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Expectations in micro data: rationality revisited

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Abstract An increasing number of longitudinal data sets collect expectations information regarding a variety of future individual level events and decisions, providing researchers with the opportunity to explore expectations over micro variables in detail. We present a theoretical framework and an econometric methodology to use that type of information to test the Rational Expectations (RE) hypothesis in models of individual behavior. This RE assumption at the micro level underlies a majority of the research in applied fields in economics, and it is the common foundation of most work in dynamic models of individual behavior. We present tests of three different types of expectations using two different panel data sets that represent two very different populations. In all three cases we cannot reject the RE hypothesis. Our results support a wide variety of models in economics, and other disciplines, that assume rational behavior.

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1 Introduction

An increasing number of large longitudinal data sets now collect expectations information regarding future individual level events and decisions, providing researchers with the opportunity to explore expectations over micro variables in detail. The growing body of research studying expectations includes the literatures that analyze wage and income expectations (Dominitz and Manski 1996, 1997; Das and van Soest 1997, 2000; Davies and Lahiri 1999), fertility expectations and pregnancy outcomes (Van Hoorn and Keilman 1997; Van Peer 2000; Walker 2003), the connection between Social Security expectations and retirement savings (Lusardi 1999; Dominitz et al. 2002), the relationship between retirement expectations and retirement outcomes (Bernheim 1989; Dwyer and Hu 1999; Disney and Tanner 1999; Coronado and Perozek 2001; Hurd and Retti 2001; Forni 2002, Dwyer 2002; Mastrogiacomo 2003), and consumption patterns after retirement (Haider and Stephens 2003; Hurd and Rohwedder 2003).

In this paper we present a theoretical framework and an econometric methodology to use expectation information to test the Rational Expectations (RE) hypothesis in models of individual behavior. We then use the Health and Retirement Study (HRS) to analyze retirement and longevity expectations, and the youth cohort of the National Longitudinal Survey of Labor Market Experience (NLSY79) to analyze education expectations. We find that these three types of expectations are consistent with the RE hypothesis. Our results support the use of a wide variety of models in economics that assume rational behavior.

Our definition and approach to testing the RE hypothesis will be consistent with the views expressed by the precursors of this assumption.[1] We will maintain that *agents' subjective beliefs about the evolution of a set of variables of interest coincide with the objectively measurable population probability measure*. This is consistent with the characterization of Muth (1961) and Lucas (1972).

The main difference is that instead of concentrating on forecasts of market level variables we focus on how individuals form expectations over micro variables that are in some cases under their control. Economists and social scientists, in an ongoing effort to improve our model specifications, are growing increasingly interested in expectation measures as possible sources of additional heterogeneity in individual characteristics that might reflect underlying differences in preference and beliefs parameters—which if left out of the models often bias the effects of related observables.

[1] For a survey of the early contributions see the special issue in the *Journal of Money, Credit and Banking* edited by McCallum (1980), also Sheffrin (1983). For a more recent discussion see Sargent (1995).

It is important to distinguish that while in macroeconomic theory the RE hypothesis is understood mainly as an equilibrium concept, thanks largely to Lucas' seminal contributions, where expectations affect the stochastic evolution of the economy and this evolution in turn affects expectations formation, in microeconomic applications the concept is used as a synonym of individual rationality or an efficient use of information with regard to individual level variables. The latter implies that somehow the economy is in equilibrium. This RE assumption at the micro level underlies a majority of the research in applied fields in economics, and it is at the forefront of most work in dynamic models of individual behavior. This is primarily because most household and individual level data sources are rich in micro variables and it is the responsibility of the researcher to try to control for the macroeconomic environment in which those decisions are made.

The debate over whether testing rational expectations is a worthwhile enterprise goes back almost three decades. Prescott (1977) expressed a strong opinion against testing the hypothesis, while Simon (1979), Tobin (1980), Revankar (1980), Zarnowitz (1984), Lovell (1986) considered the direct analysis of expectations an important project. Manski (1990) advocated for the careful use of any kind of intentions data, especially if to be used to predict behavior. More recently, Manski (2004) has emphasized the importance of analyzing expectations formation, and Hamermesh (2004) discusses the usefulness of subjective outcomes in economics.[2]

The efforts to test the hypothesis began in the context of the analysis of price expectations by Turnovsky (1970), the term structure of interest rates with the work of Sargent (1972), Shiller (1973), and Modigliani and Shiller (1973), and then with the life cycle permanent income hypothesis in a stream of literature that started with the work of Hall (1978), and then compared forecasts of market variables with realizations like in Figlewski and Wachtel (1981, 1983), Kimball Dietrich and Joines (1983), de Leeuw and McKelvey (1981, 1984), Gramlich (1983), Kinal and Lahiri (1988), and Keane and Runkle (1990), and more recently, Lee (1996), Davies and Lahiri (1999), Metin and Muslu (1999), and Christiansen (2003).[3] Finally, work by Leonard (1982) analyzed wage expectations of employers, and Fair (1993) analyzed the question in the context of large macroeconomic models. In all these cases the concern was with market level variables, and the evidence in these and many other studies is mixed. Below, we propose a slightly different approach in line with Bernheim (1990), and recent work by Benítez-Silva and Dwyer (2005), Benítez-Silva and Dwyer (2005, 2006), and use panel data available through the HRS and the NLSY79 to

[2] Friedman (1951), as quoted in Ericsson and Hendry (1999), advocates for emphasizing the testing of hypothesis in the social sciences. Also, our empirical strategy, which uses two different data sets corresponding to two different populations and three different types of questions to test an underlying structural expectation formation mechanism, we believe, passes Ericsson and Hendry (1999)'s demanding tests of how to approach empirical testing of hypothesis.

[3] Pesando (1976) tests the RE hypothesis using cash flow forecasts of life insurance companies. He finds weak evidence in favor of the hypothesis.

follow two very different cohorts of individuals in the way they form retirement and longevity expectations in one case, and education expectations in the other.

It is important to clarify that if our tests reject the Rational Expectations (RE) hypothesis, two very different, but nonetheless connected, interpretations are possible. First, we could conclude that models of rational behavior expect too much of individuals, forcing us to abandon the "full rationality hypothesis" that agents behave "as if" they were making the large number of computations implied by the theory. One possible alternative to the fully rational model could be an adaptive learning model which introduces a form of bounded rationality, in which individuals use standard econometric and statistical techniques to make and adjust their forecasts of relevant variables, with RE emerging as an equilibrium of this trial and error process (see, for example, Pesaran 1987; Evans and Honkapohja 2001 for presentations of these type of models). Second, we could conclude that reality is much more complex than even most dynamic models assume, with individuals forming expectations (maybe rational ones) not over a fixed probability distribution of uncertain events, but over a family of distributions for each source of uncertainty. This involves individuals learning over time about the characteristics of these distributions and updating their priors as new information comes along.[4]

The first conclusion would be a set back for a large body of research in economics, since it would put into question an attractive and central tool. The second, would mean that we need more realistic economic models, which are likely to be more complex, but also more attentive to details of the process of expectations formation by individuals.

Finally, if our tests do not reject the rational expectations hypothesis, we can at least continue to rely on that rationality, and the strategies used to model it, as a good first approximation to behavior by individual decision makers. Furthermore, it would then be reasonable to use some of these variables in modeling complex economic situations, an objective that Haavelmo (1958) already emphasized, as quoted in Savage (1971).[5]

The conceptual model and the econometric specifications are presented in Sect. 2. Section 3 provides information about the data sets used in the empirical work. Section 4 discusses the identification of the econometric specifications, and reports our main findings. Section 5 concludes.

2 Conceptual and econometric framework

Benítez-Silva and Dwyer (2005), building on Bernheim (1990) model of expectation formation, develop a test of rational expectations using repeated observa-

[4] This suggests a model of expectations and learning which could be interpreted as building upon the work of Bewley (1986, 1987) and his interpretation of the original ideas of Knight (1921) about decision making under risk and uncertainty.

[5] "*If we could use explicitly* [...] *variables expressing what people think the effects of their actions are going to be, we would be able to establish relations that could be more accurate and have more explanatory power,* " Haavelmo (1958, p. 357).

tions of retirement expectations. We present their methodology here with some modifications, especially in the econometric specification that we estimate, so it can be applied not only to retirement expectations but also to longevity and educational attainment expectations.

2.1 A model and a test of rational expectations using micro data

Suppose an individual and a researcher are trying to predict a variable X, which the individual has either decided will be determined as a function of a sequence of random variables (for example, retirement and educational attainment) or believes is determined (for example, longevity) by such a sequence:

$$X = h(\omega_{1,}\omega_{2,} \ldots, \omega_T). \tag{1}$$

The sequence of vector-valued variables inside the parenthesis will be observed by the individual at time periods $t = 1, 2, \ldots, T$. Then the individual will either take action X after some or all the ω_t's have been observed, or the event being predicted will occur.

Let $\Omega_t = \{\omega_t\}_{t=1}^{t}$ be the information known at period t and let $\omega_t = (\omega_t^1, \omega_t^2)$, where all of ω_t is observed by the individual, but only ω_t^1 is observed by the econometrician. Let then $\Omega_t^1 = \{\omega_t^1\}_{t=1}^{t}$. Then we can define

$$X_t^e = E\left\langle X|\Omega_t\right\rangle, \tag{2}$$

where E is the expectations operator. This is the most commonly used representation of the RE hypothesis, which takes as the rational expectation of a variable its conditional mathematical expectation (Sargent and Wallace 1976).[6] This guarantees that errors in expectations will be uncorrelated with the set of variables known at time t.

Variables included in the vector representing the information set Ω come from models of individual behavior, and typically include socio-economic and demographic characteristics. Using the law of iterated expectations and assuming that the conditional distribution (not just its mean) of the new information is correctly forecasted by the agents, from (2), we get

$$E\left\langle X_{t+1}^e \middle| \Omega_t\right\rangle = E[E\langle X|\Omega_{t,}\omega_{t+1}\rangle|\Omega_t] = E\langle X|\Omega_t\rangle = X_{t,}^e \tag{3}$$

where ω_{t+1} represents information that comes available between periods t and $t+1$. Then from (3) we can write the evolution of expectations through time as

$$X_{t+1}^e \ = \ X_t^e \ + \ \eta_{t+1}, \tag{4}$$

[6] Schmalensee (1976) using experimental data emphasizes the importance of analyzing higher moments of the distribution of expectations. Due to data limitations we are unable to do so in our analysis.

where $\eta_{t+1} = X^e_{t+1} - E[X^e_{t+1}|\Omega_t]$, and therefore $\mathrm{E}(\eta_{t+1}|\Omega_t) = 0$. Notice that η_{t+1} is a function of the new information received since period t, ω_{t+1}. From this characterization of the evolution of expectations we can test the RE hypothesis with the following regression:

$$X^e_{t+1,i} = \alpha + \beta X^e_{t,i} + \gamma \Omega^1_{t,i} + \varepsilon_{t+1,i}, \tag{5}$$

where α is a constant, and γ is a vector of parameters that estimate the effect of information in period t on period's $t+1$ expectations. The RE hypothesis implies that $\alpha = \gamma = 0$, and $\beta = 1$. A weak RE test, in the terminology of Lovell (1986) and Bernheim (1990), assumes that γ is equal to a vector of zeros, and tests for $\alpha = 0$ and $\beta = 1$—effectively testing whether expectations follow a random walk. The strong RE test is less restrictive, and also tests for γ=0.

