The Rationality of Retirement Expectations and the Role of New Information†

(Working Paper Version)

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September 22, 2004

Abstract

This paper tests the Rational Expectations (RE) hypothesis regarding retirement expectations, controlling for sample selection and reporting biases. We find that retirement expectations in the Health and Retirement Study are consistent with the RE hypothesis. We also analyze how new information affects the evolution of retirement expectations and discover that, on average, individuals correctly anticipate most uncertain events when planning their retirement, except for some health conditions and economic factors. Our results support a wide variety of models in economics that assume rational behavior.

Keywords: Rational Expectations, Retirement Expectations, New Information
JEL classification: D84, J26

† The authors are grateful to the Michigan Retirement Research Center (MRRC) and the TIAA-CREF Institute for financial support. Earlier versions of this paper circulated with the titles "*Expectations Formation using the Health and Retirement Study.*" and "*What to Expect when you are Expecting Rationality: Testing Rational Expectations using Micro Data*." We are grateful to Moshe Buchinksy, John Rust, Tom Muench, Jim Hosek, Michael Hurd, Arie Kapteyn, Stan Panis, James P. Smith, Christian Belzil, Bryan Campbell, Nikolay Gospodinov, Jenny Hunt, Peter Arcidiacono, Ahmed Khwaja, Marjorie McElroy, Julia Lynn Coronado, Don Andrews, Valentina Corradi, Albert Marcet, Ernesto Villanueva, Douglas Fore, John Ameriks, Chris Swann, Olivia Mitchell, Caroline Austin, and Anna Vellvé-Torras for insightful comments and discussions. We also would like to acknowledge excellent research assistance from Huan Ni, Selcuk Eren, and Wayne-Roy Gayle. We have benefited from comments from participants at the Society of Labor Economists Meetings in Baltimore in May 2002, the North American Meetings of the Econometric Society at UCLA in June 2002, the RAND Labor and Population group, the CIREQ Labor and Applied Econometrics Workshop at Concordia University, the Applied Microeconomics Seminar at Duke University, the Labor and Public Economics Seminar at UPF, and the Resident Scholar Program at the Board of Governors of the Federal Reserve System in Washington D.C. All remaining errors are the authors'.
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1. Introduction

The Health and Retirement Study (HRS) provides us with the rare opportunity to directly analyze the evolution of retirement expectations and test the Rational Expectations hypothesis, which is one of the most important hypotheses in economics. Due to its extensive use, it is surprising how widely the definition of the term Rational Expectations (RE) varies. Our use of the term and the approach to testing the hypothesis will be consistent with the views expressed by the precursors of this powerful assumption. We will essentially maintain that *agents' subjective beliefs about the evolution of a set of variables of interest coincide with the objectively measurable population probability measure* (Muth 1961; Lucas 1972).[1] The main difference with that seminal work is that instead of concentrating on forecasts of market level variables, we will focus on how individuals form expectations over an array of micro variables that affect them directly, or are in part under their control.

It is important to distinguish that while in macroeconomic theory the RE assumption is understood mainly as an equilibrium concept,[2] 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, and it is at the forefront of most work in dynamic models of individual behavior. This is primarily because most micro level data sources are rich in household and individual level 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), and Lovell (1986) considered the direct analysis of expectations an important project, and more recently, Manski (2003) has emphasized the importance of analyzing expectations formation, while Hamermesh (2004) discusses the usefulness of subjective outcomes in economics.

[1] For a survey of the early contributions see the special issue in the *Journal of Money, Credit and Banking* edited by McCallum (1980). For a more recent discussion see Sargent (1995).
[2] Thanks largely to Lucas' seminal contributions, where expectations affect the stochastic evolution of the economy and this evolution in turn affects expectations formation.

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). Figlewski and Watchtel (1981, 1983), Kimball Dietrich and Joines (1983), and others, compare forecasts of market variables to realizations. Finally, work by Leonard (1982) triggered interest in wage expectations of employers. 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)'s model of expectations formation, to argue that testing whether past retirement expectations are a sufficient statistic for current retirement expectations is indeed a test of the Rational Expectations hypothesis. We also study whether new information affects expectations over time by analyzing how well people anticipate changes over factors relevant to the retirement decision.

If our tests reject the Rational Expectations (RE) hypothesis, two very different, but nonetheless connected, interpretations are possible.[3] First, we could conclude that models of rational behavior expect too much of individuals, forcing us to abandon the "full rationality hypothesis" that economic agents behave "as if" they were making a 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 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, and Evans and Honkapohja 2001). 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.

[3] A third alternative is that one of the assumptions we are jointly testing along with rationality is rejected. We will later make clear the nature of these additional assumptions, which coincide with those also jointly tested along with RE by previous researchers.

The first conclusion would be a set back for research in a variety of areas since it would put into question an attractive and central tool. The second, would mean that we need more realistic models, which are likely to be more complex, but also more attentive to details of the process of expectations formation by individuals. In essence the latter would be equivalent to revisiting Muth's (1961, p. 316) point that "*dynamic economic models do not assume enough rationality*."

The main result of the paper is that our tests do not reject the RE Hypothesis. Therefore, we can at least continue to rely on rationality, and the strategies used to model it, as a good first approximation to behavior by economic decision makers. Furthermore, it is then reasonable to use some of these variables in modeling complex economic situations, an objective that Haavelmo (1958, p. 357) already emphasized.

The conceptual model and econometric specifications are presented in Section 2. Section 3 discusses the data used in the empirical analysis, and Section 4 reports our main findings. Section 5 concludes.

