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 using two different panel data sets that represent two very different populations. In both cases we cannot reject the RE hypothesis. Our results support a wide variety of models in economics, and other disciplines, that assume rational behavior.

Keywords: Rational Expectations, Household Surveys, Retirement and Education Expectations, Instrumental Variables, Sample Selection.

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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 and 1997, and Das and van Soest 1997 and 2000), fertility expectations and pregnancy outcomes (Van Hoorn and Keilman 1997, Van Peer 2000, and Walker 2003), the connection between Social Security expectations and retirement savings (Lusardi 1999, Dominitz, Manski, and Heinz 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, and Mastrogiacomo 2003), and consumption patterns after retirement (Haider and Stephens 2003, and 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) and the youth cohort of the National Longitudinal Survey of Labor Market Experience (NLSY79) to analyze retirement and education expectations, respectively. We find that these two 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. 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).[1] 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 part under their control. Economists and social scientists in general are growing increasingly interested in this type of measures as possible sources of additional variation in individual characteristics that might reflect underlying differences in preference and beliefs parameters.

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), and Lovell (1986) considered the direct analysis of expectations an important project. More recently, Manski (2004) has emphasized the importance of analyzing expectations formation, but in Manski (1990) he advocated the careful use of any kind of intentions data, especially if to be used to predict behavior.

[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).

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 Watchtel (1981, 1983), Kimball Dietrich and Joines (1983), de Leeuw and McKelvey (1981 and 1984), Gramlich (1983), Kinal and Lahiri (1988), and Keane and Runkle (1990), and more recently, Lee (1996), Davies and Lahiri (1999), and Christiansen (2003).[2] 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 Benítez-Silva and Dwyer (2004), and use panel data available through the HRS and the NLSY79 to follow two very different cohorts of individuals planning an important decision for people their age, retirement and education.

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, and 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

[2] Pesando (1976) tests the RE hypothesis using cash flow forecasts of life insurance companies, he finds weak evidence in

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]

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).[4]

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

2. A Model and a Test of Rational Expectations using Micro Data

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

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

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favor of the hypothesis.

[3] 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.

The sequence of vector-valued variables inside the parenthesis will be observed by the individual at time periods *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 can define

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

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).[5] 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 might include socio-economic and demographic characteristics. Using the law of iterated expectations and assuming that the new information is correctly forecasted by agents (its conditional distribution not just its mean), from (2) we get:

$$E\langle X_{t+1}^e \,|\, \Omega_t \rangle = E[E\langle X \,|\, \Omega_t, \omega_{t+1} \rangle \,|\, \Omega_t] = E\langle X \,|\, \Omega_t \rangle = X_t^e, \qquad (3)$$

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

$$X_{t+1}^e = X_t^e + \eta_{t+1}, \qquad (4)$$

[4] "*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)

[5] 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 $\eta_{t+1} = X^e_{t+1} - E[X^e_{t+1} \mid \Omega_t]$, 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 we can test the RE hypothesis with the following regression:

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

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 $\alpha=\gamma=0$, 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 $\gamma=0$.

Notice, that a value of α different from zero can be consistent with the rational expectations hypothesis in an analysis using a relatively short panel in the presence of a macro shock, common to all agents and difficult to control for. The fact that our study only uses short panels to average out these possible macro shocks for a given individual, works in the direction of over-rejecting the RE hypothesis, compared with a situation where we would have a very long panel that would allow to average these possible macro shocks over time. Therefore, if we find that we cannot reject the RE hypothesis, it must mean that this is not a major concern in the empirical analysis.

Econometric Specifications

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

[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.

As with all survey data, measurement error in proxy variables is a concern. We are particularly concerned with noisy self-reports of the expectation variables. We are concerned about 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 self-reports can bias the coefficient 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 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.

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 even completed education is reported with error (Black, Sanders, and Taylor 2003). We correct for this problem using instrumental variables analysis. The instruments

[7] 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.

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, and the educational attainment of the parents as instruments (exclusion restrictions) for expected years of education.