Notice, that a value of α and/or γ different from zero can be consistent with the rational expectations hypothesis in an analysis using a relatively short panel in the presence of macro shocks, common to all agents. The fact that the study of retirement and longevity expectations only uses short panels to average out these possible macro shocks for a given individual, likely works in the direction of over-rejecting the RE hypothesis regarding these coefficients, compared with a situation where we would have a very long panel that would allow to average these possible macro shocks over time.[7]

In deriving the empirical test from the conceptual framework we have assumed that individuals report the mathematical expectation (mean) of the distribution of retirement ages, surviving probabilities, and educational attainment in years. This assumption will be jointly tested with the Rational Expectation Hypothesis, but there is no clear methodology to clarify whether individuals report the mean, the median, or the mode of the distribution. Furthermore, it is reasonable to conjecture that maybe respondents are not reporting the mean (or the median) of the distribution of the variable of interest but the mode. [8]

[7] In the empirical applications using the HRS, we include a time trend in our specifications, and also performed sensitivity analysis by including unemployment rates over time. Given that in the HRS we are using micro survey data that spans only a ten-year period from 1992 to 2002, we cannot be certain that there is sufficient variation in the macroeconomic effects. However, the earlier part of the nineties was very different from the later part of the survey period, leading us to believe we do indeed have reasonable proxies of macroeconomic shocks. In any case, the findings reported in the paper do not change with the different characterization of these macroeconomic controls.

[8] From the actual wording of the questions relatively little can be inferred, since the questions are rather ambiguous and open to interpretation. In the first round of interviews there were two types of questions regarding retirement expectations, one asked: *When do you think you will retire?* Which could be answered giving an age, a date, or in years remaining. The other asked: *Are you currently planning to stop working altogether or work fewer hours at a particular date or age, to change the kind of work you do when you reach a particular age, have you not given it much thought, or what?* And we use the answer to the stop working altogether option. The only one consistently used across waves is the second way of asking. Strictly speaking this can be considered retirement plans, but are widely described as retirement expectations. In the case of longevity expectations the question is worded as follows: *What is the percent chance that you will live to be 75 or more?* For education expectations, the question is worded as follows: *As things now stand, what is the highest grade or year you think you will actually complete?*

For all purposes it is not testable whether the answers to these questions represent means of distributions, or the most likely outcomes. Davies and Lahiri (1999) analyze categorical responses to expectations questions, and state that if we believe agents are responding the mode, then having only quantitative information on the variable of interest can prevent us from performing a Rational Expectations test. However, the paper acknowledges the difficulty in disentangling what the answers to expectations actually are.

It is also reasonable to argue that reports of modes are likely to change less than reports of means, and are likely to be exposed to comparatively less measurement error problems. In our analysis of expectations there is quite a lot of change going on regarding the expectations reports over time, so this probably indicates that the assumption regarding reports of the means is not obviously wrong. For example, in the retirement expectations data, more than 50% of individuals change their retirement expectations report from wave to wave. However, the average change is rather small, around 0.4 years, but the standard deviation of this change is quite large, around 4.6 years. Both in the estimation sample and in the whole sample, of the 50% that changes their reports, a bit more than 60% change their reports upwards, which ends up resulting in the positive average change overall. Change is especially pervasive among those who report at some point that they will never retire, since almost two thirds of them end up reporting an actual expected retirement age. Even if we only restrict attention to those that actually reported a given age in two consecutive waves, the percentage changing is similar, and the average change of the same order of magnitude. The only difference is that in the latter case the standard deviation of the change is a bit smaller. Interestingly, among those that change their reports 55% change their expected retirement age by more than 2 years.

In the case of longevity expectations, where individuals report the probability of living to age 75 or more, the proportion of individuals who change their reports from wave to wave is even higher, almost 70% of them change. The changes are (almost exactly) evenly split between those that report higher and lower probabilities compared with the previous wave. The average percentage point change from wave to wave is between 1.4 and 2.2 (depending on whether we restrict attention to the estimation sample or the full sample), with a standard deviation of around 27 percentage points. Among those that change, 81% of the individuals change their reports by more than 10 percentage points, and around 50% change their reports by more than 20 percentage points. This case suggests, even more clearly than for the retirement model, that individuals report the mean of the distribution, since it seems hard to believe the reports of the mode would change so much.

Regarding educational attainment expectations, 41% of the sample changed their reports from year to year, with 56% of them changing them upwards. The average change is 0.11 years, but the standard deviation is 1.6 years. So even in this case, in which teenagers are asked only one year apart, there is considerable change in their reports.

2.2 Econometric specifications and estimation strategies

Estimating (5) is in principle straightforward, but the likely presence of measurement error in the dependent variable and its lag, along with a concern regarding endogeneity, combined with a potential sample selection bias concern (given that not all individuals answer the expectations questions) complicate the methodology.[9]

Measurement error

As with all survey data, measurement error in proxy variables is a concern. We are particularly interested in accounting for possibly noisy self-reports of the expectation variables, and reporting errors that may be correlated with measurement errors in other factors or omitted variables. We will be assuming that the measurement error that individuals incur is in no way correlated with the rationality of their expectations formation process but has more to do, for example, with the differences across individuals in the environment faced in each wave of the panel. For example, the month and year of the survey can have an effect on the amount of noise in the expectation variable; because it affects the degree of rounding in the measure of age and the variable of interest.[10] Then the interview environment would affect the report over time in a way that is not observed. This component of self-reports can bias the coefficient of interest in a significant way. In order to eliminate this noise, we want to capture the true component of the expectation and purge it of this source of bias. If measurement error was not a problem we would expect the β coefficient of the IV estimator to be very close to the one from the OLS specification, assuming validity of the instruments set.

Since people are reporting expectations over uncertain events, we expect some degree of reporting error that may be correlated with unobserved factors. In fact, Bernheim (1988) finds that retirement expectations are reported with noise, and this is also likely to be true of expected educational attainment since

[9] The possible presence of focal points in the expectations variables (retirement, longevity, and educational attainment expectations show considerable probability mass in particular values of the distribution) can give rise to non-normal regression errors, since the distribution of the dependent variable, and the main independent variable could be considered bimodal. In general the results of conditional moments estimation, for example OLS, are fairly robust to this problem, especially if the sample size is fairly large. The most important properties of the linear estimators (that they are the best linear unbiased estimators and consistent, and that the variance estimator is unbiased and consistent allowing us to use conventional tests), survive the non-normality of the errors. However, there can be a loss of efficiency. This loss of efficiency is in part ameliorated by the fact that we use a GMM estimator to estimate the IV and the Corrected IV specification. This estimator is consistent against unknown forms of heterokedasticity, which alleviates the consequences of the non-normality of the errors.

[10] Individuals responded to the retirement expectation question either reporting an expected retirement age, an expected year of retirement, or in years left to expected retirement. The last two ways of responding are likely to create considerable rounding errors, since they did not allow individuals to report a month or fractional answers.

even completed education is reported with error (Black et al. 2003), and also longevity expectations when answered as probabilities of surviving to a certain age.

Sample selection bias

As it often happens in survey data, there will be item non-response among our variables of interest. In the case of this potential selection problem we will be making the implicit assumption (and this is true in any econometric application that tries to solve the selection bias problem à la Heckman 1979, and wants to make a statement about the general population under analysis) that those that do not respond the question of interest would use the same process to analyze information if they were to actually answer the question as those that answer the question. In other words, we assume that those who do not respond to the expectations questions are not following a completely different model (maybe irrational) to decide their expectations. Rather they use the same model of behavior but for a number of observable and unobservable reasons they did not report our dependent variable, and we suspect that the inclusion in the sample is therefore non-random.

Econometric specification

We present a four equation, three step system estimation to correct for the likely measurement error problem using instrumental variables analysis, along with the potential sample selection bias concerns. This model extends to our particular problem the model presented by Wooldridge (2002, p. 567), which is a parametric version of the model presented (as an extension to their baseline case) in Sect. 2.4 of Das et al. (2003),[11] to consistently estimate the effect of previous expectation on current expectation, and from (5) we write

$$X^e_{t+1,i} = \alpha_1 + \beta X^e_{t,i} + \gamma_1 Z_{t,1i} + \varepsilon_{t+1,1i}, \tag{6}$$

$$X^e_{t,i} = \alpha_2 + \gamma_2 Z_{t,1i} + \lambda_1 Z_{t,2i} + \mu_1 Z_{t,3i} + \varepsilon_{t,2i}, \tag{7}$$

$$Y_{1i} = 1\big(\alpha_3 + \gamma_3 Z_{t,1i} + \lambda_2 Z_{t,2i} + \mu_2 Z_{t,3i} + \eta_1 Z_{t,4i} + \varepsilon_{3i} > 0\big)$$
$$\text{with } X^e_{t,i} \text{ observed when } Y_{1i} > 0, \tag{8}$$

$$Y_{2i} = 1\big(\alpha_4 + \gamma_4 Z_{t,1i} + \lambda_3 Z_{t,2i} + \mu_3 Z_{t,3i} + \eta_2 Z_{t,4i} + \varepsilon_{4i} > 0\big)$$
$$\text{with } X^e_{t,i} \text{ and } X^e_{t+1,i} \text{ observed when } Y_{2i} > 0 \tag{9}$$

[11] Even in the non-parametric setting, identification depends on the exclusion restrictions between the reduced form and the main equation(s). Given that the asymptotic theory for this particular non-parametric model has not been developed, inference is less straightforward. In addition, the non-parametric model does not identify the constant, the statistical significance of which is part of our RE test. The parametric version of the model that we implement is at the same time simple, and proves to be robust. It is flexible in terms of the correlation structure between the error terms of the equations, and no assumptions are made about the distribution of the error terms in the endogenous equation.

where we explicitly account for the fact that in the structural equation we restrict attention to individuals who report expectations in consecutive periods, but there are individuals for whom we observe the expectations in period t but not in period $t+1$, and in order to appropriately correct for the possible selection into Eq. (7), it is necessary to estimate a separate selection equation, since the propensity to being observed in period t should not be conditioned on observability in period $t+1$.