2. A Model of Expectations Formation, and a Test of Rational Expectations

Suppose an individual and an econometrician are trying to predict a variable X that the individual has decided will be determined as a function of a sequence of random variables:

$$X = h(\omega_1, \omega_2, ..., \omega_T). \qquad (1)$$

The sequence of vector-valued variables inside the parenthesis is observed by the individual at time $t=1,2,...,T$. Then the individual will take action X after some or all the ω_t's have been observed. 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 define

$$X_t^e = E\langle X | \Omega_t \rangle, \qquad (2)$$

where the variable X, retirement age, is forecasted, the full information set at time t is represented by Ω_t, and E is the expectations operator. This is the most commonly used representation of the RE hypothesis, where we take as the rational expectation of a variable its conditional mathematical expectation (Sargent and Wallace 1976). 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 standard life cycle models of retirement behavior (Lumsdaine and Mitchell 1999). It is well established that the factors that influence retirement include health, health insurance, and socio-economic status. A logical hypothesis at this point is that the factors that influence retirement also influence retirement expectations in a similar way.

Using the law of iterated expectations and assuming that the new information was correctly forecasted by agents, from equation (2) we get:

$$E\langle X^e_{t+1} | \Omega_t \rangle = E[E\langle X | \Omega_t, \omega_{t+1} \rangle \mid \Omega_t] = E\langle X | \Omega_t \rangle = X^e_t, \qquad (3)$$

where ω_{t+1} represents information that comes available between periods *t* and *t+1*. Notice that it is essential here to assume that new information (its conditional distribution, not just its mean) is correctly forecasted. Without this additional assumption expression (3) would not be correct. We are going to test this assumption jointly with the more standard RE hypothesis, once we also assume linearity of the process presented in (3). Notice that the assumption of correct forecasting is in essence no different from the assumption in the early RE literature; namely that forecast errors are normally distributed with mean zero, in a specification that regresses outcomes of a particular market variable on its expectations and a constant.

Then from (3) we can write the evolution of expectations through time as

$$X^e_{t+1} = X^e_t + \eta_{t+1}, \qquad (4)$$

where $\eta_{t+1} = X^e_{t+1} - E[X^e_{t+1} \mid \Omega_t]$, and therefore $E(\eta_{t+1}|\Omega_t)=0$. 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, as in Bernheim (1990), we can test the Rational Expectations (RE) hypothesis with the following regression:

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

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 α=γ=0, and β=1.[4] 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 α=0 and β=1, in other words it tests whether expectations follow a random walk. The strong RE test is less restrictive and also

[4] A value of α different from zero can be consistent with the rational expectations hypothesis in a cross-sectional analysis in the presence of a macro shock, common to all agents. We thank an anonymous referee for pointing this out to us. We will try to control for this type of shocks using year dummies in our empirical analysis.

tests for γ=0. In the next sections we will test these hypotheses exploiting the longitudinal nature of the HRS, while controlling for measurement error and sample selection.

We are also interested in the role of new information in expectations formation. We want to know whether new information affects the evolution of expectations, and whether this new information is to some degree anticipated. Even assuming we cannot reject the prediction of the RE hypothesis, that in (5) β=1, a characterization of the role of new information in the evolution of retirement expectations implies that individuals integrate old and new information when updating their expectations, attaching weights to each of these sources. Assuming the linearity of the function that individuals use to process information regarding the variables of interest, and further assuming that the elements of the information set Ω are jointly normally distributed we can then write

$$X^e_{t+1,i} = X^e_{t,i} + \gamma\ (\omega_{t+1} - E[\omega_{t+1} \mid \Omega^1_t]), \qquad (6)$$

where the term in parenthesis is the difference between the observed new information and the expectation individuals had of this information as of last period. If we had all these elements we could then estimate (6) and would expect a coefficient of one in front of the retirement expectation as of time *t*, and the coefficients in γ could be interpreted as the effect on changes in expectation of the unanticipated components of new information.[5] However, we do not observe the second element in the brackets, and although it could be estimated by making further assumptions about the relationship between new and current information, this is likely to be a very noisy procedure. Instead, we estimate the following equation

$$X^e_{t+1,i} = \alpha \ + \ \beta\, X^e_{t,i} \ + \ \gamma\, \omega_{t+1,i} \ + \ \varepsilon_{t+1,i}\,, \qquad (7)$$

where there is no reason to believe that β would be equal to 1, since the unobserved expectation term from (6) would enter into the error term, leading to possible biases in the coefficients of interest, which in part can be treated as a problem of measurement error and attenuated using IV techniques. Also, the estimates of the vector γ, are interpreted as the effects that changes in specific factors in Ω^1 have on expectation formation. A nonzero coefficient on a given change in a member of the information set can be interpreted as information not perfectly anticipated, and therefore not embedded in period's *t* expectations.

Econometric Specifications

Estimating equations (5) and (7) is in principle straightforward, using for example OLS, but the likely presence of measurement error in the dependent variable and its lag, and sample selection complicate the methodology.[6]

As with all survey data, measurement error in proxy variables is likely to be present. We are particularly concerned with 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.[7] Then the interview environment would affect the report over time in a way that is not observed. This component of the self-reports can bias the coefficients of interest in unpredictable ways. 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 used to tackle this problem to be very close to the one from the OLS specification, assuming validity of the instruments set. However, we will see below that the coefficient significantly changes and approximates the value predicted by the theory. Notice, that 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.

