortality for the NLSY97 sample between 1997 and 2007 was 0.011. Among those who answered the expectation question, it was a little higher at 0.013.

Fertility

In 2000, the 3922 women asked about their chances of being pregnant within the next 5 years gave a mean subjective probability of 0.283. The same question was asked to a limited sample of 621 women a year later and the mean probability was a much higher 0.447.

There is a significant underprediction of the pregnancy risk: 54% of the women who answered the 2000 question had reported at least one pregnancy between 2000 and 2005. While it may seem counterintuitive that 50% of women end up pregnant, it is worth noting the outcome variable includes all intended and unintended conceptions, regardless of whether they ended in abortion or stillbirth, for women in their prime reproductive age over the course of 5 years.

Education

In 2000, the 6890 respondents estimated an average probability of 0.45 of being enrolled in any educational institution in 5 years. Compared with the reported school enrolment status in 2005, the expectations are optimistically biased: only 25% of the sample was enrolled. Among those, the subjective probabilities given 5 years earlier averaged above 0.5 (the highest was 0.69 for those enrolled in a 4-year college). Among those who had dropped out of college, the expectation was 0.48, which was 0.12 points higher than those who finished high-school but never went to college, and nearly 0.21 points higher for those who dropped out of high-school. This distribution of expectations is another indication that the teenagers who replied to the SP questions applied some foresight when thinking about their education attainment.

B. Objective probabilities and forecast errors

Table 2 reports the logit results for the determinants of death (column 1), pregnancies between 2000-2005 (cols 2 and 3) and enrollment in 2005 (cols 4 and 5). It also gives the predicted objective probability given these determinants.

Табле 2: Objective Probability Prediction

Panel A: Logit estimation of determinants					
Outcome:	Died by 2002	Pregnant b/n 2000-2005		Enrolled in 2005	
Determinants:				All	Juniors
	(1)	(2)	(3)	(4)	(5)
Age	-0.0002	-0.0010	-0.0226	-0.0623***	-0.0158
	(0.62)	(0.97)	(0.19)	(0.00)	(0.80)
Black	-0.0007	-0.0561	0.0234	0.0892**	0.0310
	(0.64)	(0.42)	(0.61)	(0.00)	(0.77)
Hispanic	-0.0037**	0.0443	0.0058	0.1020***	0.3053***
	(0.00)	(0.53)	(0.91)	(0.00)	(0.00)
Female	-0.0039*			0.0525**	0.0802
	(0.02)			(0.00)	(0.24)
Income[1]	-0.0000	-0.0002	-0.0002**	0.0001**	0.0005**
	(0.98)	(0.08)	(0.00)	(0.01)	(0.01)
Mental and physical health					
health_chronic_1997	0.0005				
	(0.81)				
health_ins_1997	0.0017				
	(0.28)				
health_mental_2000	0.0001	0.0209*	0.0068	-0.0060	-0.0138
	(0.75)	(0.04)	(0.35)	(0.12)	(0.31)
Substance Use					
SUI_2000		-0.0033	-0.0041	-0.0459***	-0.0727*
		(0.90)	(0.82)	(0.00)	(0.02)
cigs_ever_1997	0.0016				
	(0.40)				
alc_ever_1997	0.0012				
	(0.50)				
Crime and perceived threats					
sell_drugs_1997 (d)	0.0043				
	(0.30)				
stole_ever_1997 (d)	0.0018				
	(0.54)				
gang_ever_1997 (d)	0.0004				
	(0.87)				
gangs_hood_1997	0.0006				
	(0.68)				
shoot_witness_coll	-0.0012				
	(0.44)				
Sexual activity and contraception					
sex_init_age_2000		-0.0193	-0.0302**		
		(0.23)	(0.00)		
sex_partners_2000		0.0258			
		(0.10)			
sex_freq_2000		0.0004*			
		(0.02)			

sex_BC_freq_2000		-0.1654	-0.1577**		
		(0.08)	(0.00)		
sex_BC_withdrwl_		0.0230			
		(0.74)			
Family characteristics and peer effects					
family_relig_1997		0.0001			
		(0.49)			
family_father_2000		-0.0594			
		(0.27)			
family_teen_mom		0.1269			
		(0.26)			
marr_stat_2000		0.0962	0.1232**		
		(0.17)	(0.00)		
enroll_2000		-0.0884	-0.1076**		
		(0.11)	(0.00)		
educ_mom_1997	-0.0006*			0.0081	0.0406**
	(0.03)			(0.05)	(0.01)
educ_dad_1997				0.0140***	0.0354*
				(0.00)	(0.02)
peers_coll_1997				0.0140	0.0369
				(0.13)	(0.23)
Education attainment and ability					
ASVAB_score	-0.0000	-0.0042***	-0.0031***	0.0037***	0.0049***
	(0.39)	(0.00)	(0.00)	(0.00)	(0.00)
Highest Grade 2000				-0.0124	
				(0.30)	
gpa_HS_2000					0.2075***
					(0.00)
Pseudo R^2	0.090	0.146	0.122	0.130	0.288
N	4469	499	979	2653	375
Obj_prob	0.006	0.632	0.616	0.290	0.488
(SD)	(0.01)	(0.21)	(0.19)	(0.18)	(0.30)

1)Income data from 1997 used in education variables;
Marginal effects in panel A; *p*-values in parentheses* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Standard Deviation in parentheses for objective probability;

Mortality

Column1 presents the marginal effects of estimates of the following regression:

$$Logit(Y_i) = \alpha + \beta_1 DEM + \beta_2 HEALTH + \beta_3 SUBST + \beta_4 CRIME + \varepsilon$$

Determinants include demographic controls (age, race, sex, income, highest grade attained by mother) and different explanatory variables for health, substance use and crime risk. I tested five specifications, reported here is the one with the most controls. The other four were not qualitatively different and yielded essentially identical objective probabilities despite substantial variation in sample size.