The econometric procedure first estimates the selection equations (8) and (9) using probit specifications, introducing as exclusion restrictions with respect to the structural equation two groups of variables, represented by Z_3 and Z_4, and then consistently estimates (6) by performing a modified 2SLS procedure, where the first stage, Eq. (7), includes as regressors the exogenous variables used in (8) with the exception of Z_4, the Inverse Mills' ratio from the probit equation (8), and additional instruments Z_2 which are restrictions with respect to the structural equation, the validity of which will be tested. The structural equation then includes the remaining exogenous variables and the Inverse Mills' ratio from the probit equation (9). Non-parametric identification of Eq. (6) requires only that there are at least two exclusion restrictions from Eqs. (7) and (9) to the main equation, and the non-parametric identification of equation (7) requires the existence of an element in Z_4. This procedure allows for arbitrary correlation between the disturbances in the system.[12]

Notice that this formulation makes explicit exclusion restrictions between the selection equation (8) and the first stage of the IV procedure. In general it is believed that imposing exclusion restrictions on reduced form equation is unnecessary. However, if we were not to impose this restriction the coefficient on the Inverse Mills ratio estimated in the first stage of the IV procedure would only be identified off the functional form assumption of the selection equation. Although technically correct this can be problematic. As discussed in Vella (1998, p. 135), certain variables which in our sample have a fairly small range (for example age), can lead to the apparent linearity of the inverse Mills' ratio, which can result in weak identification of the selection model, inflated second step standard errors, and what is even more troubling in our case, unreliable estimates of the coefficients of interest. Therefore, including some variable(s), Z_4 in the equations above, which affects the selection equation but does not affect the first stage of the 2SLS would be justified in order to avoid the complete reliance on the non-linearity resulting from the functional form assumptions of the selection equation, and deliver consistent estimates of the parameters of interest.

Clearly the trade off here is between reliance on nonlinearities resulting from functional form assumptions and debatable exclusion restrictions. We

[12] It is possible to estimate this system of equations by ignoring Eq. (8), and only concentrating on the possible selection of observing consecutive expectation values. The actual empirical results from that methodology are not substantially different from the ones we will discuss in Sect. 4, but we believe that not acknowledging the proper set up of the model we are tackling, would subtract from the generality of the methodology we are proposing.

have opted for estimating a model which is non-parametrically identified, and therefore robust to the convenient functional form assumption of the selection procedures.

In a related context, this strategy is actually advocated by Das et al. (2003, pp. 39 and 40) since in their set up they do not rely on functional form assumptions, and need the exclusion restrictions to identify a similar model. The main difference with the model presented in Sect. 2.4 of their paper is that we have to deal with a separate selection into the first stage of the IV procedure, given the nature of our analysis using reported expectations over time.

In the selection equation (9) we have decided to only include covariates as of time t, we have experimented with including $t+1$ variables, and also a battery of residuals of the regressions of $t+1$ variables on their lagged values, which are then also included in the main equation. Although some coefficients in the main equation changed as a result of these modifications, the results we report in the paper are robust to this characterization of the selection process.

In Sect. 4 we will discuss in some detail identification issues for each of the empirical applications, and we will also discuss the sensitivity analysis we have undertaken to check the robustness of our results to different characterizations of the instruments and exclusion restrictions in the estimation procedure.

3 The DATA: the HRS and the NLSY79

3.1 The HRS: retirement and longevity expectations

The combination of demographic, health, and socio-economic data as well as expectations data collected in the HRS make it a natural source for empirical work testing rational expectations. Here we analyze retirement and longevity expectations of older Americans using the first six waves of the HRS, a nationally representative longitudinal survey of 7,700 households headed by an individual aged 51–61 as of the first interviews in 1992–1993. The sixth round of data was collected in 2002.

3.1.1 Retirement expectations

In this analysis we include respondents that are working, full time or part time, in any wave, and non-employed (but searching for jobs) that report retirement plans. We only include respondents for waves when they are between the ages of 51 and 61 since this represents the planning horizon for retirement and avoids biases that might arise from responses to Social Security Retirement incentives that start at age 62. In each wave respondents are asked when they plan to fully or partially depart from the labor force and whether they have thought about retirement. Most of the people who have not thought about retirement do not report an expected age. Around 15% of respondents report that they will never retire. We have assigned an age of 77 for those who never retire, as a proxy for estimated longevity (based on the life tables).[13]

Column 1 of Table 1 presents summary statistics for the full HRS sample we use to study retirement expectations. Since we restrict attention to individuals that have not retired the average age is just above 56 years, most of them are employed by someone else, with around 10% reporting themselves as self-employed. Most of these individuals are in fairly good health, are married, have some kind of health insurance coverage, and over 40% of them either have a Bachelor's degree or a higher degree.

Columns 2 and 3 of the table break down the sample according to the selection criteria; whether or not individuals report thinking about retirement. Around 20% of the sample reported an expectation in two consecutive waves. Those who did not report a retirement expectation in two waves are less likely to be employed during the panel, and have lower income, and are less likely to have health insurance. They are also more likely to be female and less educated, their parents are less likely to have reached retirement age, and their parents had slightly less education.

3.1.2 Longevity expectations

As an additional test of our hypotheses we use the data on expected longevity collected in the HRS. Respondents are asked to report their expected probability of surviving to age 75 or more, and we use this as our dependent variable. Because the question is only asked for respondents who are not older than 65, our sample includes all respondents between the ages of 40 and 65 from the first six waves of the HRS.[14]

Column one of Table 2 tabulates summary statistics for the full HRS sample we use to study longevity expectations. The average age in our sample is just shy of 58 years, and on average they report a 66% probability of living up to age 75. 84% of the respondents are white, but only 35% are males. Almost 40% of the sample has either a bachelor or a professional degree, and they are on average in fairly good health.[15] From analyzing columns two and three of the table, we

[13] We have performed extensive sensitivity analysis of the treatment of those that report they plan to never retire. We have varied the age we assign, and have excluded them from the analysis (so that they are only included in the selection model). The main results regarding our hypotheses are highly robust across all specifications as discussed in Sect. 4.

[14] Hurd and McGarry (1995), Hill et al. (2005), and Benítez-Silva and Ni (2006) analyze these subjective survival probabilities in the Health and Retirement Study.

[15] Regarding health variables, the self-rated health is a categorical variable which takes values from 1 to 5, where 1 represents poor health, 2 fair health, 3 good health, 4 very good health, and 5 excellent health. We also use an index for chronic disease, which incorporates information on seven diseases; namely, high blood pressure, diabetes, cancer, lung disease, heart disease, stroke, and arthritis. The chronic disease index is 1 if the individual has all the diseases, and 0 if he has none of them. Notice that each chronic disease contributes 1/7 to the index. Similarly, we have generated an index for ADLs and IADLs, which includes information on whether the individual has problems performing 23 daily activities. This measure takes the value 1 if the individual has difficulty in doing all these 23 activities, and 0 if he has no difficulty performing any of these 23, again each ADL or IADL contributes 1/23 to the index.

Table 1 Summary statistics: retirement expectations in the HRS

Variables	Full sample $N = 18{,}322$	Thought about retirement in consecutive waves $N = 3{,}061$	Did not think about retirement in consecutive waves $N = 15{,}261$
Retirement plans and outcomes			
Expected retirement age	63.051(5.248)	62.693(4.436)	–
Employed	0.596(0.491)	0.913(0.282)	0.532(0.499)
Self employed	0.102(0.302)	0.087(0.281)	0.105(0.306)
Economic factors			
Net worth (in $10,000)	3.310(11.671)	2.987(11.406)	3.374(11.723)
Respondent' income (in $10,000)	21.564(28.167)	33.006(29.582)	19.269(27.304)
Financially knowledgeable	0.623(0.485)	0.672(0.469)	0.613(0.487)
Health insurance			
No health insurance	0.177(0.382)	0.115(0.319)	0.189(0.392)
Private health insurance	0.114(0.317)	0.089(0.284)	0.119(0.323)
Health factors			
Health limitation	0.180(0.385)	0.084(0.277)	0.200(0.400)
Good–very good–excellent health	0.836(0.371)	0.911(0.285)	0.820(0.384)
High blood pressure	0.386(0.487)	0.357(0.479)	0.392(0.488)
Diabetes	0.099(0.298)	0.077(0.267)	0.103(0.304)
Cancer	0.065(0.247)	0.059(0.235)	0.066(0.249)
Stroke	0.024(0.153)	0.018(0.134)	0.025(0.157)
Heart problems	0.090(0.287)	0.079(0.270)	0.093(0.290)
Arthritis	0.444(0.497)	0.398(0.490)	0.454(0.498)
Doctor visits	6.726(12.34)	5.850(8.806)	6.902(12.934)
Difficulty walking multiple blocks	0.156(0.363)	0.100(0.300)	0.167(0.373)
Difficulty climbing stairs	0.361(0.480)	0.295(0.456)	0.374(0.484)
Drink	0.576(0.494)	0.645(0.479)	0.562(0.496)
Smoke	0.230(0.421)	0.190(0.393)	0.238(0.426)
Probability of living up to age 85	0.452(0.312)	0.438(0.297)	0.455(0.315)
Demographic factors			
Age	56.637(3.067)	56.543(2.925)	56.656(3.095)
White	0.854(0.353)	0.855(0.352)	0.855(0.353)
Male	0.322(0.467)	0.431(0.495)	0.300(0.458)
Bachelor's degree	0.311(0.463)	0.344().475)	0.305(0.460)
Professional degree	0.119(0.324)	0.171(0.377)	0.109(0.311)
Married	0.752(0.432)	0.775(0.418)	0.747(0.435)
Father's education	9.462(3.794)	9.692(3.649)	9.416(3.821)
Mother's education	9.755(3.421)	10.038(3.236)	9.699(3.455)
Father lived up to age 85	0.125(0.330)	0.126(0.332)	0.124(0.330)
Mother lived up to age 85	0.159(0.366)	0.147(0.354)	0.161(0.368)
Father reached retirement age	0.723(0.447)	0.736(0.441)	0.721(0.449)
Mother reached retirement age	0.835(0.371)	0.837(0.369)	0.834(0.372)