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[5] Depending on the covariance structure of model used by individuals to process information, these coefficients could be time dependent. This could potentially affect the strategy to estimate these coefficients. In the sequel we will assume they are time invariant. We thank Tom Muench for helping us understand this point.

[6] The possible presence of focal points in the retirement expectations variable 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.

[7] Individuals responded with a retirement expectation either as 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.

We correct for the measurement error problem using instrumental variables analysis. The instruments 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. We use time *t* subjective survival to age 85 probabilities and an indicator of smoking behavior as instruments (exclusion restrictions correlated with the rate of time preference) of retirement expectations.

In the case of the 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. Meaning that those that we do not observe answering the expectations questions are not following a completely different model (maybe irrational) to decide their retirement ages, but instead that for a number of observable and unobservable reasons they did not report our dependent variable.

Here we follow Wooldridge (2002, p.567) to consistently estimate the effect of previous expectation on current expectation in the presence of measurement error and selection, and from (5):

$$X^e_{t+1,i} = \alpha_1 + \beta X^e_{t,i} + \gamma_1 Z_{t,1i} + \varepsilon_{t+1,1i}, \qquad (8)$$

$$X^e_{t,i} = \alpha_2 + \lambda_1 Z_{t,1i} + \gamma_2 Z_{t,2i} + \varepsilon_{t,2i}, \qquad (9)$$

$$Y_i = 1(\alpha_3 + \gamma_3 Z_{t,3i} + \varepsilon_{3i} > 0), \qquad (10)$$

where we first estimate the selection equation (10) using a probit specification, where Y_i is equal to one if both the expectation in period *t* and the expectation in period *t+1* are observed, which means that the individual answers a question about her future retirement. This procedure allows for arbitrary correlation between the disturbances in the three equations.

It is important, to clarify the reason why we believe that the disturbances in (10) could be correlated with the disturbances in (9), and (8). Among the many possible explanations the one that seems more appealing 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 (10). This makes them more likely to expect to retire earlier, on average, than what they reported earlier. 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 severe downward bias in β, since we would be left with a sample more likely to expect to retire earlier than previously reported. We would also 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. Other reasons, like the possible correlation between thinking about retirement and time to retirement, we believe should be captured by the inclusion of age (which always has a positive effect) in the selection equation.

Z_3 in equation (10) includes all the exogenous variables and any exclusion restriction of the selection equation with respect to the structural equation. The exclusion restrictions include indicators for whether the father and mother of the respondent reached retirement age, and the age of the respondent. When estimating this Corrected IV specification we assume that age is a proxy for the information set, and only matters in terms of making you more or less likely to think about retirement, but does not directly affect the expected retirement age. The reason for this is twofold: First, as Vella (1998, p. 135) discusses, including a variable which has a fairly small range 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 it is even more troubling, unreliable estimates of the coefficients of interest. Second, on economic grounds we believe it is reasonable to assume that age matters for whether you have thought about retirement and the timing of that retirement, but, consistent with the assumption we are testing, should not be included when estimating the structural equation. Relaxing this assumption does not change the qualitative results presented in the paper.[8]

We then consistently estimate (8) by performing a modified 2SLS procedure, where the first stage includes as regressors the exogenous variables used in (10), which might or might not include the exclusion restrictions of the selection equation with respect to the structural equation, the Inverse Mills' ratio from the probit equation, and any additional instruments (exclusion restrictions), Z_2 in (9), the validity of which will be tested.

This procedure has been rarely used in empirical work, which is rather surprising given the pervasiveness of the two problems tackled here, measurement error (or endogeneity) and selection. In the results section we will discuss in some detail identification issues, 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.

The consistent estimation of (7) in order to assess the effect of new information on expectations formation uses the same Corrected IV procedure, which in this case means we estimate the system presented in equations (8) to (10) but where (8) is substituted by equation (7). All the other properties of the estimator we have discussed apply to this specification.

3. Data

The HRS is a nationally representative longitudinal survey of 7,700 households headed by an individual aged 51 to 61 as of the first round of interviews in 1992-93. In this analysis we use the first five waves of data, covering the period from 1992 to 2000. The primary purpose of the HRS is to study the labor force transitions between work and retirement with particular emphasis on sources of retirement income and health care needs. It is a survey conducted by the Survey Research Center (SRC) at the University of Michigan and funded by the National Institute on Aging. The data for the respondents are merged across the five waves, and we construct a set of consistent variables on different sources of income, wealth, health, health insurance, and socio-economic characteristics that will be assigned to each decision maker appropriately.

We include any observation for respondents that are working, full time or part time, in any wave and non-employed (but searching for jobs) that report retirement plans. We exclude respondents who do not report retirement plans for more than two consecutive years which results in more than 11,000 respondents in the sample and around 24,000 person-period observations once missing values in the main variables of interest are considered. Table 1 provides summary statistics for a selected number of variables, by the selection criterion. We also construct a transitions dataset that consists of changes to these covariates across waves, since for part of the analysis we are interested in changes of variables over time.

[8] In the selection equation we include covariates as of time t. We experiment with including $t+1$ variables, and also a battery of residuals of regressions of $t+1$ variables on their lagged values, which we then include in the main equation. Although some coefficients in the main equation changed from these modifications, the reported results are robust to this characterization of the selection process.