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, and from (5) we write

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

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

$$Y_i = 1(\alpha_3 + \gamma_3 Z_{t,3i} + \varepsilon_{3i} > 0), \tag{8}$$

where we first estimate the selection equation (8) 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, in both periods, a question about her future retirement or future educational attainment. This procedure allows for arbitrary correlation between the disturbances in the three equations.

Z_3 in equation (8) includes all the exogenous variables and any exclusion restriction of the selection equation with respect to the structural equation. The exclusion restrictions in the selection equation include indicators for whether the father and mother of the respondent reached retirement age, and the age of the respondent, in the HRS. In the case of the NLSY79 the selection model is identified solely on the non-linearity of the Inverse Mills' ratio.

Notice that in the HRS 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 like age, which in our sample 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. In section 4 we discuss the consequences of relaxing this assumption.

In the selection equation 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.

We then consistently estimate (6) by performing a modified 2SLS procedure, where the first stage includes as regressors the exogenous variables used in (8), 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 (7), the validity of which will be tested.[8]

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.

3. The HRS and the NLSY79

To test the RE hypothesis on the retirement expectations of older Americans we use the first five waves of the HRS, a nationally representative longitudinal survey of 7,700 households headed by an individual aged 51 to 61 as of the first interviews in 1992-93. The fifth round of interviews was in the field during 2000. 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. 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. 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. We have assigned an age of 77 for those who never retire, as a proxy for estimated longevity.

Table 1a presents summary statistics for the full HRS sample we use. Since we restrict attention to individuals that have not retired the average age is just above 57 years, most of them are employed for someone else, with around 17% reporting themselves as self-employed. Most of these individuals

[8] Notice that the variables in Z_2 are part of the information set Ω^1 we characterized in equation (5), but they only enter in the structural equation through their effect on the expectations as of time t. They are in this sense exclusion restrictions

are in fairly good health, are married, have some kind of health insurance coverage, and almost 40% of them either have a Bachelor's degree or a higher degree.

Table 1b breaks down the sample of Table 1a according to the selection criteria; whether or not individuals report thinking about retirement. Around 47% of the sample gave retirement some thought. Those who have not thought about retirement are less likely to be employed during the panel, and are financially worse off. They are also more likely to receive government health insurance. They are also more likely to be female and less educated, and their parents are less likely to have reached retirement age.

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 to 2000, who were 14 to 21 years of age as of 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 2,395 respondents.

Table 2a presents summary statistics for the sample of 2,395 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. Table 2b, 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

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that allow us to identify the parameters of the main equation (6).

females, their parents completed less years of education, and are more likely to be white. Contrary to the case of the HRS, 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

Table 3 presents the weak and strong RE tests for the sample from the HRS, and Table 4 presents the tests for the NLSY79 sample.[9] The HRS data support the weak and strong RE hypotheses in the augmented model that corrects for sample selection and measurement error in the report of expected retirement age, and the NLSY79 supports the RE hypotheses in expected educational attainment both in the IV and the corrected IV specifications. For the HRS all these 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 $\beta=1$ in equation (4), to test the weak RE hypothesis. We obtain coefficients for β of 1.05 for the weaker test using the retirement expectations data, and 0.981 using the education expectations data, which cannot reject the hypothesis that both expectations follow a random walk, even though both coefficients are fairly precisely estimated. 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, Nauges, and Windmeijer (2002), we 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 RE test we estimate the model of equations (6) to (8) using the corrected IV procedure. Also we estimate equation (6) by pooled OLS, equations (6) and (8) by the traditional selection correction à la Heckman (1979), and equations (6) and (7) by IV. In the corrected IV procedure the β parameter is estimated to be equal to 0.94 in the HRS and 0.991 in the NLSY79, in both cases very precisely estimated, and clearly failing to reject the RE hypothesis. Notice the importance in the HRS of both instrumenting the previous period's expectations, and controlling for sample selection. Interestingly, in the HRS, 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.[10]