Table 2 Summary statistics: longevity expectations in the HRS

Variables	Full sample $N = 31,279$	Responded to longevity expectations questions $N = 23{,}230$	Did not respond to longevity expectations $N = 8{,}049$
Survival probability			
Probability of living up to age 75	0.664(0.280)	0.664(0.280)	–
Probability of living up to age 85	0.452(0.315)	0.454(0.313)	0.445(0.323)
Economic factors			
Net worth (in $10,000)	3.249(12.209)	3.189(11.231)	3.421(14.670)
Respondent' income (in $10,000)	19.884(27.393)	20.199(27.387)	18.975(27.394)
Financially knowledgeable	0.597(0.491)	0.602(0.489)	0.581(0.493)
Health Insurance			
No health insurance	0.176(0.381)	0.174(0.379)	0.183(0.387)
Health factors			
Self-reported health	3.417(1.133)	3.508(1.104)	3.154(1.172)
Self-reported health change	0.200(0.639)	−0.197(0.647)	−0.211(0.615)
ADL index	0.151(0.165)	0.149(0.158)	0.159(0.184)
Chronic disease index	0.185(0.163)	0.175(0.156)	0.215(0.177)
Doctor visits in the last year	7.627(14.560)	7.278(13.593)	8.632(17.006)
Hospital stays in the last year	0.289(1.391)	0.245(1.239)	0.415(1.750)
Demographic factors			
Age	57.651(4.864)	56.805(4.573)	60.092(4.853)
White	0.840(0.367)	0.859(0.348)	0.785(0.411)
Male	0.351(0.477)	0.306(0.461)	0.483(0.500)
Bachelor's degree	0.293(0.455)	0.306(0.461)	0.255(0.436)
Professional degree	0.102(0.302)	0.110(0.313)	0.078(0.268)
Married	0.791(0.406)	0.792(0.406)	0.790(0.407)
Children living close	0.532(0.499)	0.531(0.499)	0.535(0.499)
Num. of grand children	3.921(4.814)	3.611(4.512)	4.815(5.499)
Num. of siblings	2.952(2.437)	2.904(2.397)	3.091(2.544)
Newly father's death	0.031(0.174)	0.035(0.184)	0.020(0.141)
Newly mother's death	0.046(0.210)	0.048(0.214)	0.041(0.197)
Father's education	9.249(3.856)	9.460(3.780)	8.623(4.006)
Mother's education	9.495(3.515)	9.709(3.410)	8.877(3.735)

can observe that those that did not answer the expectations questions in two consecutive waves are less likely to have health insurance, are 4 years older on average, and are less likely to be white and more likely to be male. Non-respondents have more grandchildren and they are less likely to have experienced the death of a parent in the two years prior to the interview.

3.2 Educational attainment expectations

To test the RE hypothesis on educational attainment expectations of the youth we use the NSLY79, a nationally representative longitudinal survey that follows individuals over the period 1979–2000, who were 14–21 years of age as of

Table 3 Summary statistics NLSY79

Variables	Full sample $N = 2{,}398$	Answered expectations $N = 2{,}319$	Did not answer $N = 79$
Education plans and outcomes			
Highest grade expected to complete	13.692(2.245)	13.692(2.245)	–
Highest grade completed	9.888(0.878)	9.918(0.856)	9.013(1.044)
Economics factors			
Avg. family income (1981 in \$1,000)	18.324(15.877)	18.420(15.959)	15.491(13.034)
Demographic factors			
Male	0.521(0.500)	0.522(0.500)	0.468(0.502)
Black	0.265(0.441)	0.268(0.443)	0.190(0.395)
Hispanic	0.179(0.384)	0.177(0.382)	0.228(0.422)
Number of siblings	3.605(2.518)	3.611(2.521)	3.418(2.442)
Siblings in school	2.125(1.511)	2.134(1.516)	1.886(1.32)
Number of older siblings	2.194(2.29)	2.198(2.292)	2.0886(2.242)
Years of labor market experience	0.492(0.678)	0.476(0.680)	0.342(0.597)
Mother's education	10.865(2.960)	10.886(2.937)	10.266(3.533)
Father's education	10.837(3.642)	10.848(3.635)	10.494(3.846)
Catholic	0.339(0.473)	0.341(0.474)	0.291(0.457)
Northeastern residence	0.188(0.391)	0.187(0.390)	0.203(0.404)
North-central residence	0.247(0.431)	0.252(0.434)	0.089(0.286)
Southern residence	0.362(0.481)	0.387(0.483)	0.114(0.320)
Rural residence	0.231(0.421)	0.236(0.425)	0.076(0.267)
Local unemployment rate (metropolitan area, or state if M.A. not available)	3.248(0.965)	3.258(0.967)	2.962(0.854)

January 1, 1979. Interviews were conducted on an annual basis through 1994, after which they adopted a biennial interview schedule. In the 1979, 1981, and 1982 surveys, each respondent was asked what the highest educational grade level they expected to complete. This analysis makes use of the responses in the 1981 and 1982 waves. The sample is selected by excluding respondents of ages greater than 15 as of January 1, 1979 (to avoid individuals that have completed their schooling), military entrants, and respondents never observed to enroll in high school. The resulting sample size includes 2,398 respondents.

Table 3 presents summary statistics for the sample of 2,398 respondents just described. On average individuals expect to complete a bit less than 14 years of education, which translates in almost two years of college, their parents on average completed almost 11 years of schooling, they have some labor market experience, around a fourth of them are black, and 18% are Hispanic. They have an average of 3.6 siblings and on average 2.1 of them are in school and are older than the respondent. The table also shows that only around 3% of the sample did not answer the question on expected educational attainment. This small group comes from slightly poorer families, are younger, more likely to be females, their parents completed less years of education, and are more likely to be white. Additionally, they have fewer siblings in school, and less of them are older than the respondent. Contrary to the case of the HRS (especially for retirement expectations), selection plays a minor role in the NLSY79 sample due to the fact that most individuals did answer the main question of interest.

4 Empirical results

4.1 The retirement expectations model

Identification of the models we are going to estimate to account for measurement error require some exclusion restrictions which must be correlated with the expectation as of time t but not with the error term or any new information relevant to the $t+1$ expectation. Our instruments include time t subjective survival to age 85 probabilities and an indicator of smoking behavior as instruments correlated with the rate of time preference. We also use whether the respondent is financially knowledgeable, trying to capture the likelihood of planning more accurately or after gathering more information. Additionally, we have also included a number of time invariant measures as exclusion restrictions, since they are natural candidates to affect the expectations at time t, but not the expectations at time $t+1$, once we account for the former. These variables include an indicator for being white, an indicator for being male, and indicators of whether the individual has a bachelor's degree or a professional degree.

Finally, we also use age as an exclusion restriction. This restriction requires some attention. We consider age to be a good proxy for the information set which can affect how individuals form expectations, since as we age we learn more about uncertain relevant factors regarding retirement so that older respondents might plan more accurately. It is then reasonable to include it in the first stage regression of the lagged dependent variable as an exclusion restriction (and consequently in the selection equation, following the estimation strategy outlined in the last section) given that the natural and predictable evolution of age across waves for all respondents makes it unnecessary to account for it in the structural equation.

Given the over-identification of the IV models we will be estimating, we will test the validity of all these restrictions.[16]

In order to estimate the selection corrected, and the corrected IV models we need additional exclusion restrictions in the selection equation (9) with respect

[16] Given the large number of exclusion restrictions, it is natural to inquire about the need for such a large set, given that we only have one endogenous variable. We have performed an extensive sensitivity analysis of the instrument set and it is worth emphasizing that age is the key exclusion restriction in our estimations of retirement expectations. Even in a just identified IV specification with age as the only exclusion restriction, the coefficient of the lagged expectation variable moves very close to unity, but the standard error is twice as large as in the preferred specification. The rest of the exclusion restrictions by themselves only move the coefficient to around 0.7, even though they pass the robustness and exogeneity tests, but help improve the efficiency of the estimator considerably when used along with age.

to the structural equation (Z_3 and Z_4 in the formulations presented in Sect. 2). These include indicators for whether the father and the mother of the respondent reached retirement age, the father's and mother's educational attainment, and whether or not each parent lived to age 85. The latter capture whether the parents lived long during their retirement years. In the full corrected IV estimation we also need some exclusion restriction in the selection equation (8) with respect to the first stage of the 2SLS (Z_4 in the formulation of equation (8)) in order to avoid relying only on the probit assumption regarding the propensity to answer the retirement expectations questions as of time t. We use whether the father and mother of the respondent reached retirement age. Even though it could be argued that this could have an effect on the reported expectations, robustness checks have shown that this relationship is quite weak, especially once we control for whether the parents reached age 85, since parents who reached age 85 were almost surely retired during a considerable period of their lives. Identification of these three step model is of course contingent on whether the restrictions are exogenous and valid, and we will test them appropriately.

Table 4 presents the weak and strong RE tests for the expected retirement model using four different specifications. [17] In all cases the estimators control for clustering (Deaton 1997), given that we often have more than one observation per person over time. First, we perform an F-test based on the null hypothesis that β=1 in equation (4), to test the weak RE hypothesis. [18] Once we control for measurement error, and selection, we obtain a coefficients for β of 0.908 for the weaker test, and given the precision of the estimate we can reject that is equal to unity at the 5% significance level but not at the 10%, and therefore that retirement expectations follow a random walk. Given that the selection term is estimated to be significant, the corrected-IV is our preferred specification. This relatively borderline negative result is in large part due to the fact that this weak test can be quite problematic, since is likely affected by omitted variable biases, in particular by the macro indicators that turn out to be significant in the strong test, and the assumption that all the time t variables do not affect the time $t+1$ expectation is therefore rather arbitrary and econometrically suspect. If we include the wave indicators as the only additional regressors in this specification then the β parameter for the weak test is equal to 0.9697 with a standard error of 0.05, clearly failing to reject the RE hypothesis in its weak form.

For the strong RE test, which should be considered as the more general and robust, we estimate the model of Eqs. (6)–(9) using the corrected IV procedure. Also we estimate Eq. (6) by pooled OLS, Eqs. (6) and (9) by the traditional

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[17] In all the tables that follow the level of statistical significance of the coefficients is represented, as is customary, by asterisks indicating significance or rejection of a null hypothesis of the coefficient being equal to zero.

[18] For the pooled OLS estimation this test is effectively a unit root test, and as such, following the literature on testing unit roots in panel data surveyed by Bond et al. (2002), we perform a correction to obtain the appropriate critical value. However, this matters very little since the unit root hypothesis is soundly rejected.