Gender and race are significant predictors of sample mortality with females and Hispanics being less likely to die than Whites. The parameters for mental and physical health are all insignificant: contrary to my expectations, the few deaths in the sample cannot be explained by poor health. In specifications not reported here having a chronic condition increases the likelihood one died to almost significant levels. All coefficients for substance use were highly insignificant, implying smoking and drinking are not very good proxies for risk seeking behavior. None of the criminal involvement variables were significant, indicating few of the deaths in the sample could be attributed to violent causes. Mother's highest grade completed had a significant negative effect, implying more educated families are less likely to lose their children. The objective death probability forecasted by the model was 0.006, about 30 times lower than what respondents stated in the survey.

Fertility

Columns 2 and 3 estimate the following regression:

$$Logit(Y_i) = \alpha + \beta_1 DEM + \beta_2 SEX + \beta_3 FAMILY + \beta_4 EDUC + \varepsilon$$

where Y = 1 if the respondent reported a pregnancy between 2000 and 2005;

I report two specifications, where the first model includes all planned variables and second one drops the pull-out dummy (*sex_BC_withdrawl*), some insignificant family controls (religiosity index, whether the respondent grew up with a father figure, or had a teen mother) in order to increase the sample size from 499 to 979; highest grade completed (*ind_HGC*) variables and the sexual activity variables were taken out to avoid multicollinearity with the enrollment status dummy and the birth control-to-sex frequency ratio respectively.

As expected, poorer individuals are more likely to get pregnant with the result robust across specifications, although the marginal effect of the income-to-poverty-ratio is very small. Lower initiation age increases the likelihood of pregnancy, however the count of sexual partners does not[28]. The frequency of birth control use is the most significant predictor among the sex variables, decreasing pregnancy by 15 percentage points on average. Birth control includes all methods, including withdrawal. However, I was unable to controll for use of the withdrawal method, or for knowledge whether it prevents STDs (coefficient not reported) because it significantly limited the sample size and yielded no significant results.

All family and education controls have coefficients of the expected sign. Being married or permanently cohabitating increases the likelihood of pregnancy by 12 percentage points. These pregnancies are largely intended and part of natural family planning (consequently, I expect married/cohabitating partners will have much smaller forecast errors). Expectedly, respondents that are enrolled are less likely to get pregnant, in part owing to the higher opportunity cost of raising a child, in part because pregnant teens will be more likely to drop out. Higher ability is significantly negative, probably because the opportunity cost of raising a child is higher if one has higher expected earnings. It is also possible that more cognitively able individuals have more knowledge about birth control and conception.

The two models predicted nearly identical values for the objective 5-year pregnancy risk faced by respondents: 62% and 63% for the larger and smaller sample. Both are higher than the subjective expectation.

Education

Columns 4 and 5 present the results of the following regression:

$$Logit(Y_i) = \alpha + \beta_1 DEM + \beta_2 EDUC + \beta_3 FAMILY + \beta_4 HLTH\ \varepsilon$$

where Y = 1 if the respondent was enrolled in any institution in 2005;

[28] The initiation age variable became significant, with estimate of around 3.5 percentage points when the religiosity index was dropped.

I report two specifications: the first is non-restricted, including demographic, educational, family and health/substance use determinants. The second one is identical, but I restrict the sample to those who had completed their junior year in high school in 2001, and add a GPA control. This decreases sample size, from 2653 to 357, but makes the analysis more applied: the assumption is that to juniors, the question surveys their expectations of going to college.

All else held constant, Hispanics are more likely to attend college than Whites. Blacks are more likely to be enrolled, but not to attend a higher institution. Possibly, this is because minorities are more likely to repeat grades (in the non-restricted specification, enrollment in 5 years could also mean the individual has not graduated). As expected, there is a positive income-attendance relationship, and the effect is stronger for the likelihood of attending college, borrowing constraints can undermine education attainment. However, education controls had a larger effect. A full point increase in GPA increases college probability by 20 percentage points. Ability is positively correlated, but the marginal effect is not larger than in other domains. Substance users are less likely to attend college, probably because engaging in risky behaviors also correlates with effort. Peer and family effects are important, especially for college: having a parent with a college degree increases the probability of enrollment by 4 percentage points.

The predicted 5-year objective enrollment probability was 29% for the non-restricted and 49% for the high school junior sample, in both cases lower than the expectation. The difference between these values shows how enrollment in 5 years can imply many different outcomes.

B. Forecast error

I difference out the subjective expectations with the forecasted objective estimates from the previous subsection to derive individual forecast errors. The means of the actual and absolute errors are given in Table 3. Chi-square tests rejected the null hypothesis that the error is zero in all specifications.