In each wave respondents are asked when they plan to fully or partially depart from the labor force.[9] They are also asked if they thought much about retirement. These questions are not mutually exclusive, but most of the people who have not thought about retirement do not report an expected age.[10] A number of individuals report they will never retire, although these same people often change their minds at some point and report an age. In this paper we assign an age of 77 for those who never retire (estimated longevity). Omitting this group from the analysis, but correcting for the selection into this group, does not change the qualitative results presented in this paper. These latter results are available from the authors upon request.[11]

Expected retirement ages are distributed similarly to actual retirement ages with peaks at ages 62 and 65 as well as a peak for the bunching at 77 for those who never plan to retire. Over time these expectations converge to between 62 and 65 with fewer people maintaining plans of retirement before age 62 or after age 65. Table 2 provides an analysis of how these expectations compare with a number of retirement measures. Interestingly, expectations are much more concentrated on the traditional peaks than actual retirement which, except for a measure that uses the age at which individuals start to receive Social Security, is much smoother. In any case, besides the apparent focal points that ages 62 and 65 play when people form expectations, it seems clear that retirement expectations are measuring retirement itself. This is encouraging evidence if we are to use this data to further characterize the process of how these expectations are formed.

Finally, the last row of Table 2 shows the frequency of changes to retirement expectations, which is quite large among those reporting valid ages in consecutive interviews. However, the average change is under a year, with a standard deviation of around 5 years.

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[9] In wave 1 they were only asked about a full departure.

[10] Many of them report that they will never retire. If they have not given it any thought, and they say they will never retire, we treat their expected retirement age as missing. If they give a retirement age we treat them as non-missing.

4. Empirical Results

Tests of Rational Expectations

Table 3 reports the weak and strong RE tests for the full sample. The data support the weak and strong RE hypotheses only in an augmented model that corrects for sample selection and measurement error in the report of expected retirement age, resulting in a selection corrected IV specification.[12]

Notice that we perform an F-test based on the null hypothesis that $\beta=1$ in equation (5), to test the RE hypothesis. We obtain a coefficient for β of 1.05 for the weaker test, which given the precision of the estimate cannot reject the hypothesis that expectations follow a random walk. For the pooled OLS estimation the weak test is effectively a unit root test, and as such, and following the literature on testing unit roots in panel data surveyed by Bond, Nauges, and Windmeijer (2002), we have to perform a correction to obtain the appropriate critical value. However, this matters very little since the unit root hypothesis is soundly rejected.

For the strong test we estimate the full model of equations (8) to (10), using the Corrected IV procedure. The β parameter is estimated to be equal to 0.9397, which clearly fails to reject the RE hypothesis. Notice the importance of both instrumenting the previous period's expectations, and controlling for sample selection. Interestingly, this Corrected IV technique seems to circumvent one of the traditional drawbacks of instrumental variables estimation, that is, the large increase in standard errors in the IV estimates. Notice that the standard errors of the β parameter are less than half that of the uncorrected IV estimator, although still larger than in the OLS estimation. The importance of the selection correction in this setting, contrasts with the results in Bernheim (1990) where selection was not important, and the inability to reject rationality was in part the product of large standard errors.

It is natural at this time to ask ourselves whether the identification strategy used to estimate the IV model and the Corrected IV model is appropriate. The issue comes down to whether we trust the exclusion restrictions we have made regarding the fact that the smoking behavior and the self-assessed probability of

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[11] Using age 77 creates a larger variance in this variable, which affects the constant in the regressions.

[12] 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). The justification for including these time-invariant components in the test is because they may be correlated with other time-varying unobservables.

living to age 85 affect retirement expectations at time *t* but are not correlated with the disturbances in the main equation (8). The best we can do to convince the reader of the validity of the instruments is to perform the tests introduced in the literature, so we follow the suggestions in Bound, Jaeger, and Baker (1995), Staiger and Stock (1997), Stock, Wright, and Yogo (2002), and Baum, Schaffer, and Stillman (2003), and find that we have robust instruments, with large F statistics in the first stage of the IV procedure, several times larger, especially for the Corrected IV procedure, than the minimum value (around 10) suggested in Staiger and Stock (1997), and also discussed in Stock, Wright, and Yogo (2002), as a good rule of thumb to check whether we are in the presence of weak instruments (first stage results are available from the authors upon request). Also, the model is overidentified, which allow 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.[13] The reported results are the product of robustly estimating the system of equations via GMM, which provides robustness against unknown forms of heterokedasticity.

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 (5). After controlling for sample selection and measurement error we find that most of these factors are no longer significant. The joint hypotheses that all the coefficients are equal to zero cannot be rejected at the 5% significance level, and the same is true of the estimates of the constant (this is also true for the weak test), validating the other predictions of the RE hypothesis regarding retirement expectations.

The Role of New Information

In this part of our analysis we are interested in the effect of new information on expected retirement age. We examine the effects of changes to all of the relevant factors on plans by estimating equation (7) but correcting for sample selection bias and measurement error, following the same strategy as in equations (8) to (10). We hypothesize that there will be no significant effects if, on average, people are able to completely

[13] We also estimated just identified models using either the probability of living to 85 or the smoking indicator as exclusion restrictions. In both cases we could not reject the RE hypothesis, given that although the point estimates of the β parameter changed to 0.88 and 1.05

anticipate the new information. A significant coefficient on any covariate does not indicate surprise, since it is easy to write an example where even if individuals perfectly know the distribution over the uncertain event, once this happens, the estimated coefficient would be different from zero. An statistically significant coefficient can be interpreted to mean that the individual could have known the probabilities, but not what will happen.