Table 4 Tests of rational expectations: retirement expectations in the HRS

Variables	Pooled-OLS	Selection	IV	Corrected IV
Weak RE test ($H_0 : \beta = 1$):	*Reject*	*Reject*	*Cannot reject*	*Reject*
Constant	37.708(1.355)**	37.860(1.740)**	−5.750(3.453)	7.648(2.854)**
Expected retirement age$_t$	0.405(0.022)**	0.417(0.026)**	1.096(0.055)**	0.908(0.046)**
Inverse Mills' ratio	–	−0.648(0.269)**	–	−1.048(0.290)**
Test of over-Id restrictions	–	–	Reject. P-v=.03	Reject. P-v=.00
Test of weak instruments	–	–	Reject. P-v=.00	Reject. P-v=.00
Strong RE test ($H_o : \beta = 1$):	*Reject*	*Reject*	*Cannot reject*	*Cannot reject*
Constant	38.333(1.609)**	38.145(1.980)**	−4.833(3.908)	0.512(3.705)
Expected retirement age$_t$	0.410(0.025)**	0.404(0.026)**	1.082(0.061)**	1.045(0.060)**
Inverse Mills' ratio	–	0.294(0.630)	–	−1.755(0.754)**
Economic factors at time t				
Net worth (in $10,000)	0.003(0.005)	−0.006(0.006)	−0.010(0.007)	−0.009(0.007)
Respondent income (in $10,000)	0.0003(0.002)	0.002(0.003)	0.001(0.003)	−0.008(0.004)*
Self-employed	0.621(0.293)**	0.476(0.299)	−0.151(0.320)	−0.084(0.322)
No health insurance	0.158(0.249)	0.091(0.313)	−0.052(0.303)	0.372(0.372)
Private health insurance	0.403(0.245)	0.456(0.272)	0.016(0.318)	0.367(0.349)
Health factors at time t				
Health limitation	−0.065(0.249)	−0.320(0.313)	−0.593(0.332)*	−0.184(0.379)
Good–very good–excellenthealth	−0.144(0.235)	−0.158(0.279)	−0.173(0.292)	−0.525(0.329)
High blood pressure	0.003(0.134)	0.027(0.144)	−0.157(0.157)	−0.066(0.163)
Diabetes problems	−0.073(0.232)	0.004(0.262)	−0.303(0.274)	−0.448(0.295)
Cancer	−0.036(0.276)	0.040(0.289)	−0.245(0.371)	−0.153(0.380)
Stroke	−0.105(0.415)	−0.142(0.383)	0.284(0.413)	0.634(0.384)
Heart problems	0.072(0.234)	0.259(0.269)	−0.037(0.323)	0.217(0.313)
Arthritis	0.027(0.139)	−0.068(0.150)	0.060(0.361)	0.027(0.169)
Doctor visits	−0.005(0.006)	−0.003(0.007)	−0.002(0.008)	−0.002(0.008)
Diff. walking multiple blocks	−0.131(0.229)	0.169(0.240)	0.315(0.288)	0.338(0.297)
Difficulty climbing stairs	−0.236(0.146)	−0.242(0.157)	−0.050(0.188)	−0.129(0.196)
Drink	0.017(0.136)	0.119(0.151)	0.367(0.169)**	0.327(0.179)
Demographic factors at time t				
Married	−0.488(0.160)**	−0.319(0.169)*	0.255(0.192)	0.198(0.196)
Wave 1–2 indicator	−1.839(0.176)**	−1.889(0.209)**	−1.144(0.250)**	−0.923(0.280)**
Wave 2–3 indicator	−0.232(0.182)**	−0.283(0.195)	0.904(0.226)**	0.673(0.223)**
Wave 3–4 indicator	−0.451(0.183)**	−0.418(0.201)**	−0.373(0.278)	−0.375(0.249)
Adj. R^2	0.2147	0.2071	–	–
Test of sig. of macro covariates	Reject. P-v=.00	Reject. P-v=.00	Reject. P-v=.00	Reject. P-v=.00
Test of sig. of indiv. covariates	Cannot Rej. P-v=.27	Cannot Rej. P-v=.41	Cannot Rej. P-v=.41	Cannot Rej. P-v=.25
Test of over-Id restrictions	–	–	Cannot Rej. P-v=.34	Cannot Rej. P-v=.26
Test of weak instruments	–	–	Reject. P-v=.00	Reject. P-v=.00
Number of observations	3,583	3,061	3,401	3,061

selection correction à la Heckman (1979), and Eqs. (6) and (7) by IV. In the corrected IV procedure the β parameter is estimated to be equal to 1.045 with a fairly small standard error, and the selection term is significant, again indicating that this is our preferred specification.[19] Notice, however, that the selection bias

[19] We can observe here a common drawback of IV estimation procedures; the increase in standard errors of the estimates, which in the strong RE test more than double those of the OLS and selection corrected models. However, notice that the coefficient of interest also more than doubles, therefore the level of significance remains unchanged.

is not too large since the uncorrected-IV estimates of the β parameter is 1.08 with a very similar standard error.[20]

The reported results for the uncorrected IV and corrected IV procedures are the product of robustly estimating the system of equations via GMM, which provides robustness against unknown forms of heterokedasticity.[21] These results clearly indicate that we cannot reject the RE hypothesis regarding retirement expectations.[22]

Comparing the different specifications, it is worth emphasizing that the coefficient of interest significantly changes, and approximates the value predicted by the theory, after controlling for measurement error. Nothing constrains the β coefficient of the IV specification to move towards 1, and the fact that it does, can be interpreted as support of our estimation strategy to uncover the structural parameters of the models of rational expectations formation.[23]

It is natural to ask ourselves the reason behind the difference in point estimates we obtain for our main parameter of interest, which allows us to test the RE hypothesis, when we go from the OLS results to the IV estimators. Notice that the OLS estimates, strongly reject the RE hypothesis, with a β coefficient only slightly above 0.4. If endogeneity is a problem, with its source either in measurement error or a classical problem of omitted variable biases, it is possible to justify this negative result as resulting from the violation of the OLS assumption about the lack of correlation between the variable of interest and the errors in Eq. (6). The measurement error problem, as explained in Sect. 2, seems to us as a more plausible explanation, especially because a comparison of the variance of the residuals of the first stage of the IV with the variance of the predicted value of the endogenous variable suggests a significant measurement

[20] We have performed extensive sensitivity analysis of the treatment of those that report they plan to never retire. First, our results change very little if instead of using age 77 as the default for this response we use a lower or higher number. And even if we eliminate completely this group and control for it in the selection correction procedure, the results do not change in any significant way. In general, if the default value is a higher age the standard errors of the parameters of interest go up (0.12 instead of 0.06, with a parameter estimate for the Strong RE test of 1.017, when the *never* age is set to 90), and the parameter estimate is a bit higher when the default value is a bit lower (1.07859, with a standard error of 0.0579 when the never age is set to 70). Also, if we assimilate a never response to a missing then the coefficient on the lagged expectation is a bit higher (goes up to 1.088) than the one reported in our preferred specification, but still not different from 1 given its precision.

[21] In the implementation of this procedure we have followed the practical suggestions in Baum et al. (2003).

[22] The findings are robust across many specifications and empirical techniques including panel data methods. Much of the individual component is explained by time-invariant variables (there is no remaining individual component in a random effects model if we exclude these covariates).

[23] Notice that in columns three and four of Table 4 (and also Tables 5 and 6), we do not report the adjusted R^2 measure of fit as is common practice. These types of measures do not have independent significance in structural IV estimation. Our objective is to estimate population parameters, which we consider invariant to the particular identification method (instrumental variables), which leads to a calculation of the adjusted coefficient of determination which can easily result in negative values of this summary measure. See Ruud (2000, pp. 515–516) for a discussion.

Table 5 Tests of rational expectations: longevity expectations in the HRS

Variables	Pooled-OLS	Selection	IV	Corrected IV
Weak RE test (H_o: β=1) :	*Reject*	*Reject*	*Reject*	*Cannot reject*
Constant	0.296(0.005)**	0.321(0.006)**	0.037(0.008)**	0.018(0.010)
Expected survival probability$_t$	0.544(0.006)**	0.542(0.008)**	0.941(0.012)**	0.972(0.014)**
Inverse Mills' ratio	–	−0.049(0.007)**	–	0.004(0.007)
Test of over-Id restrictions	–	–	Reject. P-v=.00	Reject. P-v=.00
Test of weak instruments	–	–	Reject. P-v=.00	Reject. P-v=.00
Strong RE test (H_o: β=1):	*Reject*	*Reject*	*Cannot reject*	*Cannot reject*
Constant	0.361(0.008)**	0.370(0.010)**	0.018(0.018)	−0.001(0.019)
Expected survival probability$_t$	0.503(0.007)**	0.504(0.008)**	0.964(0.024)**	0.986(0.024)**
Inverse Mills' ratio	–	−0.028(0.010)**	–	0.003(0.009)
Economic factors at time t				
Net worth (in $10,000)	0.0004(0.0001)**	0.0005(0.0001)**	0.0002(0.0014)	0.00027(0.00015)
Respondent income (in $10,000)	0.00003(0.00005)	0.00004(0.00005)	0.00003(0.000005)	0.00004(0.00005)
No health insurance	−0.003(0.005)	0.0001(0.005)	0.006(0.005)	0.006(0.005)
Health factors at time t				
Self-reported Health Change	−0.004(0.003)	−0.006(0.003)**	−0.016(0.003)**	−0.018(0.003)**
ADL index	−0.154(0.013)**	−0.144(0.014)**	−0.002(0.015)	0.008(0.015)
Chronic disease	−0.115(0.012)**	−0.103(0.012)**	−0.015(0.012)	−0.005(0.012)
Doctor visits	0.00004(0.0001)	−0.00002(0.0001)	0.00010(0.0001)	0.0001(0.0001)
Hospital stays	−0.003(0.001)**	−0.0027(0.0014)*	0.0004(0.001)	0.001(0.001)
Demographic factors at time t				
Bachelor's degree	0.027(0.003)**	0.024(0.004)**	0.004(0.003)	0.003(0.003)
Professional degree	0.034(0.005)**	0.032(0.005)**	0.013(0.004)**	0.013(0.004)**
Married	0.003(0.004)	0.003(0.004)	0.005(0.004)	0.004(0.004)
Children living close	−0.003(0.003)	−0.004(0.003)	0.003(0.003)	0.003(0.003)
Number of grand children	0.0002(0.0004)	0.00075(0.0004)*	−0.0002(0.0004)	−0.0002(0.0004)
Number of siblings	−0.0005(0.0007)	−0.0003(0.0007)	−0.0007(0.0006)	−0.0005(0.006)
Wave 1–2 indicator	−0.009(0.004)**	−0.018(0.005)**	−0.018(0.005)**	−0.019(0.005)**
Wave 2–3 indicator	−0.003(0.004)	−0.005(0.005)	0.002(0.005)	0.005(0.005)
Wave 3–4 indicator	−0.012(0.004)**	−0.011(0.004)**	−0.010(0.005)**	−0.010(0.005)*
Adj. R^2	0.314	0.3126	–	–
Test of sig. of macro covariates	Reject. P-v=.00	Reject. P-v=.00	Reject. P-v=.00	Reject. P-v=.00
Test of sig. of indiv. covariates	Cannot Rej. P-v=.31	Reject. P-v=.00	Reject. P-v=.00	Reject. P-v=.00
Test of over-Id restrictions	–	–	Cannot Rej. P-v=.16	Cannot Rej. P-v=.16
Test of weak instruments	–	–	Reject. P-v=.00	Reject. P-v=.00
Number of observations	25,493	23,230	24,911	23,230

error problem that could be biasing the coefficient of interest by as much as 50%, since those two variances are of similar magnitude.[24]

[24] This suggests a noise to signal ratio of around 1, which as discussed in Arellano (2003) is not an uncommon situation in micro data, especially in a survey in the field every two years. The estimated bias is of a similar magnitude for the longevity expectations, and slightly smaller for education expectations.