Table 3: Average forecast errors

	%chance die by 2002 – Obj prob mortality	% chance pregnant in 5 yrs – Obj prob fertility		% chance enrolled in 5 yrs – Obj prob education	
				All	HS Juniors
Forecast_err_act	0.198 (0.22)	-0.262 (0.34)	-0.246 (0.36)	0.164 (0.35)	0.111 (0.39)
Forecast_err_abs	0.201 (0.22)	0.354 (0.24)	0.354 (0.25)	0.312 (0.22)	0.318 (0.25)
N	1631	551	1077	3037	1038

Standard Deviation in parentheses;

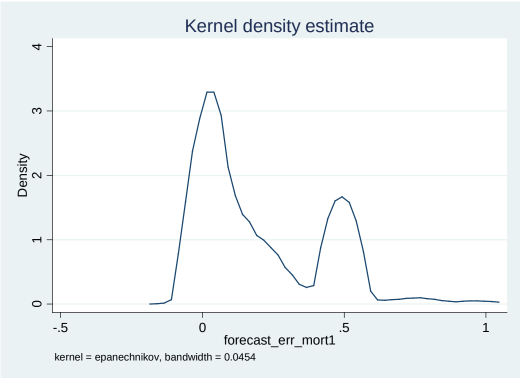
Mortality

Contrary to the REH, there is a significant and very large bias: the forecast error is 0.198 on average, nearly 33 times the value of the objective mortality probability. The standard deviation and the difference between the actual and absolute values of the bias is smaller than for pregnancy or enrollment errors, meaning the bias is more unidirectional. However, there are a lot of focal 0.5 responses (20% of the distribution), perhaps due to epistemic uncertainty: respondents give a 50/50 answer because they are not aware of the exact causal mechanism of their death (especially since a lot of the deaths in the sample are most likely accidental). Figure 1a presents the kernel density function of the actual error, which has two peaks, one centered around 0 and the other around 0.5.

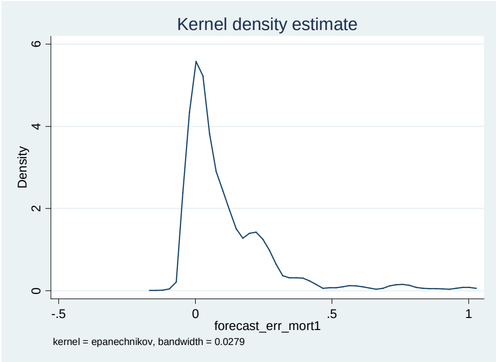
When 50/50 responses to the expectation question were taken out (eliminating 357 observations), the average forecast error fell nearly twice to 0.12, which still overestimates true probability nearly 15 times (Figure 1b). The persistent large magnitude of this bias is inconsistent with studies on older populations that find much smaller divergences: Khwaja et al (2007) find the bias in mortality hazard is 9.6% of the objective measure and elimination of focal responses led to no significant changes.

Figure 1: Kernel density estimation of the forecast error, mortality

A) Full sample



B) Excluding 50/50 responses



Even if we assume 50/50 responses express lack of knowledge as to how death probability is formed rather than underlying expectation, and eliminate these observations, the large positive bias persists. To cast an insight into what is driving the bias, table 4 regresses the actual (cols 1 and 3) and absolute (cols 2 and 4) forecast errors on demographic characteristics, ability, smoking status and mental health. The general form is given below, with specifications 3 and 4 using the restricted sample without 50/50 responses.

$$\varepsilon_i = \alpha + \beta_1\, DEM + \beta_2\, ASVAB + \beta_3\, SMOKER + \beta_4\, MENTAL\_HLTH\_INDEX$$

Table 4: Absolute and Actual Forecast Error Regression, Mortality

	(1) Actual Error	(2) Absolute Error	(3) Actual Error	(4) Absolute Error
Female	0.0187	0.0153	0.0058	0.0015
	(0.09)	(0.16)	(0.56)	(0.88)
Age	-0.0163*	-0.0165*	-0.0114	-0.0117
	(0.04)	(0.03)	(0.12)	(0.10)
Black	0.0334*	0.0311*	0.0401**	0.0369**
	(0.03)	(0.03)	(0.00)	(0.01)
Hispanic	0.0045	0.0009	0.0289*	0.0237
	(0.77)	(0.95)	(0.04)	(0.09)
Income_1997	-0.0000	-0.0000	-0.0000	-0.0000
	(0.07)	(0.06)	(0.88)	(0.80)
ASVAB_score	-0.0004	-0.0005*	0.0000	-0.0001
	(0.07)	(0.03)	(1.00)	(0.58)
cigs_ever	0.0438***	0.0454***	0.0138	0.0166
	(0.00)	(0.00)	(0.18)	(0.10)
Health_mental	-0.0072**	-0.0070**	-0.0050*	-0.0048*
	(0.00)	(0.00)	(0.02)	(0.02)
R^2	0.036	0.039	0.017	0.018
N	1631	1631	1274	1274

Marginal effects; *p*-values in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Overall, a lot of the bias is driven by an inability to answer probability questions and express true expectation results, which can be explained by lower ability. The full sample has an R-squared about twice as high, implying a lot of the variation in the error is due to focal responses. However, at least some of the bias is due to pessimism and is psychological, perhaps due to an inherent tendency to overpredict small probabilities. The biases in both samples are conditional on demographics and behaviors, contrary to the REH. The strong relation of 50/50 responses with smoking, a behavior widely held to decrease life expectancy, suggests public information could increase epistemic uncertainty about death.

The coefficients for actual and absolute errors are essentially identical since most people are pessimistic about mortality and overestimate. As expected, older individuals tend to be accurate because of life experience. The effect is stronger for the full sample, suggesting younger individuals give more 0.5 responses. Age coefficients also confirm subjective probabilities are adequately stated and behave in line with probability rules. The question asked about the chance of death by age 20: so, older individuals who are closer to that age (correctly) stated lower probabilities, decreasing the bias.