Table 4 reports the results of estimating equation (7) and correct for selection bias and measurement error in order to attenuate the biases resulting from the fact that we do not have all the information of the structural model in (6), we find that the coefficient on the expected retirement age reported in the previous period is not significantly different from 1, suggesting that we have greatly reduced the biases, and increased the reliability of the estimated coefficients.[14] The only factors that significantly alter retirement plans are related to some health conditions, the availability of private health insurance, and job transitions. Focusing on the IV specification (which is the preferred one given the lack of significance of the Inverse Mills' ratio in the corrected-IV specification) we observe that individuals who have been newly diagnosed with diabetes or high blood pressure expect to delay retirement. One explanation for postponing retirement with the onset of diabetes or high blood pressure may be an increase in consumption necessary to cover health care requirements, particularly if health insurance is tied to work. Most changes to economic status have little effect, except for those individuals who have changed jobs or have returned to work who expect to retire later than expected, capturing the role of employment uncertainty. Also, those with new access to private health insurance expect to retire later, this seems to capture possible offset of losses of coverage on the job, given that we are controlling for changes in health status and employment transitions.

We conclude from these results that researchers need to pay special attention to incorporating the uncertainty of health shocks, the decisions to purchase health insurance, and employment uncertainty in dynamic models, or models that assume rational expectations. This is something the research community has been relatively aware of for some time, but that requires considerable modeling efforts.

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respectively, the standard errors increased by 50%. In both we were able to reject the hypothesis that we had a weak instrument.

[14] The error term seems to be more correlated with the expected retirement age as of time t than the new information set, since the estimated effects (γ) are not significantly different after correcting for measurement error but β was biased downward without the measurement error correction. The Inverse Mills' Ratio is not very precisely estimated suggesting that in this case selection might be less of a problem than in the specification that tests the RE Hypothesis.

5. Conclusions

In this paper we test the Rational Expectations hypothesis in the formation of expectations for retirement, and cannot reject the RE hypothesis after controlling for reporting errors and sample selection.[15] This result has important implications for a wide variety of models that use this assumption, and for dynamic models that are often identified under rational expectations assumptions.

We also examine the role of new information in retirement expectation formation. This time we focus on how well people anticipate changes over factors relevant to the retirement decision. A model of perfect foresight is rejected with respect to health variables and some economic variables, so on average not all changes are anticipated. We find that some components of health that are associated with various health conditions, the purchase of health insurance, and the role of unemployment uncertainty warrant extra attention in models that assume some type of rationality, if we seek to better fit the data.

The results in this analysis are meant to foster further discussion and research on the issues surrounding the role of expectations in economic modeling. We bring back to center stage the debate about whether we should be testing one of our key working hypotheses, in particular the RE hypothesis, now that large data sets provide us with the opportunity to explore expectations over micro variables in more detail than ever before. The methodology we present can be easily applied in many other contexts where repeated observations of expectations variables at the micro level are collected, such as fertility expectations, and educational attainment expectations (see Benítez-Silva et al. 2004).

[15] We have done most of the analysis in this paper on married couples, assuming first that the spouse's information is exogenous to the individual utility maximization problem, and then constructing a joint expectations test. In both cases we find that we cannot reject the Rational Expectations Hypothesis. See Benítez-Silva and Dwyer (2004) for a detailed analysis.

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Table 1. Summary Statistics by Sample Selection.

Variables	Thought About N=11,062	Not Thought N= 12,607
Expected retirement age	64.584(6.478)	-
Employee	0.840(0.367)	0.753(0.431)
Net worth (in $100,000)	2.612(5.484)	2.305(4.895)
Respondent's Income (in $1,000)	33.583(67.258)	25.379(39.192)
Has a private pension	0.657(0.475)	0.538(0.499)
Employer Provided Health Insurance	0.748(0.434)	0.652(0.476)
No Health Insurance	0.063(0.244)	0.107(0.309)
Health limitation	0.185(0.388)	0.189(0.391)
Good-Very Good-Excellent Health	0.872(0.334)	0.861(0.346)
Doctor visits	5.311(7.054)	5.086(7.093)
Probability of living to age 85	0.468(0.305)	0.472(0.307)
Smoke	0.202(0.402)	0.234(0.423)
Age	57.558(4.824)	56.880(5.528)
Male	0.506(0.500)	0.428(0.495)
Married	0.802(0.398)	0.786(0.410)
Bachelor's degree	0.290(0.454)	0.252(0.434)
Mother reached retirement age	0.728(0.445)	0.702(0.457)
Father reached retirement age	0.603(0.489)	0.590(0.492)

Table 2. Distribution of Retirement Expectations and Actual Retirement.

	Exp. W1	Exp. W2	Exp. W3	Exp. W4	Exp. W5	Self-R Ret.	Social Sec.	Fully Retired	Full and Partial Retirement
Age <50	0.19%	0.25%	0.14%	-	0.23%	9.11%	0.7%	11.8%	13.1%
Age 50	0.54%	0.34%	0.39%	0.22%	0.11%	2.1%	0.2%	2.51%	2.73%
Age 51-54	1.76%	1.14%	0.97%	0.9%	0.69%	11.3%	1.13%	12.7%	14.1%
Age 55	6.07%	4.7%	2.64%	2.24%	1.25%	6.4%	1%	6.18%	6.54%
Age 56-59	7.09%	7.34%	7.19%	5.43%	3.37%	**20.5%**	5.34%	**21.2%**	**21.5%**
Age 60	8.71%	9.71%	7.73%	7.13%	4.68%	7.4%	4.91%	7.22%	6.81%
Age 61	1.24%	1.1%	1.53%	1.48%	1.31%	7.51%	5.57%	6.56%	6.37%
Age 62	**30.8%**	**29.9%**	**27.5%**	**27.3%**	**22.6%**	**15.8%**	**49.4%**	**13.5%**	**12.9%**
Age 63-64	3.62%	4.79%	4.66%	5.29%	5.99%	9.63%	16.4%	9.18%	7.84%
Age 65	**19.2%**	**20.4%**	**23.1%**	**23%**	**23.3%**	**5.67%**	**10.6%**	**4.77%**	**4.54%**
Age >65	20.8%	20.3%	24.3%	27%	35.4%	4.54%	4.63%	4.36%	3.45%
Never	17.1%	15.8%	17.1%	14.8%	17.3%	-	-	-	-
# Obs.	3,708	3,256	2,808	2,230	1,753	5,346	3,967	4,902	6,404
% Changing	-	54%	54.2%	52.6%	59.8%	-	-	-	-
# Not Think	3,273	2,366	2,079	1,668	1,398	-	-	-	-