Table 6 Tests of rational expectations: educational attainment expectations in the NSLY79

Variables	Pooled-OLS	Selection	IV	Corrected IV
Weak RE test (H_o: β=1):	*Reject*	*Reject*	*Cannot reject*	*Cannot reject*
Constant	3.682(0.199)**	4.066(0.207)**	0.358(0.527)	0.415(0.410)
Expected education level$_t$	0.739(0.014)**	0.721(0.015)**	0.982(0.038)**	0.982(0.029)**
Inverse Mills' ratio	–	−2.385(0.398)**	–	−1.004(0.517)**
Test of over-Id restrictions	–	–	Cannot Rej. P-v=.82	Cannot Rej. P-v=.74
Test of weak instruments	–	–	Reject. P-v=.00	Reject. P-v=.00
Strong RE test (H_o: β=1):	*Reject*	*Reject*	*Cannot reject*	*Cannot reject*
Constant	3.132(1.118)**	3.364(1.207)**	−0.884(1.527)	−0.982(1.689)
Expected education level$_t$	0.662(0.016)**	0.662(0.016)**	0.991(0.067)**	1.003(0.066)**
Inverse Mills' ratio	–	−0.367(0.718)	–	0.015(0.888)
Economic factors at time t				
Avg. family income ($1,000)	0.007(0.002)**	0.007(0.002)	0.002(0.002)	0.001(0.002)
Demographic factors at time t				
Age	−0.166(0.071)**	−0.163(0.071)**	0.001(0.088)	0.003(0.088)
Male	0.005(0.064)	−0.001(0.064)	0.001(0.070)	−0.003(0.072)
Black	0.283(0.085)**	0.273(0.088)**	0.167(0.095)	0.163(0.095)
Hispanic	0.055(0.105)	0.048(0.107)	0.095(0.119)	0.102(0.120)
Number of siblings	−0.021(0.013)	−0.022(0.014)	0.009(0.017)	0.011(0.017)
Highest grade completed	0.407(0.044)**	0.387(0.059)**	0.070(0.086)	0.057(0.092)
Labor market experience	−0.003(0.049)	−0.008(0.050)	−0.003(0.054)	−0.003(0.054)
Northeastern residence	0.154(0.106)	0.128(0.118)	0.144(0.122)	0.149(0.133)
North-central residence	0.099(0.102)	0.057(0.131)	0.068(0.112)	0.076(0.142)
Southern residence	0.147(0.100)	0.097(0.139)	0.120(0.116)	0.134(0.155)
Rural residence	−0.041(0.082)	−0.053(0.086)	0.125(0.093)	0.130(0.098)
Local unemployment rate	0.023(0.035)	0.018(0.037)	0.058(0.038)	0.060(0.040)
Catholic	0.065(0.084)	0.051(0.088)	−0.043(0.089)	−0.048(0.091)
Adj. R^2	0.556	0.5559	–	–
Test of joint Sig. of Covariates	Reject. P-v=.00	Reject. P-v=.00	Cannot Rej. P-v=.41	Cannot Rej. P-v=.69
Test of over-Id Restrictions	–	–	Cannot Rej. P-v=.50	Cannot Rej. P-v=.56
Test of weak Instruments	–	–	Reject. P-v=.00	Reject. P-v=.00
Number of observations	2,319	2,319	2,319	2,319

Given that measurement error is a valid concern regarding our variables of interest, it all comes down to whether we trust the exclusion restrictions we have made regarding the fact that some variables affect retirement expectations as of time t but are not correlated with the disturbances in Eq. (6). The best we can do to convince the reader of the validity of the instruments is to perform the tests suggested in the literature, so we follow the suggestions in Bound et al. (1995), Staiger and Stock (1997), Stock et al. (2002), and Baum et al. (2003), and find that we have robust instruments, with very large F statistics in the first stage of the IV procedure, considerably larger than the minimum value (around 10) suggested in Staiger and Stock (1997), and also discussed in Stock et al. (2002), as a good rule of thumb to check whether we are in the presence of weak instruments (see Tables 8 and 9 in the Appendix).

Also, the model is overidentified, which allows us to test whether our instruments are exogenous with respect to the error term in the structural equation. A rejection of this test would suggest that the instruments are either not truly exogenous or they should be included in the main regression of interest. In all cases we cannot reject the overidentifying restrictions.

It is also important, given the impact on our conclusions for the retirement model, to clarify the reason why we believe that the disturbances in Eq. (9), the main selection equation, could be correlated with the disturbances in (6). Among the many possible explanations, the one that seems more plausible to us is that those more likely to have thought about retirement seem to have been exposed to some events or information, which we fail to capture with the set of exogenous variables that we use to estimate (9). This makes them more likely to change their expectations. This suggests that among those that report not thinking about retirement there are many that have not been exposed to a situation where they have been forced to think about it beyond minimum plans. If this is the reason for the correlation, estimating an uncorrected model will lead to an upward bias in β, since we would be left with a sample more likely to report changes in their plans, and a majority of the adjustments are upwards as discussed in Sect. 2. It is also reasonable to expect biases in the other coefficients, including the constant. The key is that the correlation is still present after controlling for a large set of observed characteristics.

Notice that the RE hypothesis also predicts that in the strong test the information available at time t should not be significant after controlling for time t expectations when estimating (6). In this case we find that after controlling for sample selection and measurement error most of these factors are no longer significant, but it is important to separate the individual level variables from the proxies for the macro shocks, represented by the wave indicators. The joint hypotheses that all the individual level coefficients are equal to zero cannot be rejected at any traditional level of significance, and the same is true of the estimates of the constant, validating the other predictions of the RE hypothesis regarding retirement expectations.[25]

Our results show that the wave indicators are jointly significant, suggesting that individuals are not perfectly accounting for some macroeconomic effects, and the relatively short panel we have available cannot average out those effects over time.

Finally, Tables 7, 9 and 9, in the Appendix, provide the results of the estimation of the main selection equation (9), and the first stage estimation of the traditional IV and the corrected IV estimators for the weak and strong RE test.

[25] It is true, however, that this is trivially the case if individuals never adjust their expectations, which might be consistent with modal responses rather than expected outcomes. But as discussed in Sect. 2 plenty of adjustment goes on in the data.

4.2 The longevity expectations model

To identify this model we can follow exactly the same methodology as in the retirement expectations model, and therefore need instruments for the lagged dependent variable to account for the measurement error problem, and some exclusion restrictions to identify the selection correction equations. The exclusion restrictions of the first stage of the IV procedure with respect to the structural equation include age, self-reported health at time t, and indicators for being male and white. These exclusions strike us as quite reasonable since their effects on the $t + 1$ expectations are likely to work only through the time t expectations.[26]

We then use indicators of the recent death of the father or mother, and the mother's educational attainment as exclusion restrictions from the selection equation to the structural equation (Z_3 in the notation of Eqs. (6)–(9)). Notice, however, that the estimation procedure allows these variables to affect the time t longevity expectations. Additionally, the indicator of whether the respondent is financially knowledgeable is another exclusion restriction in the selection model of Eq. (9), since we believe this is correlated with one's propensity to respond to expectation data. This financial knowledge indicator is also an exclusion restriction of the selection model of Eq. (8) with respect to the first stage of the IV procedure (Z_4 in the notation of the econometric model).

Table 5 presents the tests for the expected longevity model, using the HRS sample. For the strong test the main prediction of the RE hypothesis, that the coefficient on the lagged expectation variable is equal to unity, cannot be rejected once we account for measurement error. In this case there is no evidence of selection bias, and the uncorrected IV specification is the preferred one. For the strong test the main parameter of interest is estimated to be equal to 0.964, with fairly small standard errors. The exclusion restrictions are tested as very robust and highly correlated with the longevity expectation as of time t, and they also pass the test of over-identifying restrictions, suggesting that we cannot reject they are valid instruments. For the weak RE test the β parameter is estimated to be equal to 0.941, and is estimated with a lot of precision, and in this case we can reject the RE hypothesis, likely a result of omitted variable biases since some of the coefficients of the exogenous variables are actually significant in the strong test, including the macro indicators.

One difference with the model of retirement expectations is that the prediction of the theory regarding the lack of joint significance of the information available at time t is rejected not only for the macro level variables, but also regarding the individual level variables. The latter is mainly driven (they are the only significant ones in the estimation on top of the wave indicators) by two

[26] Notice that in contrast to the retirement expectations model, education indicators are not used as exclusion restrictions since education is strongly correlated with health investments and health attitudes, and therefore these measures are not exogenous with respect to the structural equation. Also, it is worth emphasizing that just about any combination of these four exclusion restrictions leads to parameter estimates of our coefficient of interest very close to unity.

variables; the self-reported health change from time $t-1$ to time t, and the indicator for having a professional degree. Our interpretation for the significance of the health change variable is that this measure of health dynamics is likely to be serially correlated, and reporting, for example, a health improvement in the recent past is likely to be followed by a period where health might not necessarily improve, delivering a kind of mean reversion effect that would explain the negative and significant coefficient in the estimation. This suggests that this variable might be capturing health deviations from the mean health as estimated by individuals. On the other hand, highly educated individuals have different attitudes towards their health and health investments, which could result in unobserved behavior, or be correlated with unobserved characteristics, with a time invariant component.