One source of potential unobserved heterogeneity is correlated responses due to macroeconomic shocks. In a micro survey, this may pose a problem given the short panels we are working with since in the presence of these shocks we would tend to over-reject the RE hypothesis compared with a specification where we could control for these shocks. However, this is a problem one can deal with to pursue the test of the Rational Expectations Hypothesis. To control for this in the retirement model, we include a time trend in our specifications, and we have also performed sensitivity analysis by including unemployment rates over time. Given that for the retirement model we are using micro survey data that spans only an eight year period from 1992-2000, 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 do not change with the different characterization of these macroeconomic controls

[9] 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.
[10] Notice that in columns three and four of Tables 3 and 4, we do not report the adjusted R^2 measure of fit. This is common practice, but it is rarely mentioned in empirical work. These types of measures do not have independent significance in structural estimation à la IV, given that we are after estimating population parameters, which we consider invariant to the particular way of identifying the parameters (instruments), not after minimizing a particular prediction problem. See Ruud (2000, p. 515-516 for a discussion)

It is natural at this time 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 traditional IV estimator to the corrected IV estimator. In the NLSY79 the case is less controversial since traditional IV estimation, without correcting for sample selection, already delivers the main result, that is, that we cannot reject the RE hypothesis. For this sample it comes down to whether we trust the exclusion restrictions we have made regarding the fact that the education of the mother and the father affect educational attainment at time t but are not correlated with the disturbances in equation (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, 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 very large F statistics in the first stage of the IV procedure, several times larger 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 (see Tables A.5. and A.6. in the Appendix). 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.

In the HRS the corrected IV estimator is clearly higher than the traditional IV estimator and almost twice as large as the estimates from OLS and selection corrected procedures. The mechanism behind this result is in part due to the inclusion of age, along with other variables as explained in section 2, as an exclusion restriction of the selection equation. If age is not included as a regressor of the selection equation (8), then the corrected IV procedure delivers an estimate of β essentially identical to that of the traditional IV procedure, which depending on the specification almost always rejects the RE hypothesis. Again, we believe that the inclusion of age in the selection equation is uncontroversial. Whether we should also include it when jointly estimating equations (6) and (7) is less clear. Wooldridge (2002) suggests that unless there is a clear reason for not including all the exogenous variables of the selection equation as additional instruments when estimating the corrected IV model, these should be included. In Section 2 we have provided two justifications for why we do not include age when estimating equations (6) and (7). However, as a sensitivity analysis we have included it. When we do, the point estimate of the β parameter goes up to 1.08, with a standard error a bit lower than the one reported in Table 3, but even in this case we are not able to reject that the coefficient is equal to 1 at the 5% significance level.

It is important given the impact on our conclusions for the retirement model, to clarify the reason why we believe that the disturbances in equation (8), the selection equation, could be correlated with the disturbances in and (6) and (7).[11] 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 (8). 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

[11] We thank an anonymous referee for pointing out that the selection at time t should not be expected to create large biases in our estimations since it should be included in the information set as of that period. Therefore, most of the possible biases that our selection correction strategies will take care of are connected with answering or not the expectations questions in $t+1$. In the estimation of the structural equation, however, we should only include observations for which we have both the expectations as of time $t+1$ and as of time t, and then perform the appropriate selection correction. This means that the construction of the Inverse Mills ratio might have included what could be considered as redundant information. A variety of robustness checks indicate that the procedure we present in this paper, as discussed in Wooldridge (2002, p. 567-570), consistently estimate the parameters of our structural model.

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.

In the HRS, as with the NLSY79, when testing the exclusion restrictions of the IV procedures we could soundly reject the hypothesis that we had weak instruments (see Tables A.2. and A.3. in the Appendix), and the validity of the overidentifying restrictions could not be rejected at any traditional level of significance.[12]

It is important to mention that the importance of the selection correction when using the HRS contrasts with the results by Bernheim (1990) where selection was not important, and the inability to reject rationality was in part the product of large standard errors. In the NSLY79 although we cannot reject the presence of sample selection in the weak test, the RE results do not depend on this additional correction. The reported results are the product of robustly estimating the system of equations via GMM, which provides robustness against unknown forms of heterokedasticity. In the implementation of this procedure we have followed the practical suggestions in Baum, Schaffer, and Stillman (2003).