W1 to W5: the expected retirement age reported in the respective rounds of data. In Wave 1 0.19% of the eligible sample reports they expect to retire before the age of 50.
Self-R Ret.: self reported age of actual retirement in the employment section of the survey. 9.11% of the sample reporting that they are retired is under the age of 50 (pooled sample of all waves). Respondents' answers were non-exclusive. This means that someone under 50 could report at the same time that he or she was retired and working, maybe indicating that they retired from their career job, but they could still be labor market participants.
Social Sec.: age at which they started to receive Social Security benefits. 0.7% of the sample reports receiving Social Security benefits before the age of 50. This is likely to reflect misreports regarding benefits other than retirement.
Fully Retired: answer to a direct question regarding when did they fully withdrawn from the labor force. 11.8% of the sample reporting that they are fully retired is under the age of 50. This could include disable individuals.
Full and Partial Retirement: includes those fully retired and those partially retired. This could include disable individuals.
Not Think: Number of individuals by wave reporting not having thought about retirement.
% Changing: Percentage changing their responses among those reporting valid retirement expectations in both waves

Table 3. Tests of Rational Expectations.

Variables	Pooled OLS	IV	Corrected IV
Weak RE Test (H_0: β=1):	***Reject***	***Reject***	***Cannot Reject***
Constant	31.112(1.170)**	20.388(11.655)*	-2.529(2.569)
Expected Retirement Age_t	0.520(0.018)**	0.687(0.183)**	1.050036(0.042123)**
Inverse Mills' Ratio	-	-	-0.293(0.4699)
Test of Over-Id Restrictions	-	Cannot Rej. P-v=.7710	Cannot Rej. P-v=.1830
Test of Weak Instruments	-	Reject P-v=.0000	Reject P-v=.0000
Strong RE Test (H_0: β =1):	***Reject***	***Reject***	***Cannot Reject***
Constant	20.725(1.347)**	10.345(6.655)	11.4678(7.4364)
Expected Retirement Age_t	0.390(0.021)**	0.673(0.170)	0.93978(0.08395)**
Inverse Mills' Ratio	-	-	-4.237(2.049)**
Economic factors at time t			
Net Worth (in $100,000)	0.003(0.016)	0.019(0.019)	0.029(0.018)
Respondent Income (in $1,000)	-0.001(0.001)	-0.001(0.001)	-0.003(0.001)**
No Health Insurance	0.918(0.396)**	0.505(0.584)	0.429(0.665)
Private Health Insurance	0.014(0.191)	-0.066(0.207)	-0.092(0.238)
Self-employed	0.869(0.277)**	0.434(0.323)	-0.082(0.306)
Pension	-0.821(0.182)**	-0.488(0.254)	-1.719(0.650)**
Financially Knowledgeable	0.012(0.169)	-0.066(0.171)	-0.242(0.189)
Health factors at time t			
Health limitation	0.108(0.200)	0.030(0.210)	-0.046(0.236)
Good-Very Good-Exc. Health	-0.364(0.253)	-0.231(0.255)	-0.499(0.306)
Doctor visits	-0.004(0.010)	0.001(0.010)	0.006(0.011)
High blood pressure	-0.115(0.178)	-0.106(0.189)	-0.190(0.222)
Diabetes problems	-0.497(0.291)*	-0.518(0.318)	-0.380(0.368)
Cancer	-1.552(0.533)**	-1.108(0.652)*	-0.562(0.770)
Stroke	-0.944(0.612)	-0.115(0.726)	0.609(0.766)
Heart Problems	0.002(0.291)	0.049(0.333)	0.082(0.384)
Arthritis	0.000(0.171)	0.021(0.184)	-0.029(0.211)
Difficulty walking multiple blocks	-0.477(0.287)*	-0.370(0.316)	-0.447(0.372)
Difficulty climbing stairs	0.282(0.375)	0.356(0.383)	0.259(0.431)
Demographic factors at time t			
Age	0.340(0.022)**	0.200(0.078)**	-
White	0.013(0.182)	-0.093(0.198)	-0.134(0.210)
Male	0.526(0.161)**	0.511(0.169)**	0.172(0.232)
Bachelor's Degree	0.425(0.195)**	0.376(0.189)**	0.305(0.203)
Professional Degree	-0.560(0.241)**	-0.466(0.224)**	-0.829(0.348)**
Married	-0.306(0.192)	-0.159(0.221)	-0.076(0.231)
Wave 1-2	0.1625(0.1701)	-0.0016(0.196)	-0.263(0.208)
Wave 2-3	0.1912(0.1866)	0.182(0.200)	-0.209(0.284)
Adj. R^2	0.328	-	-
Test of joint Significance of Covariates	Reject. P-v=.000	Reject P-v=.008	Cannot Rej. P-v=.0775
Test of Over-Id Restrictions	-	Cannot Rej. P-v=.5773	Cannot Rej. P-v=.5338
Test of Weak Instruments	-	Reject P-v=.0000	Reject P-v=.0000
Number of Observations	4,987	4,721	4,634

Table 4. New Information and Retirement Expectations.