Given the nature of the analysis regarding longevity expectations, it would be natural to worry about an additional source of selection into the sample used for estimation, which can result in biased coefficients, survivorship bias. It is plausible to expect that those dying between the waves would be the ones reporting lower probabilities of surviving to certain ages, leaving our sample of survivors as a selected group of respondents that expect to live longer. In fact, we have used the exit interview information from all available waves of the HRS to compare the expected survival probabilities of those we know survived to the next wave, with the expected probabilities of those we know die between waves (about 7% of the original wave 1 sample had died by wave 6). Our findings indicate that eventual survivors reported significantly higher probabilities of living to age 75 and 85, suggesting that survivorship bias could be an issue in our data. In order to assess the effects of this additional source of selection in our sample we have followed the recommendations in Portrait et al. (2004) to construct additional selection correction terms, and have included them in our preferred specifications. Even though in most cases these additional selection terms were significant, the effects on the results we have reported in this section were negligible.[27] One possible problem of actually controlling for this additional selection concern is that the correction terms we have constructed to account for this possible bias are likely to be correlated with the selection term regarding responses to the longevity questions. The reason for this concern is that those that ended up dying between waves were considerably less likely to report expected longevity probabilities. In fact, the difference in response rates is around 14 percentage points, and it is highly significant. If the probability to respond is serially correlated, it is likely that the unobserved components that make someone more likely to respond are correlated with the unobserved components that make that same individual more likely to survive. This would mean that the introduction of the additional correction terms would result in collinearity problems and additional biases of its own.

Tables 10 and 12, in the Appendix, provide the results of the estimation of the main selection equation (9), and the first stage estimation of the traditional IV

[27] These results are available from the authors upon request.

and the corrected IV estimators for the weak and strong RE test using longevity expectations.

4.3 The educational attainment model

In this case the measurement-error robust IV estimates are identified off the parents' educational attainment measures, which we assume only affect the educational attainment expectations through the lagged expectations. The latter also means that the selection model has as exclusion restrictions with respect to the structural equation the parents' educational attainments, and the exclusion restrictions with respect to the first stage of the IV procedure (Z_4 in Eqs. 8, which are also additional exclusion restriction with respect to the main equation) are the number of siblings in school, and the number of older siblings. These exclusions restrictions imply that in this case Z_3 is the empty set in the formulation of Eqs. (6)–(9). For the NLSY, selection is unlikely to be an important issue in this empirical application since only 79 of almost 2,400 individuals did not answer the expectations questions.

Table 6 reports the results for the NLSY79 sample of testing rational expectations for educational attainment. The results show that we cannot reject the RE hypotheses regarding educational attainment once we control for measurement error. The weak RE test estimates the β parameter to be 0.982, with a small standard error, and in this case we cannot reject the presence of sample selection, however, the results of the corrected IV model are virtually identical in this case. For the strong RE test we find little evidence of selection bias, therefore, our preferred specification estimates an overidentified IV model. In that model we estimate β to be 0.991 with a larger standard error than in the weak test.

In both cases we can soundly reject that we have weak instruments, given the strong correlation between the parents' education and the individuals' education expectations as of time t. Additionally, the test of over-identifying restrictions widely supports the validity of the instrument set at any traditional level of significance (see Tables 14 and 15 in the Appendix).[28]

Finally, the additional predictions of the RE hypothesis cannot be rejected in this case, with strong support, at any traditional level of significance, for the joint hypotheses that all the coefficients of the exogenous variables as of time t are equal to zero, and the same is true of the estimates of the constant.

5 Conclusions

We have tested the Rational Expectations hypothesis in the formation of expectations for retirement and longevity using a representative sample of older Americans, and educational attainment expectations using a representative

[28] Just identified models, using either of the parents' education variables, delivered almost identical parameter estimates, but with slightly larger standard errors.

sample of younger Americans, relying on the same methodology. In all three types of expectations applications we cannot reject the RE hypothesis after controlling for reporting errors, and in some cases sample selection. These results support the use of the expectations variables in the growing number of data sets that provide this type of information, and support the use of models that use this assumption in micro data.

The methodology we present can be easily applied in many other contexts where repeated observations of expectations variables at the micro level are collected. The results of this analysis are meant to foster further discussion and research on the issues surrounding the role of expectations in economics and the social sciences, and in particular the importance and validity of the Rational Expectations hypothesis.

Appendix

Table 7 Selection equation results: probability of thinking about retirement, HRS

Variables	Probit	Marginal effects
Economic factors		
Net wealth (in \$10,000)	−0.002(0.002)	−0.001
Income (in \$10,000)	0.005(0.001)**	0.001
Self-employed	−0.092(0.049)*	−0.021
No health insurance	−0.225(0.038)**	−0.049
Private health insurance	−0.149(0.042)**	−0.033
Financially knowledgeable	0.054(0.035)	0.013
Health factors		
Health limitation	−0.383(0.045)**	−0.079
Good–very good–excellent health	0.224(0.045)**	0.049
High blood pressure	−0.041(0.031)	−0.01
Diabetes problems	−0.065(0.052)	−0.015
Cancer	0.040(0.058)	0.009
Stroke	0.035(0.120)	0.008
Heart problems	−0.0009(0.051)	−0.0002
Arthritis	−0.004(0.030)	−0.001
Doctor visits	−0.0003(0.001)	−0.0001
Diff. walking multiple blocks	−0.009(0.046)	−0.002
Difficulty climbing stairs	0.055(0.032)*	0.013
Drink	0.073(0.030)**	0.017
Smoke	−0.127(0.036)**	−0.029
Probability of living up to 85	−0.218(0.046)**	−0.051
Demographic factors		
Age	−0.015(0.005)**	−0.004
White	−0.103(0.043)**	−0.025
Male	0.173(0.038)**	0.042
Bachelor's degree	0.074(0.036)**	0.018
Professional degree	0.137(0.053)**	0.034
Married	0.059(0.038)	0.014
Years of education of father	−0.0098(0.005)*	−0.002
Years of education of mother	0.003(0.006)	0.001

Table 7 continued

Variables	Probit	Marginal effects
Father lived up to age 85	0.014(0.045)	0.003
Mother lived up to age 85	−0.062(0.041)	−0.014
Father reached retirement age	0.026(0.034)	0.006
Mother reached retirement age	−0.009(0.040)	−0.002
Wave 1–2 indicator	−0.133(0.041)**	−0.03
Wave 2–3 indicator	0.015(0.035)	0.004
Wave 3–4 indicator	0.015(0.030)	0.004
Constant	−0.220(0.300)	–
Predicted probability	0.1522	
Log likelihood	−7775.94	
Pseudo-R^2	0.0594	
Number of observations	18,322	

Table 8 First stage results for weak RE test on retirement expectations using IV

Variables	First stage of IV	First stage of corrected IV
Constant	38.842(1.302)**	29.980(4.966)**
Prob. of living to 85	1.111(0.225)**	0.775(1.154)
Smoking	0.549(0.170)**	0.345(0.689)
Age	0.402(0.023)**	0.487(0.118)**
White	0.178(0.192)	−0.392(0.475)
Male	0.433(0.139)**	1.095(0.854)
Bachelor's degree	−0.120(0.151)	−0.079(0.480)
Professional degree	−0.167(0.195)	−0.290(0.879)
Financially knowledgeable	0.621(0.147)**	0.889(0.320)**
Years of education of father	–	0.024(0.054)
Years of education of mother	–	0.035(0.033)
Father lived up to age 85	–	0.536(0.278)*
Mother lived up to age 85	–	0.183(0.395)
Inverse Mills' ratio: period t	–	10.527(4.028)**
Economic factors at time t		
Inverse Mills' ratio: periods t and $t+1$	–	−4.721(8.406)
Net worth (in $10,000)	–	−0.009(0.013)
Respondent income (in $10,000)	–	0.023(0.019)
Self-employed	–	1.488(0.936)
No health insurance	–	−0.212(1.118)
Private health insurance	–	−0.069(0.794)
Health factors at time t		
Health limitation	–	−1.501(1.756)
Good–very good–excellent health	–	0.386(1.194)
High blood pressure	–	−0.021(0.263)
Diabetes	–	0.340(0.420)
Cancer	–	0.296(0.373)
Stroke	–	−1.241(0.621)**
Heart problems	–	−0.041(0.298)
Arthritis	–	0.011(0.283)
Doctor visits	–	−0.003(0.009)
Diff. walking multiple blocks	–	−0.221(0.288)

Table 8 continued

Variables	First stage of IV	First stage of corrected IV
Difficulty climbing stairs	–	−0.125(0.345)
Drink	–	−0.284(0.380)
Demographic factors at time t		
Married	–	−0.813(0.428)*
Wave 1–2 Indicator	–	−0.038(0.736)
Wave 2–3 Indicator	–	−1.506(0.316)**
Wave 3–4 Indicator	–	0.241(0.220)
Adj. R^2	0.0841	0.1315
Test of weak instruments	$F(8, 4341) = 50.92$	$F(34, 3025) = 13.77$
Number of observations	4,350	3,061

Table 9 First stage results for strong RE test on retirement expectations using IV

Variables	First stage of IV	First stage of corrected IV
Constant	39.802(1.578)**	29.980(4.966)**
Prob. of living to 85	1.014(0.248)**	0.775(1.154)
Smoking	0.499(0.185)**	0.345(0.689)
Age	0.395(0.027)**	0.487(0.118)**
White	0.587(0.209)**	−0.392(0.475)
Male	0.390(0.176)**	1.095(0.854)
Bachelor's degree	0.046(0.165)	−0.079(0.480)
Professional degree	0.034(0.221)	−0.209(0.879)
Financially knowledgeable	0.538(0.181)**	0.889(0.320)**
Years of education of father	–	0.024(0.054)
Years of education of mother	–	0.035(0.033)
Father lived up to age 85	–	0.536(0.278)*
Mother lived up to age 85	–	0.183(0.395)
Inverse Mills' ratio of period t	–	10.527(4.028)**
Inverse Mills' ratio: periods t and $t+1$	–	−4.721(8.406)
Economic factors at time t		
Net Worth (in $10,000)	0.008(0.006)	−0.009(0.013)
Respondent income (in $10,000)	−0.004(0.003)	0.023(0.019)
Self-employed	0.690(0.267)**	1.488(0.936)
No Health Insurance	0.467(0.245)*	−0.212(1.118)
Private Health Insurance	0.346(0.261)	−0.069(0.794)
Health factors at time t		
Health limitation	0.794(0.275)**	−1.501(1.756)
Good–very good–excellent health	0.052(0.271)	0.386(1.194)
High blood pressure	0.073(0.156)	−0.021(0.263)
Diabetes	0.338(0.276)	0.340(0.420)
Cancer	0.053(0.312)	0.296(0.373)
Stroke	−0.896(0.526)*	−1.241(0.621)**
Heart problems	0.154(0.274)	−0.041(0.298)
Arthritis	−0.162(0.153)	0.011(0.183)
Doctor visits	0.001(0.009)	−0.003(0.009)
Diff. walking multiple blocks	−0.265(0.268)	−0.221(0.288)
Difficulty climbing stairs	−0.173(0.181)	−0.125(0.345)