As expected, individuals who had a higher mental health index, which measures optimism, tend to be less biased. This result holds for both samples, hinting that pessimistic attitudes explain some of the bias. Surprisingly, the effect of ability is not very significant and is smaller in magnitude than for fertility and enrollment (sometimes by magnitude of 10). More interestingly, ability relates to the bias in the first sample, but is highly insignificant in the restricted one: less able individuals have more difficulty forming and expressing probabilities about mortality, so they are more likely to give a focal response. However, the effect is not strong: those with 0.5 answers had an average ASVAB score of 42.07, about 7 points lower than the full sample. Also, there is no threshold for ability above which 0.5

responses disappear: the error distribution for the top 10% ASVAB scores (not shown) also has a pronounced peak around 0.5.

The bias in the first sample is similarly conditional on smoking, but the effect was smaller in the restricted sample. This suggests smokers tend to give more 0.5 responses. There is an evident psychological link between smoking and increased mortality, which implies 0.5 responses express low confidence in survival chances rather than just an inability to answer. However, smoking increased the bias across all samples (although the effect weakened). One explanation is that the information on the risks of smoking is widely disseminated and aggravates feelings of uncertainty (Viscusi 1990). More cognitively able individuals (those who do not give focal responses) are less prone to such effects. Another explanation is that more pessimistic individuals pick up smoking because they believe they will die anyways. In an unreported specification I included an interaction term between mental health and smoking. Results suggested that while smokers who are more pessimistic are more biased, the effect is not stronger than for the general population (coefficient of interaction is less than of *health_mental*). The coefficients were jointly significant.

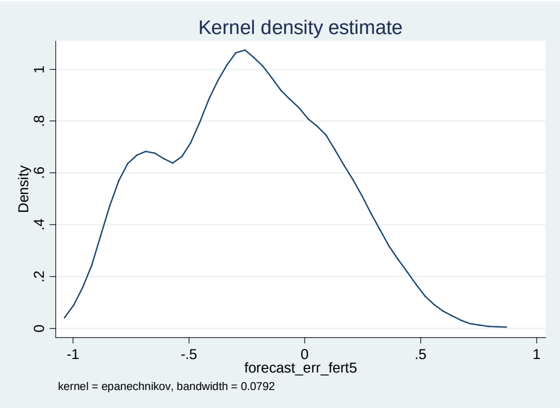
Fertility

There is a consistent tendency to underestimate the 5-year probability of getting pregnant: the forecast error is -0.262 for the small and -0.249 for the larger sample. In terms of magnitude, this is almost 40% of the actual probability. The result is robust to variations in sample size. However, in terms of direction and dispersion, the bias is less consistent than for mortality. At 0.354, the absolute errors are larger than the actual ones by 10 percentage points, suggesting at least some portion of the sample overestimates the risk. The standard deviation is also higher, perhaps because respondents used a fuller range of probabilities.

The Kernel density presented in Figure 2a is left-skewed, with two peaks. The one around -0.6 is due to 0 responses, meaning a lot of women that were certain not to have a baby actually faced average risk. In fact, the density of the limited sample of 267 zero-responses in Figure 2b peaks around 0.75, showing a lot of these women faced higher risk. Almost an eight of pregnancies were unintended: 110 women, almost half of the restricted sample and 16% of the full sample, actually got pregnant even though they reported a 0% chance. While there are also a lot of 50/50 responses, because the true probability is much closer to the 0.5 value, the analysis with epistemic uncertainty from the mortality subsection cannot be performed without losing a lot of information.

Figure 2: Kernel density estimation of the forecast error, fertility

A) Full sample



B) Zero-responses

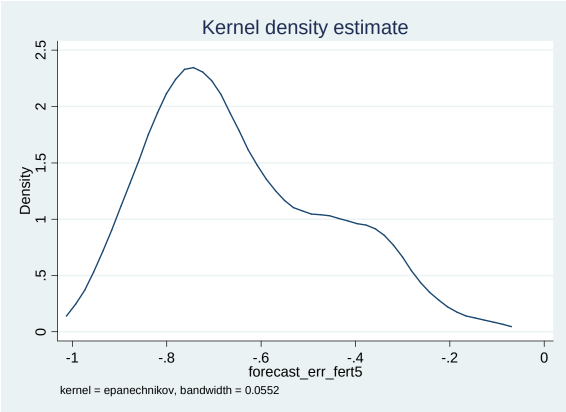


Table 5 contains the OLS estimates of the actual (cols 1 and 3) and absolute (cols 2 and 4) forecast errors on individual characteristics. The regression equations are the same as for mortality, only including marital status. I was unable to run a regression with the birth control knowledge dummy due to missing observations that limited sample size to 35 observations. Columns 1 and 2 use the error from the larger sample. (Regressions with the small sample not reported here did not differ qualitatively). Columns 3 and 4 exclude women who gave 0-responses. Excluding focal responses did not change the fit of the actual error by nearly as much as in the mortality analysis. The coefficient estimates are qualitatively unchanged. This suggests the heterogeneity in accuracy is not driven by focal responses.

Table 5: Absolute and Actual Forecast Error Regression, Fertility

	(1) Actual Error	(2) Absolute Error	(3) Actual Error	(4) Absolute Error
Age	0.0616***	-0.0291***	0.0532***	-0.0179**
	(0.00)	(0.00)	(0.00)	(0.00)
Black	-0.0300	0.0268	0.0022	-0.0009
	(0.26)	(0.16)	(0.93)	(0.96)
Hispanic	0.0213	-0.0424*	0.0030	-0.0384*
	(0.45)	(0.03)	(0.91)	(0.03)
Income	0.0003***	-0.0001***	0.0002***	-0.0000*
	(0.00)	(0.00)	(0.00)	(0.03)
ASVAB_score	0.0026***	-0.0019***	0.0018***	-0.0011***
	(0.00)	(0.00)	(0.00)	(0.00)
Enroll_2000	0.1019***	-0.0622***	0.0851***	-0.0372*
	(0.00)	(0.00)	(0.00)	(0.01)
Subst Use	0.0194	-0.0189*	0.0036	-0.0088
	(0.06)	(0.01)	(0.73)	(0.19)
Health_mental	-0.0006	-0.0003	-0.0020	-0.0001
	(0.89)	(0.93)	(0.62)	(0.97)
Married_coha	0.0298	0.0180	0.0513*	0.0057
	(0.24)	(0.32)	(0.04)	(0.72)
R^2	0.210	0.172	0.177	0.159
N	1077	1077	810	810