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 both data sets 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 any traditional level of significance, and the same is true of the estimates of the

[12] We have 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 respectively, the standard errors increased by around 50%. In both cases we were able to reject the hypothesis that we had a weak instrument.

constant, validating the other predictions of the RE hypothesis regarding retirement and education expectations.[13]

Finally, Tables A.1., to A.6., in the Appendix, provide the results of the estimation of the selection equation, and the first stage estimation of the traditional IV and the corrected IV estimators for the weak and strong RE test, both for the HRS sample and the NLSY79 sample.

5. Conclusions

We have tested the Rational Expectations hypothesis in the formation of expectations for retirement and educational attainment, using representative samples of older and younger Americans, respectively. In both samples we cannot reject the RE hypothesis after controlling for reporting errors and 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.

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.

[13] It is true, however, that this is trivially the case if individuals never adjust their expectations. But plenty of adjustment goes on in the data, and it seems implausible that all can be blamed on measurement error.

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Table 1a. Summary Statistics. HRS.

Variables	Full Sample N=23,669
Retirement Plans and Outcomes	
Expected retirement age	64.584(6.478)
Employee	0.794(0.405)
Self employed	0.173(0.378)
Financially Knowledgeable	0.657(0.475)
Economic factors	
Net worth (in $100,000)	2.449(5.181)
Housing wealth (in $100,000)	0.769(1.248)
Respondent' Income (in $1,000)	29.213(54.304)
Has a private pension	0.593(0.491)
Health Insurance	
Employer provided	0.699(0.459)
Retiree	0.814(0.389)
Government	0.082(0.274)
Private	0.188(0.391)
No health insurance	0.087(0.282)
Health factors	
Health limitation	0.187(0.390)
Good-Very Good-Excellent Health	0.866(0.340)
Doctor visits	5.191(7.075)
Probability of living to age 85	0.470(0.306)
High blood pressure	0.228(0.419)
Diabetes	0.060(0.238)
Arthritis	0.283(0.450)
Difficulty walking multiple blocks	0.082(0.275)
Difficulty climbing stairs	0.047(0.212)
Stroke	0.003(0.052)
Heart problems	0.075(0.263)
Cancer	0.007(0.083)
Smoke	0.219(0.414)
Demographic factors	
Age	57.197(5.222)
Male	0.465(0.499)
Married	0.794(0.405)
Bachelor's degree	0.270(0.444)
Professional degree	0.101(0.301)
Mother reached retirement age	0.714(0.452)
Father reached retirement age	0.596(0.491)

Table 1b. Summary Statistics by Sample Selection. HRS.

Variables	Thought About N=11,062	Not Thought N= 12,607
Retirement Plans and Outcomes		
Expected retirement age	64.584(6.478)	-
Employee	0.840(0.367)	0.753(0.431)
Self employed	0.160(0.367)	0.185(0.388)
Financially Knowledgeable	0.670(0.470)	0.647(0.478)
Economic factors		
Net worth (in $100,000)	2.612(5.484)	2.305(4.895)
Housing wealth (in $100,000)	0.798(1.278)	0.744(1.221)
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)
Health Insurance		
Employer Provided	0.748(0.434)	0.652(0.476)
Retiree	0.804(0.397)	0.823(0.382)
Government	0.065(0.247)	0.095(0.294)
Private	0.184(0.388)	0.191(0.393)
No health insurance	0.063(0.244)	0.107(0.309)
Health factors		
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)
High blood pressure	0.233(0.423)	0.223(0.416)
Diabetes	0.061(0.239)	0.060(0.238)
Arthritis	0.285(0.452)	0.280(0.449)
Difficulty walking multiple blocks	0.081(0.272)	0.083(0.277)
Difficulty climbing stairs	0.048(0.213)	0.047(0.211)
Stroke	0.003(0.051)	0.003(0.053)
Heart Problems	0.077(0.266)	0.074(0.261)
Cancer	0.008(0.087)	0.006(0.079)
Smoke	0.202(0.402)	0.234(0.423)
Demographic factors		
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)
Professional degree	0.119(0.323)	0.085(0.280)
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 2a. Summary Statistics NLSY79