Table 9 continued

Variables	First stage of IV	First stage of corrected IV
Drink	−0.506(0.155)	−0.284(0.380)
Demographic factors at time t		
Married	−0.730(0.197)**	−0.813(0.428)*
Wave 1–2 Indicator	0.199(0.239)	−0.038(0.736)
Wave 2–3 Indicator	−1.004(0.203)**	−1.506(0.316)**
Wave 3–4 Indicator	0.218(0.203)	0.241(0.220)
Adj. R^2	0.1201	0.1315
Test of weak instruments	$F(8, 3371) = 37.10$	$F(13, 3025) = 22.82$
Number of observations	3,401	3,061

Table 10 Selection equation results: probability of reporting survival probability, HRS

Variables	Probit	Marginal effects
Economic factors		
Net wealth (in $10,000)	−0.003(0.001)**	−0.001
Income (in $10,000)	0.0002(0.0004)	0.00005
No health insurance	−0.096(0.024)**	−0.03
Financially knowledgeable	0.246(0.024)**	0.076
Health factors		
Self-reported health	0.113(0.011)**	0.034
Self-reported health change	0.018(0.015)	0.006
ADL index	0.083(0.075)	0.025
Chronic disease	0.124(0.070)*	0.037
Doctor visits	0.0003(0.0007)	0.0001
Hospital stays	−0.016(0.009)*	−0.005
Demographic factors		
Age	−0.078(0.003)**	−0.024
White	0.286(0.029)**	0.092
Male	−0.333(0.024)**	−0.104
Bachelor's degree	0.077(0.025)**	0.023
Professional degree	0.168(0.039)**	0.048
Married	0.009(0.026)	0.003
Kids living close	0.065(0.060)	0.02
Number of grand children	−0.006(0.002)**	−0.002
Number of siblings	−0.004(0.005)	−0.001
Newly father's death	0.125(0.053)**	0.036
Newly mother's death	0.036(0.040)	0.011
Years of education of mother	0.020(0.003)**	0.006
Wave 1–2 Indicator	0.227(0.031)**	0.065
Wave 2–3 Indicator	0.297(0.024)**	0.085
Wave 3–4 Indicator	0.008(0.020)	0.002
Constant	4.229(0.200)**	–
Predicted probability	0.7722	–
Log likelihood	–15610.8	–
Pseudo-R^2	0.1248	–
Number of observations	31,279	–

Table 11 First stage results for weak RE test on longevity expectations using IV

Variables	First stage of IV	First stage of corrected IV
Constant	0.227(0.020)**	0.363(0.054)**
Age	0.003(0.0003)**	0.001(0.001)
White	−0.053(0.004)**	−0.043(0.006)**
Male	−0.034(0.003)**	−0.051(0.005)**
Self-reported health	0.095(0.001)**	0.070(0.002)**
Newly father's death	–	0.029(0.009)**
Newly mother's death	–	0.018(0.008)**
Years of education of mother	–	0.005(0.001)**
Inverse Mills' ratio of period t	–	−0.005(0.045)
Inverse Mills' ratio: periods t and $t+1$	–	0.096(0.042)**
Economic factors at time t		
Net worth (in $10,000)	–	0.0001(0.0002)
Respondent income (in $10,000)	–	0.0001(0.0001)
No health insurance	–	−0.012(0.005)**
Health factors at time t		
Self-reported health change	–	0.018(0.003)**
ADL index	–	−0.144(0.015)**
Chronic disease	–	−0.095(0.014)**
Doctor visits	–	0.0003(0.0001)**
Hospital stays	–	−0.007(0.001)**
Demographic factors at time t		
Bachelor's degree	–	0.028(0.004)**
Professional degree	–	0.024(0.006)**
Married	–	−0.004(0.005)
Kids living close	–	−0.011(0.004)**
Number of grand children	–	0.001(0.0004)**
Number of siblings	–	0.002(0.001)**
Wave 1–2 indicator	–	0.014(0.006)**
Wave 2–3 indicator	–	0.003(0.006)
Wave 3–4 indicator	–	0.0003(0.005)
Adj. R^2	0.136	0.1457
Test of weak instruments	$F(4, 32560) = 282.78$	$F(25, 23203) = 148.46$
Number of observations	32,565	23,230

Table 12 First stage results for strong RE test on longevity expectations using IV

Variables	First stage of IV	First stage of corrected IV
Constant	0.343(0.026)**	0.363(0.054)**
Age	0.003(0.0004)**	0.001(0.001)
White	−0.054(0.005)**	−0.043(0.006)**
Male	−0.041(0.004)**	−0.051(0.005)**
Self-reported health	0.069(0.002)**	0.070(0.002)**
Newly father's death	–	0.029(0.009)**
Newly mother's death	–	0.018(0.008)**
Years of education of mother	–	0.005(0.001)**
Inverse Mills' ratio of period t	–	−0.005(0.045)

Table 12 continued

Variables	First stage of IV	First stage of corrected IV
Inverse Mills' ratio: periods t and $t+1$	–	0.096(0.042)**
Economic factors at time t		
Net Worth (in $10,000)	0.00027(0.00015)*	0.0001(0.0002)
Respondent income (in $10,000)	0.0001(0.0001)	0.0001(0.0001)
No health insurance	−0.007(0.005)	−0.012(0.005)**
Health factors at time t		
Self-reported health change	0.016(0.003)**	0.018(0.003)**
ADL index	−0.153(0.014)**	−0.144(0.015)**
Chronic disease	−0.100(0.013)**	−0.095(0.014)**
Doctor visits	0.0004(0.0001)**	0.0003(0.0001)**
Hospital stays	−0.005(0.001)**	−0.007(0.001)**
Demographic factors at time t		
Bachelor's degree	0.032(0.004)**	0.028(0.004)**
Professional degree	0.027(0.006)**	0.024(0.006)**
Married	0.00002(0.004)	−0.004(0.005)
Kids living close	−0.013(0.004)**	−0.011(0.004)**
Number of grand children	0.0007(0.0004)*	0.00077(0.0004)*
Number of siblings	0.001(0.001)	0.002(0.001)**
Wave 1–2 Indicator	0.002(0.005)	0.014(0.006)**
Wave 2–3 Indicator	−0.013(0.005)**	0.003(0.006)
Wave 3–4 Indicator	−0.005(0.005)	0.0003(0.005)
Adj. R^2	0.1444	0.1457
Test of weak instruments	$F(4, 24889) = 369.43$	$F(8, 23203) = 174.35$
Number of observations	24,911	23,230

Table 13 Selection equation results: NLSY79

Variables	Probit	Marginal effects
Economic factors		
Avg. family income ($1,000)	0.005(0.005)	0.0002
Demographic factors		
Mother's education	0.030(0.027)	0.0009
Father's education	−0.018(0.022)	−0.0006
Male	0.126(0.118)	0.004
Black	0.263(0.170)	0.007
Hispanic	0.103(0.186)	0.003
Number of siblings at school	0.073(0.042)*	0.002
Number of older siblings	0.024(0.028)	0.0008
Highest grade completed	0.495(0.067)**	0.015
Labor market experience	0.168(0.098)*	0.005
Northeastern residence	0.423(0.151)**	0.01
North-central residence	0.888(0.186)**	0.019
Southern residence	1.124(0.174)**	0.03
Rural residence	0.373(0.191)**	0.009

Table 13 continued

Variables	Probit	Marginal effects
Constant	−4.713(0.716)**	–
Predicted probability	0.988	
Log likelihood	−262.585	
Pseudo-R^2	0.2439	
Number of observations	2,398	

Table 14 First stage results for weak RE test using IV: NSLY79

Variables	First stage of IV	First stage of corrected IV
Constant	10.835(0.170)**	10.810(1.539)**
Mother's education	0.109(0.020)**	0.088(0.020)**
Father's education	0.154(0.016)**	0.110(0.016)**
Inverse Mills' ratio of period *t*	–	−1.231(0.940)
Inverse Mills' ratio: periods *t* and $t+1$	–	−0.918(0.959)
Economic factors at time t		
Avg. family income (in $1,000)	–	0.008(0.003)**
Demographic factors at time t		
Age	–	−0.423(0.091)**
Male	–	−0.025(0.083)
Black	–	0.337(0.113)**
Hispanic	–	0.345(0.143)
Number of siblings	–	−0.031(0.018)*
Highest grade completed	–	0.811(0.083)**
Labor market experience	–	−0.045(0.064)
Northeastern residence	–	−0.081(0.151)
North-central residence	–	−0.048(0.170)
Southern residence	–	0.005(0.182)
Rural residence	–	−0.439(0.109)**
Local unemployment rate	–	−0.093(0.047)**
Catholic	–	0.253(0.113)**
Adj. R^2	0.1285	0.2644
Test of weak instruments	$F(2, 2316) = 171.93$	$F(17, 2300) = 42.25$
Number of observations	2,319	2,319

Table 15 First stage results for strong RE test using IV: NSLY79

Variables	First stage of IV	First stage of corrected IV
Constant	9.788(1.417)**	10.810(1.539)**
Mother's education	0.089(0.019)**	0.088(0.020)**
Father's education	0.108(0.016)**	0.110(0.016)**
Inverse Mills' ratio of period t	–	−1.231(0.940)
Inverse Mills' ratio: periods *t* and $t+1$	–	−0.918(0.959)
Economic factors at time t		
Avg. family income (in $1,000)	0.009(0.003)**	.008(0.003)**

Table 15 continued

Variables	First stage of IV	First stage of corrected IV
Demographic factors at time t		
Age	−0.456(0.090)**	−0.423(0.091)**
Male	0.006(0.081)	−0.025(0.083)
Black	0.387(0.109)**	0.337(0.113)**
Hispanic	0.384(0.142)**	0.345(0.143)**
Number of siblings	−0.025(0.018)	−0.031(0.018)*
Highest grade completed	0.932(0.053)**	0.811(0.083)**
Labor market experience	−0.015(0.062)	−0.045(0.064)
Northeastern residence	0.017(0.135)	−0.081(0.151)
North-central residence	0.058(0.130)	−0.048(0.170)
Southern residence	0.122(0.127)	0.005(0.182)
Rural residence	−0.406(0.105)**	−0.439(0.109)**
Local unemployment rate	−0.067(0.045)	−0.093(0.047)*
Catholic	0.303(0.107)**	0.253(0.113)**
Adj. R^2	0.2639	0.2644
Test of weak instruments	$F(2, 2302) = 72.25$	$F(3, 2300) = 48.65$
Number of observations	2,319	2,319

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