Marginal effects; *p*-values in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Columns 3 and 4 have identical values because the forecast error for 0-reposnses is universally negative;

Results support the hypotheses that teens underestimate their conception risk because of misinformation about birth control, rather than that they underestimate the costs associated with an unexpected pregnancy because of short foresight. Less cognitively able individuals have higher errors, assuming ability proxies for birth control knowledge. In separate tests unreported here, the bias was higher on average for respondents that practice the withdrawal method and for respondents who said it is a more efficient in preventing STDs[29]. Also, higher income makes teens more accurate, although the magnitude is small. Respondents enrolled in school are less biased by almost 10 percentage points. These groups have more to lose in terms of foregone earnings from childbirth, assuming education and higher income imply higher future earnings.

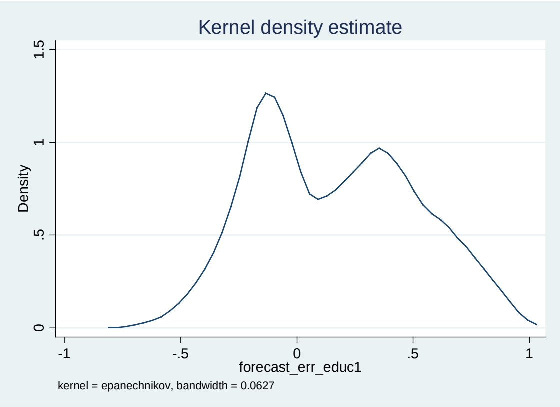
[29] I could not include these in the regression because they limit my sample size; Less than 100 women answered the STD question wrong.

A higher score on the substance use index makes one significantly more accurate (in the full sample). Possibly, smokers in the 0-response sample face an even higher objective risk because they engage in riskier behaviors (e.g. unprotected sex), and are of lower socio-economic background. However, substance use has no significant impact on the objective probability (see Table 2, cols 2 and 3). Another problem with this explanation is that the effect is not significant for the non-focal sample, suggesting it could be due to spurious correlation.

<u>Education</u>

The results for education are broadly consistent with the REH. Table 3 shows teens are positively biased about their chances of being enrolled someplace in 5 years. The errors are smaller than for death or pregnancy and depend on the outcome being predicted: 0.164 for the entire sample (about 50% relative to the objective probability) and 0.111 for high school juniors (less than 20% of the objective probability). They are also less consistent in their direction: the absolute errors are two to three times higher. The Kernel density of each error is shown in Figures 3 and 4. The first has a distribution with two peaks-one centered around 0 and the other around 0.5. The second peak is due to a high prevalence of 50/50 responses, since the question poses more uncertainty. In the second distribution, the mean looks centered around 0, possibly because the outcome is concrete and respondents have control over it.

Figure 3: distribution of average education forecast error for entire (left) and restricted (right) samples



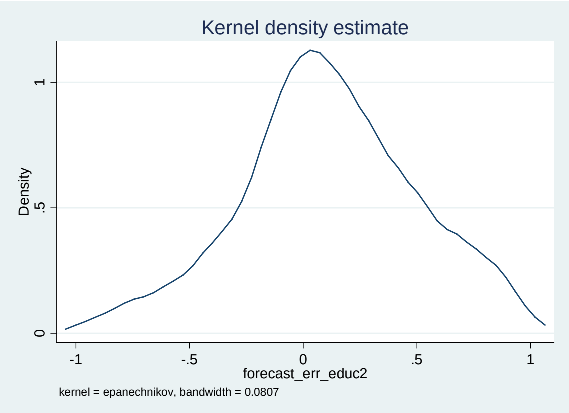


Table 6 contains the OLS estimates of the actual (cols 1 and 3) and absolute (cols 2 and 4) forecast errors on individual characteristics. Columns 3 and 4 use the error for high school juniors. The equation follows the form from the previous subsections.

Table 6: Absolute and Actual Forecast Error Regression, education

	(1) Actual Error	(2) Absolute Error	(3) Actual Error	(4) Absolute Error
	All		*High School Juniors*	
Age	-0.0171*	-0.0231***	-0.1329***	-0.0123
	(0.01)	(0.00)	(0.00)	(0.19)
Female	0.0039	0.0205*	-0.0218	0.0054
	(0.76)	(0.01)	(0.32)	(0.73)
Black	-0.0274	0.0319**	0.1165***	0.0933***
	(0.14)	(0.01)	(0.00)	(0.00)
Hispanic	0.0535**	0.0575***	-0.0295	0.0170
	(0.00)	(0.00)	(0.35)	(0.45)
Income_1997	-0.0001**	-0.0000	-0.0003***	-0.0001*
	(0.01)	(0.99)	(0.00)	(0.04)
ASVAB_perc	-0.0013***	-0.0002	-0.0036***	-0.0012***
	(0.00)	(0.19)	(0.00)	(0.00)
Health_mental	0.0031	-0.0003	0.0101*	0.0013
	(0.24)	(0.88)	(0.03)	(0.69)
Subst Use	0.0197***	-0.0003	0.0249*	0.0092
	(0.00)	(0.93)	(0.02)	(0.21)
Highest Grade Completed	-0.0118	0.0016		
	(0.10)	(0.73)		
R^2	0.043	0.035	0.226	0.057
N	3037	3037	1038	1038

Marginal effects; *p*-values in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The stratifying of the sample shows that if the outcome in question is specific and the mechanism behind achieving it is clear, the prevalence of 0.5 responses goes down along with the bias, confirming the assumption made in the mortality analysis that 50/50 responses voice epistemic uncertainty.