Variables	Full Sample. N=2,395
Education Plans and Outcomes	
Highest Grade Expected to Complete	13.692(2.245)
Highest Grade Completed	9.888(0.878)
Economics Factors	
Avg. Family Income (1981 in $1,000)	18.324(15.877)
Demographic Factors	
Male	0.521(0.500)
Black	0.265(0.441)
Hispanic	0.179(0.384)
Number of Siblings	3.605(2.518)
Years of Labor Market Experience	0.492(0.678)
Mother's Education	10.865(2.960)
Father's Education	10.837(3.642)
Northeastern Residence	0.188(0.391)
North-Central Residence	0.247(0.431)
Southern Residence	0.362(0.481)
Rural Residence	0.231(0.421)
Local Unemployment Rate (Metropolitan Area, or State if M.A. not available)	3.248(0.965)

Table 2b. Summary Statistics by Sample Selection NLSY79

Variables	Thought About N=2,316	Not Thought N=79
Education Plans and Outcomes		
Highest Grade Expected to Complete	13.692(2.245)	-
Highest Grade Completed	9.918(0.856)	9.013(1.044)
Economics Factors		
Avg. Family Income (1981 in $1,000)	18.420(15.959)	15.491(13.034)
Demographic Factors		
Male	0.522(0.500)	0.468(0.502)
Black	0.268(0.443)	0.190(0.395)
Hispanic	0.177(0.382)	0.228(0.422)
Number of Siblings	3.611(2.521)	3.418(2.442)
Years of Labor Market Experience	0.476(0.680)	0.342(0.597)
Mother's Education	10.886(2.937)	10.266(3.533)
Father's Education	10.848(3.635)	10.494(3.846)
Northeastern Residence	0.187(0.390)	0.203(0.404)
North-Central Residence	0.252(0.434)	0.089(0.286)
Southern Residence	0.387(0.483)	0.114(0.320)
Rural Residence	0.236(0.425)	0.076(0.267)
Local Unemployment Rate (Metropolitan Area, or State if M.A. is not available)	3.258(0.967)	2.962(0.854)