Variables	Pooled OLS	IV	Corrected IV
Expected Retirement Age$_t$	0.5074(0.020)**	1.011(0.066)**	1.077(0.0443)**
Inverse Mills' Ratio	-	-	-0.0657(0.557)
Constant	31.66(1.271)**	-0.487(4.18)	-4.629(2.655)*
Economic Factors			
Changes in Net Worth (in $100K)	-0.0099(0.016)	-0.0001(0.017)	-0.0009(0.017)
Changes in Earnings (in $1,000)	-0.0003(0.0006)	-0.0001(0.0007)	-0.00006(0.0007)
Changes in Priv. Health Insurance	0.192(0.183)	0.531(0.211)**	0.557(0.219)**
Changes in No Insurance Status	-0.498(0.429)	-0.532(0.518)	-0.464(0.552)
Changes in Pension	0.0035(0.324)	0.116(0.402)	0.109(0.421)
New Job Transition	1.541(.264)**	1.234(0.315)**	1.171(0.359)**
Health Factors			
Health limitation transitions[20]	-0.202(0.191)	-0.222(0.228)	-0.247(0.238)
Good-V.Gd-Exc.Hlt. transitions[21]	0.417(0.249)*	0.051(0.308)	0.0101(0.318)
Stroke transitions[22]	-0.679(0.867)	-1.315(0.979)	-1.532(1.015)
Heart problems transitions	0.112(0.294)	0.084(0.355)	0.036(0.377)
Cancer transitions	1.140(0.660)*	0.512(0.743)	0.487(0.787)
Diabetes transitions	0.983(0.358)**	0.764(0.444)*	0.719(0.476)
High blood pressure transitions	0.227(0.174)	0.361(0.212)*	0.378(0.22)*
Arthritis transitions	-0.129(0.151)	-0.089(0.185)	-0.087(0.193)
Doctor visits	-0.0005(0.009)	-0.009(0.011)	-0.011(0.012)
Difficulty climbing stairs	0.322(0.325)	0.119(0.396)	0.107(0.406)
Difficulty walking multiple blocks	-0.06180.308)	-0.4841(0.366)	-0.493(0.383)
Demographic Factors			
Marriage transitions[23]	-0.3937(1.021)	-0.7257(1.123)	-1.438(1.127)
Adj. R^2	0.2633	-	-
Test of Over-Id Restrictions	-	Cannot Rej. P-v=.293	Cannot Rej. P-v=.3368
Test of Weak Instruments	-	Reject P-v=.0000	Reject P-v=.0000
Number of Observations	4,755	4,422	4,340

[20] =1 if new limitation, 0 if no change, and -1 if you got better

[21] positive means health improved

[22] positive means condition (Stroke, high blood pressure) worsened or newly diagnosed (0 no change, -1 if better)

[23] =1 means new marriage, = 0 no change, =-1 dissolved marriage (widow, divorced)

Appendix.

Table A.1. Selection Equation Results - Probability of Thinking about Retirement

Variables	Probit	Marg. Effects	RE Probit	Marginal Effects
Economic Factors				
Net wealth (in $100,000)	0.001(0.002)	0.001	0.003(0.002)	0.001
Income (in $1,000)	0.002(0.000)**	0.001	0.002(0.000)**	0.001
No Health Insurance	-0.21(0.034)**	-0.082	-0.229(0.039)**	-0.089
Private Health Insurance	-0.028(0.023)	-0.011	-0.026(0.026)	-.010
Self-Employed	-0.024(0.028)	-0.010	-0.026(0.032)	-0.010
Pension	0.233(0.022)**	0.092	0.262(0.025)**	0.103
Financially Knowledgeable	-0.004(0.023)	-0.002	0.000(0.026)	0.000
Health Factors				
Health limitation	-0.002(0.025)	-0.001	-0.014(0.028)	-0.006
Good-V.Good-Exc. Health	0.033(0.028)	0.013	0.024(0.031)	0.009
Doctor visits	0.001(0.001)	0.000	0.001(0.001)	0.000
Probability of living to 85	-0.004(0.030)	-0.001	0.020(0.034)	0.008
Diff. walking multiple blocks	-0.005(0.036)	-0.002	-0.005(0.041)	-0.002
Diff. climbing stairs	0.104(0.044)	0.041	0.148(0.050)**	0.059
High blood pressure	0.010(0.023)	0.004	0.015(0.026)	0.006
Diabetes	0.006(0.039)	0.002	0.017(0.044)	0.007
Cancer	0.131(0.102)	0.052	0.149(0.113)	0.059
Stroke	-0.128(0.156)	-0.050	-0.192(0.185)	-0.075
Heart problems	-0.007(0.036)	-0.003	-0.014(0.040)	-0.005
Arthritis	0.044(0.022)	0.018	0.033(0.024)	0.013
Demographic Factors				
Age	0.248(0.026)**	0.099	0.296(0.029)**	0.117
Age squared	-0.002(0.000)**	-0.001	-0.002(0.000)**	-0.001
Male	0.121(0.023)**	0.048	0.134(0.026)**	0.053
White	-0.040(0.025)	-0.016	-0.034(0.029)	-0.014
Bachelor's degree	-0.007(0.028)	-0.003	-0.003(0.032)	-0.001
Professional degree	0.121(0.041)**	0.048	0.143(0.046)**	0.057
Married	0.056(0.027)**	0.022	0.065(0.030)**	0.026
Mother reached retirement age	0.016(0.022)	0.006	0.022(0.026)	0.009
Father reached retirement age	0.001(0.020)	0.000	0.004(0.023)	0.002
Wave 1	-0.012(0.025)	-0.005	-0.0184(0.0282)	-0.0073
Wave 2	0.1007(0.0026)**	0.040	0.108(0.0295)**	0.0432
Wave 3	0.0855(0.0238)**	0.0340	0.0937(0.027)**	0.0372
Constant	-7.796(0.7489)**	-	-9.315(0.822)**	-
Predicted Probability	0.46611		0.4586	
Log Likelihood	-16048.77		-15689.41	
Pseudo-R^2	0.0266		0.0215	
Number of Observations	23,860		23,860	