While a much smaller error persists in the college sample, it is likely due to general uncertainty about one's ability rather than limitations in answering the question. Consistent with this, the effect of ability is the largest of all domains and persists in the college sample, despite the lack of 0.5 responses (this did not hold for mortality or fertility). The error is also more pronounced for certain demographics (those who have a less certain college future): being a year younger or black increases it by about 10 percentage points. More optimistic teens (higher mental score) are more likely to overpredict their college prospects, suggesting there is some psychological tendency to the error. Low income and high ability individuals are less biased. Since income and ability are one of the strongest determinants for enrollment (see Table 2), this result implies agents are well aware of what factors relate to their success. Because of this, and the many unobservable determinants of educational attainment, I expect there to be significant private information in the subjective probabilities.

D. Updating

Tables 7, 8 and 9 present the results of the Bayesian updating model where for each domain the subjective mortality probabilities from 2002 P_{t+1} are regressed on the 1997 or 2001 probabilities P_t , demographic controls (not shown) and a vector of change variables R_j.

Mortality

Table 7 presents the regression results for mortality. Overall, subjective death probabilities respond to exogenous shocks, there is evidence probabilities converge, but youths may rely on heuristic rules when updating. The parameter for the prior probability in both specifications is 0.26 and is highly significant and less than one, indicating that when updating their probabilities youths place little weight on prior statements. The value of the risk equivalent of new information r_t was - 0.017; The weight of the risk equivalent vector is $\psi = \frac{1}{\alpha} - 1$ = 2.85 ; The negative product of these parameters suggests probabilities converge and there is rational learning: new information decrease the risk by 0.048.

Table 7: OLS Bayesian Updating Model, Mortality

	(1) Expect to die (2002)
Prior prob (1997)	0.2621***
	(0.00)
Changes in health	
D_health_chron	0.0209
	(0.44)
D_health_unhappy	0.0208
	(0.32)
D_health_worse	0.0139
	(0.26)
Changes in Substance Use, Crime	
D_cigs_ever	0.0049
	(0.84)
D_gang_join	0.0508
	(0.65)
D_gang_left	0.0724*
	(0.02)
D_gangs_hood	-0.0565
	(0.19)
D_sell_drugs	-0.0055
	(0.90)
D_stole_ever	0.0147
	(0.86)
D_victim_1997_2002	0.0865**
	(0.00)
D_witness_1997_2002	0.0185
	(0.83)
D_death_unexp	-0.0441
	(0.23)
R^2	0.099
N	877

Marginal effects; *p*-values in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Parameters for new chronic illness, reported worse average health and feeling happy less frequently all have positive signs, but are insignificant. (both as predictors of mortality risk and as factors that affect its evolution. Contrary to older populations (e.g. in Smith et al 2001), mortality and mortality perception in the NLSY sample is not affected by health shocks.

Initiating smoking does not lead to an upward revision, despite the higher likelihood of smokers to be biased. An explanation is that either the decision to start smoking is anticipated, or that it takes more than a year for smoking risk information to be internalized and contribute to the overestimation bias. Another surprising result is that joining a gang does not significantly increase subjective mortality perceptions, but leaving it does.

Importantly, being victimized has a significant positive impact and causes more overestimation, even though it is not a significant predictor. It is easy to see how salient violent episodes like being mugged or bullied increase feelings of vulnerability and affect risk perception. This suggests that while information is in fact used to form new probabilities, it is not used rationally and agents rely on the representative heuristic. However, other salient, unexpected events like seeing someone get shot on the street or new gangs in the neighborhood do not affect the risk perception.

Fertility

Overall, pregnancy expectations converge with experience (there is rational learning) and respond to new events in meaningful ways. The estimated weight on the prior probability is 0.509, suggesting youths place a relatively high weight on new information when forming their probability a year later. The value is higher than the estimate for mortality owing to the shorter period between the SP elicitations. The value for the risk equivalent $r_{t\ i}$ was 0.2 and the weight ψ is 1.087. The positive product is in line with my hypothesis that expectations converge, increasing by 0.21 due to new information.

Table 8 presents the regression results for updating of pregnancy risk.

Table 8: OLS Bayesian Updating Model, Fertility

	(1) Expect pregn in 5yr (2001)
Prior prob (2000)	0.5093***
	(0.00)
Changes in sexual activity	
d_sex_freq	0.0001
	(0.53)
d_sex_BCfreq_more	-0.0479
	(0.23)
d_sex_BC_use	0.0146
	(0.66)
d_sex_BC_withdrawl	0.0170
	(0.71)
Changes in family	
d_marr_new	0.1631**
	(0.00)
d_enroll_new	0.0918
	(0.18)
d_inc_shock_2000	-0.0507
	(0.13)
R^2	0.711
N	359

Marginal effects; *p*-values in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Changes in sexual behavior and contraception all had the expected signs, but none were significant. New marriage or cohabitation with a partner significantly increased the self-reported pregnancy risk, which is consistent with the determinant regression in subsection B (married couples are more likely to have children). The significance of the parameter, despite the fact marriage is an important decision and should be anticipated over a horizon of 1 year, implies two things: 1) the decision is not reflected in the prior probability because of short foresight or 2) after marriage, teens learn about their true probability of conception. The second explanation supports the idea expressed early that teenagers underestimate pregnancy changes due to imperfect knowledge of contraception.