Table 3. Tests of Rational Expectations- Health and Retirement Study

Variables	Pooled-OLS	Selection	IV	Corrected IV
Weak RE Test (H_0: β=1):	***Reject***	***Reject***	***Reject***	***Cannot Reject***
Constant	31.11(1.170)**	30.5(0.93)**	20.388(11.655)*	-2.529(2.569)
Expected Retirement Age_t	0.520(0.018)**	0.499(0.013)**	0.687(0.183)**	1.051(0.042123)**
Inverse Mills' Ratio	-	1.5(0.424)**	-	-0.293(0.4699)
Test of Over-Id Restrictions	-	-	Cannot Rej. P-v=.77	Cannot Rej. P-v=.18
Test of Weak Instruments	-	-	Reject P-v=.000	Reject P-v=.000
Strong RE Test (H_0: β=1):	***Reject***	***Reject***	***Reject***	***Cannot Reject***
Constant	35.81(1.313)**	49.44(3.720)**	22.10(11.13)**	11.4678(7.4364)
Expected Retirement Age_t	0.465(0.019)**	0.454(0.013)**	0.671(0.172)**	0.9398(0.08395)**
Inverse Mills' Ratio	-	-8.49(2.261)**	-	-4.237(2.049)**
Economic factors at time t				
Net Worth (in $100,000)	0.018(0.015)	0.024(0.019)	0.021(0.016)	0.029(0.018)
Respondent Income (in $1,000)	-0.001(0.001)*	-0.01(0.002)**	-0.001(0.001)	-0.003(0.001)**
No Health Insurance	0.495(0.403)	2.046(0.549)**	0.326(0.576)	0.429(0.665)
Private Health Insurance	0.135(0.198)	0.259(0.268)	-0.02(0.220)	-0.092(0.238)
Self-employed	0.720(0.282)**	0.438(0.329)	0.362(0.343)	-0.082(0.306)
Pension	-1.27(0.200)**	-3.58(0.662)**	-0.93(0.313)**	-1.719(0.650)**
Financially Knowledgeable	0.047(0.176)	-0.11(0.236)	-0.02(0.180)	-0.242(0.189)
Health factors at time t				
Health limitation	0.005(0.208)	-0.02(0.284)	-0.03(0.212)	-0.046(0.236)
Good-V.Good-Exc. Health	-0.49(0.262)*	-0.75(0.356)**	-0.25(0.259)	-0.499(0.306)
Doctor visits	-0.003(0.010)	-0.003(0.015)	0.001(0.010)	0.006(0.011)
High blood pressure	0.126(0.188)	-0.12(0.271)	0.043(0.205)	-0.190(0.222)
Diabetes problems	-0.38(0.312)	-0.22(0.469)	-0.43(0.327)	-0.380(0.368)
Cancer	-0.96(0.605)	-0.72(1.196)	-0.80(0.649)	-0.562(0.770)
Stroke	-0.80(0.718)	-1.10(2.271)	-0.16(0.803)	0.609(0.766)
Heart Problems	0.135(0.311)	0.089(0.422)	0.123(0.342)	0.082(0.384)
Arthritis	0.227(0.180)	-0.10(0.255)	0.190(0.180)	-0.029(0.211)
Diff. walking multiple blocks	-0.41(0.300)	-0.56(0.435)	-0.283(0.318)	-0.447(0.372)
Difficulty climbing stairs	0.328(0.377)	0.248(0.564)	0.363(0.385)	0.259(0.431)
Demographic factors at time t				
White	0.143(0.188)	0.234(0.256)	0.083(0.231)	-0.134(0.210)
Male	1.163(0.168)**	0.437(0.303)	0.926(0.280)**	0.172(0.232)
Bachelor's Degree	0.473(0.201)**	0.288(0.267)	0.416(0.192)**	0.305(0.203)
Professional Degree	-0.61(0.251)**	-1.48(0.455)**	-0.50(0.234)**	-0.829(0.348)**
Married	-0.70(0.197)**	-0.82(0.280)**	-.467(0.311)	-0.076(0.231)
Wave 1-2	-0.81(0.174)**	-0.45(0.253)*	-0.56(0.219)**	-0.263(0.208)
Wave 2-3	-0.21(0.190)	-0.69(0.306)**	-0.02(0.217)	-0.209(0.284)
Adj. R^2	0.2845	0.2828	-	-
Test of Joint Sig. Covariates	Reject. P-v=.00	Reject P-v=.00	Reject P-v=.016	Cannot Rej. P-v=.077
Test of Over-Id Restrictions	-	-	Cannot Rej. P-v=.52	Cannot Rej. P-v=.533
Test of Weak Instruments	-	-	Reject P-v=.000	Reject P-v=.000
Number of Observations	4,993	4,634	4,724	4,634