Table A.2. First Stage Results for Weak RE Test using IV.

Variables	1st Stage of IV	1st Stage of Corrected IV
Weak RE Test:		
Constant	63.186(0.156)**	111.013(4.217)**
Prob. Of Living to 85	1.120(0.275)**	3.571(0.337)**
Smoking	0.610(0.208)**	2.479(0.284)**
Inverse Mills' Ratio	-	-31.512(2.789)**
Economic factors at time t		
Net Worth (in $100,000)	-	0.010(0.015)
Respondent Income (in $1,000)	-	-0.019(0.002)**
No Health Insurance	-	6.578(0.562)**
Private Health Insurance	-	1.233(0.227)**
Self-employed	-	0.778(0.284)**
Pension	-	-9.953(0.783)**
Financially Knowledgeable	-	-0.114(0.200)
Health factors at time t		
Health limitation	-	0.346(0.237)
Good-V.Good-Exc. Health	-	-2.004(0.327)**
Doctor visits	-	-0.018(0.013)
High blood pressure	-	-0.337(0.229)
Diabetes	-	1.295(0.404)**
Cancer	-	0.287(1.014)
Stroke	-	-4.506(1.861)**
Heart Problems	-	0.266(0.350)
Arthritis	-	-0.880(0.222)**
Difficulty walking multiple blocks	-	-1.169(0.373)**
Difficulty climbing stairs	-	-0.407(0.473)
Demographic factors at time t		
White	-	0.828(0.215)**
Male	-	-1.500(0.315)**
Bachelor's Degree	-	-0.120(0.223)
Professional Degree	-	-3.856(0.436)**
Married	-	-1.305(0.234)**
Wave 1-2	-	0.419(0.223)*
Wave 2-3	-	-2.279(0.280)**
Adj. R^2	0.004	0.098
Test of Weak Instruments	F(2,5021)=12.01	F(27, 4605)=17.80
Number of Observations	5,024	4,634

Table A.3. First Stage Results for Strong RE Test using IV.

Variables	1st Stage of IV	1st Stage of Corrected IV
Strong RE Test:		
Constant	37.959(1.236)**	111.013(4.217)**
Prob. of living to 85	1.191(0.268)**	3.571(0.337)**
Smoking	0.754(0.202)**	2.479(0.284)**
Inverse Mills' Ratio	-	-31.512(2.789)**
Economic factors at time t		
Net Worth (in $100,000)	-0.050(0.017)**	0.010(0.015)
Respondent Income (in $1,000)	0.000(0.001)	-0.019(0.002)**
No Health Insurance	2.096(0.365)**	6.578(0.562)**
Private Health Insurance	0.340(0.209)	1.233(0.227)**
Self-employed	1.117(0.269)**	0.778(0.284)**
Pension	-1.048(0.201)**	-9.953(0.783)**
Financially Knowledgeable	0.434(0.184)**	-0.114(0.200)
Health factors at time t		
Health limitation	0.212(0.225)	0.346(0.237)
Good-V.Good-Exc. Health	-0.018(0.271)	-2.004(0.327)**
Doctor visits	-0.007(0.012)	-0.018(0.013)
High blood pressure	0.133(0.207)	-0.337(0.229)
Diabetes	0.082(0.374)	1.295(0.404)**
Cancer	-1.252(0.958)	0.287(1.014)
Stroke	-2.638(1.690)	-4.506(1.861)**
Heart Problems	-0.033(0.331)	0.266(0.350)
Arthritis	-0.238(0.193)	-0.880(0.222)**
Difficulty walking multiple blocks	-0.167(0.340)	-1.169(0.373)**
Difficulty climbing stairs	-0.065(0.448)	-0.407(0.473)
Demographic factors at time t		
Age	0.445(0.020)**	-
White	0.481(0.205)**	0.828(0.215)**
Male	0.369(0.179)**	-1.500(0.315)**
Bachelor's Degree	0.018(0.212)	-0.120(0.223)
Professional Degree	-0.071(0.283)	-3.856(0.436)**
Married	-0.669(0.225)**	-1.305(0.234)**
Wave 1-2	0.5591(0.198)**	0.419(0.223)*
Wave 2-3	0.1462(0.2107)	-2.279(0.280)**
Adj. R^2	0.161	0.098
Test of Weak Instruments	F(2,4692)=16.01	F(2, 4605)=68.10
Number of Observations	4,721	4,634