<u>Education</u>

Columns 1 and 2 of Table 9 report OLS coefficients of the entire and restricted (high school junior) samples. In column 3, the sample was further restricted to those who transitioned to being college students in 2002. Respondents place less importance on prior probability in the full v the college sample, respectively 0.27 and 0.38. The coefficients are lower than fertility, suggesting there is more learning. The value of r_t is 0.006 with a weight of 2.67, yielding a weighted revision of 0.016 for the general sample, and r_t of 0.007 with a weight of 1.71, yielding a revision of 0.012. The results indicate there is convergence and rational learning, but it is much smaller in magnitude than for the other two domains. This is consistent with Viscusi's (1985) rational learning framework since the bias is the smallest.

Also, the revision is likely due to private information as none of the "events" found in the data had a significant impact. Such information could be learning about one's own ability: the estimates for GPA become significant for the sample of college students (col 3), indicating that students who improve their grades revise their education attainment expectations upwards. This result is in line with earlier statement that biases about enrollment probabilities come from uncertainty about one's academic ability.

Table 9: OLS Bayesian Updating Model, Education

	Expect enroll (2001)	Expect enroll (2001)	Expect enroll (2001)
	All	High Schl	College
Prior Prob (2000)	0.2719***	0.3854***	0.1849*
	(0.00)	(0.00)	(0.02)
d_income	-0.0001		-0.0001
	(0.13)		(0.16)
d_enroll_new_school	-0.0012	0.0715	-0.2315
	(0.98)	(0.73)	(0.15)
d_family_divorce	-0.0107	0.0882	0.2052
	(0.93)	(0.67)	(0.37)
d_death_unexp	-0.0111	-0.0490	-0.0055
	(0.64)	(0.23)	(0.91)
d_gpa_HS		0.0198	
		(0.66)	
d_gpa_coll			0.0065
			(0.11)
R^2	0.138	0.151	0.158
N	776	307	170

Marginal effects; *p*-values in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

E. Private Information

I run the following model to test whether subjective probabilities contain information that explains the outcomes over and above the estimated objective probabilities.

$$R_i = \alpha + \beta S_i + \gamma O_i + \varepsilon$$

Table 10 contains estimates for each of the objective probabilities predicted by the models in Table 2.

Table 10: OLS Predictive Power of Subjective and Objective Probabilities

Outcome: / Probabilities	Died by 2002	Pregnant b/n 2001 2006		Enrolled in 2005	
Mortality					
exp_die_20yrs_1997	-0.0030				
	(0.73)				
obj_prob_mort1	1.1184^{***}				
	(0.00)				
Fertility					
exp_pregn_5yrs_2000		0.1513^{*}	0.1396^{**}		
		(0.02)	(0.00)		
obj_prob_model1		0.9839^{***}			
		(0.00)			
obj_prob_model2			0.9867^{***}		
			(0.00)		
Education					
exp_school_5yrs_2000				0.2322^{***}	0.2694^{***}
				(0.00)	(0.00)
obj_prob_educ1				0.8136^{***}	
				(0.00)	
obj_prob_educ2					0.6509^{***}
					(0.00)
R^2	0.018	0.199	0.167	0.190	0.254
N	1631	494	973	2647	951

Marginal effects; p-values in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The mortality estimate shows subjective probabilities have little relevance in predicting outcomes, affirming my hypotheses that they are not expressed properly and biased by heuristic factors. The R-squared of this regression is noticeably smaller, perhaps because the outcome measured is based on random factors not known to either researcher or agent, so both subjective and objective measurement struggle with explaining it.

The estimates for fertility and education show that even though objective probabilities were very close to the realizations, subjective probabilities have significant explanatory power, e.g. there is relevant private information not captured in the objective estimate. Such information could be the intention to have a child because one expects to marry in the next five years: I ran regressions for fertility on a restricted sample of people who were single in 2000 but got married in the next 5 years. The parameter for subjective probability was still significant at the 5% level and rose to from 0.151 to 0.247 for the specification in (2) and from 0.139 to 0.176 for (3). These results support the idea subjective probabilities are a trustworthy measure of underlying expectation, especially in cases where intentions are unobservable.

VI. Conclusion

This paper analyzes subjective probabilities from a national longitudinal study of individuals in their teenage years regarding their short-run chances of death, becoming pregnant and being in school. I ask whether subjective responses match objective risk, and if there is systematic bias, can it be attributed to survey responses or individual characteristics. I propose a framework of rational learning and test for private information. The overarching purpose of the paper is to see if subjective beliefs reveal any biases or hold information, either of which is sufficient reason to include them in behavioral choice models in place of the Rational Expectations Hypotheses.

Contrary to the assumptions of the rational expectations hypothesis, I find substantial individual-level biases in the data. I show the largest of these biases, the one for mortality, is partially explained by focal responses that could reflect epistemic uncertainty among less cognitively able individuals. I speculate the remaining bias in mortality among those who give non-focal responses can be attributed to underlying pessimism that is aggravated by a natural tendency to overestimate small probabilities. For fertility, I find many young women from lower socio-economic standing underestimate their pregnancy risk, possibly due to imperfect information about the conception risk posed by sexual activity. Regarding education outcomes, young people are least biased, especially those expressing their college prospects. While general optimistic attitude and uncertainty about ability could explain some of the overconfidence, agents are more certain about this outcome since it is something one has more control over.

This suggests teenage expectations are more accurate in situation where the mechanism behind the outcome is clear. High school juniors can reasonably predict their college chances because they know it takes good grades/a certain family background. They also have significant private information undetermined by my logit estimation. On the other hand, death is not only a small probability that tends to be overestimated, but is also harder to reasonably predict since the process behind it is unknown to the researcher as well as the predicting agent.

There is evidence of convergence for all three domains, pointing to a rational learning process. However, I could not establish many of the specific events that constitute the learning process. Victimization leads to higher death perception, but this is psychological rather than objective. On the other hand, marriage and learning about ability are possible factors that update fertility and education expectations in meaningful ways. Finally, I find subjective probabilities possess predictive power, and illustrate how certain anticipated events are included in this private information.

For future research, this paper finds that teenagers' expectations are not fully accurate and homogenous as suggested by the REH. This implies models of behavior under uncertainty should relax their expectation assumptions and combine subjective probability data with observed choices to accommodate these forecast biases. In cases where respondents have control over the outcome, there is private information in subjective beliefs, which may arise from the effect of anticipating certain behaviors. This motivates the further investigation of such data in economic analysis. While my work finds evidence of partial learning and hidden information, future research on expectations should focus on what exactly makes teens hold positive or negative biases about certain events in the first place, and what types of private information are available in such data.

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Appendix 1: The Rational Expectations Hypothesis (REH)

There are several expectation measures that are relevant to analyzing the REH and the formation of beliefs: $\hat{E}\ (X_{t+1}|S_t)$ or the subjective probability that an agent attaches to an event X happening in time $t+1$ using his available information set S_t (which is only partially observable to the econometrician; any information that is used by agents but not observed is referred to as private information[30]); $E(X_{t+1}|S_t)$ or the corresponding true objective probability that an event will happen from the perspective of time t; the actual outcome X_{t+1}; Under rational expectations, the forecast error, equal to the difference of $\hat{E}\ (X_{t+1}|S_t)$, and $E(X_{t+1}|S_t)$, should converge to a conditional mean of zero over multiple observations. Because the formation process is homogenous, the forecast error should also be independent of individual characteristics. Such a correlation and/or a systematic bias $\delta = E(X_{t+1}|S_t)- \hat{E}\ (X_{t+1}|S_t) \neq 0$ when the number of observations is high enough and there are no unexpected time-effects would be evidence against the REH.. If there are unexpected macro shocks that influence the outcome of interest, $\delta \neq 0$ alone does not violate rational expectations since unexpected events could not be predicted only using S_t. However, assuming the shock equally affects the entire sample, the homogeneity of expectation formation should still hold (Schwandt 2009)

[30] Hence the measurement of bias in expectations will hinge on an assumption that survey responses obtain unbiased elicitations of $\hat{E}\ (X_{t+1}|S_t)$ and have an information set that matches S_t

Table 1: Summary of reviewed literature

Study	Population	Questions	Methods	Findings
Studies on Subjective Probability (SP) of mortality				
Hammermesh (1985)	cross-sections of: -male economists -non-representative males	-longevity forecast	-comparison of mortality SP w actuarial data	-people able to form probabilities -update probabilities
Viscusi (1991)	cross-section of teenagers	-is risk perception of lung cancer risk accurate -are young smokers Bayesian learners	-comparison of SP w/ Surgeon General stats -partial learning model	- risk overestimated -risk perception updated in a rational manner (convergence of beliefs)
Smith et al (2001)	HRS – -longitudinal -51-61 years old -2-year interval	-is SP mortality accurate -do smokers update mortality SP differently	-compare mortality SP with sample realizations -partial learning model	- SPs accurate on average; smokers are more pessimistic -more responsive to smoking-related health shocks
Hurd and McGarry (2002)	same	- is SP mortality accurate -what sources are used to update mortality SPs -is there private information in SPs	-compare mortality SP with sample realizations -modified partial learning model	-SPs accurate on average -info unrelated to mortality is used to update mortality SPs -SPs are superior predictors
Khwaja et al (2007)	same + HRS follow up (10-year interval)	same+ -what factors drive bias in SP mortality	- use realizations to derive subjective and objective proportional hazard f-ns of mortality -partial learning -regress outcomes on hazards	-no bias on average; -smokers more pessimistic -Bayesian updating among smokers and non-smokers -private information, both in regression and analysis of anticipated beliefs
Domain-specific studies: Education				

Reynolds and Pemberton (2001)	NLSY97 and NLSY79	-how have expectations of college degree evolved in two cohorts -determinants of objective prob for college education	-compare expectations of attainment to realizations	- increase in expectations follows increase in enrollment -diminishing effect of income and labor mkt conditions -high optimistic bias of 79 cohort
Belley and Lochner (2007)	same	same	same	same + -ability most important determinant -importance of income and parental educ
Stinebrickner and Stinebrickner (2009)	Berea Panel Study -420 entering college freshmen	-is drop-out decision caused by optimism about performance	-compare expectations of future grades to realizations -partial learning, new info about ability proxied by GPA change	-optimistic about performance -SPs revised rationally -new info about ability
Domain-specific studies: Fertility				
Walker (2003)	NLSY97 -15-17 year old women	-is teenage pregnancy due to bias in expectations or difficulty perceiving expected costs -determinants of pregnancy	-compare SPs of pregnancy with objective probs, derived by structural model of conception	-SPs accurate on average -poverty and early initiation of sex related to optimism
Haveman et al (1997)	PSID	same (emphasis on economic costs of childbearing and determinants)	-structural model of pregnancy decision	-income most sign effects choice -family background and neighborhood economic characteristics -welfare generosity had no effects