Table 4. Tests of Rational Expectations- NSLY79

Variables	OLS	Selection	IV	Corrected IV
Weak RE Test (H_0: β=1):	***Reject***	***Reject***	***Cannot Reject***	***Cannot Reject***
Constant	3.688(0.199)**	4.075(0.207)**	0.366(0.528)	0.415(0.409)
Expected Education Level$_t$	0.739(0.014)**	0.721(0.145)**	0.981(0.038)**	0.982(0.029)**
Inverse Mills' Ratio	-	-2.422(0.395)**	-	-0.996(0.501)**
Test Over-Id Restrictions	-	-	Can't Rej. Pv=.795	Can't Rej. Pv=.523
Test of Weak Instruments	-	-	Reject P-v=.0000	Reject P-v=.0000
Strong RE Test (H_0: β=1):	***Reject***	***Reject***	***Cannot Reject***	***Cannot Reject***
Constant	3.206(1.119)**	3.673(1.200)**	-0.882(1.534)	-0.856(1.678)
Expected Education Level$_t$	0.662(0.016)**	0.661(0.016)**	0.991(0.067)**	0.991(0.067)**
Inverse Mills' Ratio	-	-0.728(0.680)	-	-0.056(0.825)
Economic Factors at time t				
Avg. Family Income ($1,000)	0.007(0.002)**	0.007(0.002)**	0.001(0.002)	0.001(0.002)
Demographic Factors at t				
Age	-0.170(0.071)**	-0.163(0.071)**	0.001(0.089)	0.001(0.088)
Male	0.004(0.064)	-0.007(0.064)	0.002(0.070)	0.001(0.072)
Black	0.272(0.084)**	0.257(0.085)**	0.177(0.093)*	0.175(0.093)*
Hispanic	0.093(0.095)	0.063(0.099)	0.074(0.109)	0.071(0.112)
Number of Siblings	-0.021(0.013)	-0.024(0.014)	0.009(0.017)	0.009(0.017)
Highest Grade Completed	0.407(0.044)**	0.367(0.058)**	0.069(0.086)	0.065(0.091)
Labor Market Experience	4E-04(0.049)	-0.012(0.050)	0.004(0.054)	-0.006(0.054)
Northeastern Residence	0.162(0.106)	0.105(0.118)	0.136(0.122)	0.130(0.132)
North-Central Residence	0.098(0.103)	0.013(0.129)	0.067(0.112)	0.059(0.140)
Southern Residence	0.139(0.099)	0.042(0.134)	0.122(0.116)	0.114(0.151)
Rural Residence	-0.049(0.082)	-0.071(0.084)	0.130(0.093)	0.129(0.097)
Local Unemployment Rate	0.023(0.035)	0.013(0.036)	0.057(0.038)	0.056(0.040)
Adj. R^2	0.556	0.558	-	-
Test of Joint Sig. Covariates	Reject. P-v=0.00	Reject. P-v=0.000	Can't Rej. Pv=.386	Can't Rej. Pv=.698
Test of Over-Id Restrictions	-	-	Can't Rej. Pv=.478	Can't Rej. Pv=.471
Test of Weak Instruments	-	-	Reject P-v=.0000	Reject P-v=.0000
Number of Observations	2,316	2316	2,316	2,316

Appendix

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

Variables	Probit	Marginal Effects
Economic Factors		
Net wealth (in $100,000)	-0.001(0.002)	-0.000
Income (in $1,000)	0.001(0.000)**	0.000
No Health Insurance	-0.18(0.047)**	-0.055
Private Health Insurance	-0.03(0.030)	-0.010
Self-Employed	-0.01(0.040)	-0.000
Pension	0.353(0.030)**	0.111
Financially Knowledgeable	0.023(0.031)	-0.007
Health Factors		
Health limitation	-0.001(0.040)	-0.003
Good-V.Good-Exc. Health	0.077(0.036)**	0.024
Doctor visits	0.000(0.001)	0.000
Probability of living to 85	-0.102(0.041)**	-0.033
Diff. walking multiple blocks	0.049(0.048)	0.016
Diff. climbing stairs	0.24(0.063)	0.008
High blood pressure	0.033(0.031)	0.011
Diabetes	-0.042(0.055)	-0.013
Cancer	-0.036(0.125)	-0.011
Stroke	0.056(0.251)	0.018
Heart problems	-0.010(0.049)	-0.003
Arthritis	0.040(0.028)	0.013
Smoking	-0.085(0.032)**	-0.027
Demographic Factors		
Age	0.0047(0.003)	0.002
Male	0.105(0.307)**	0.034
White	-0.014(0.033)	-0.005
Bachelor's degree	-0.003(0.036)	-0.000
Professional degree	0.156(0.053)**	0.052
Married	0.001(0.036)	0.000
Mother reached retirement age	0.061(0.031)**	0.020
Father reached retirement age	0.002(0.028)	0.000
Wave 1-2	-0.032(0.028)	-0.011
Wave 2-3	0.089(0.027)**	0.029
Constant	-1.288(0.184)**	-
Predicted Probability	0.2568	
Log Likelihood	-9836.57	
Pseudo-R^2	0.0299	
Number of Observations	17,579	

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

Variables	1st Stage of IV	1st Stage of Corrected IV
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)**
Diff. 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. HRS

Variables	1st Stage of IV	1st Stage of Corrected IV
Constant	63.689(0.486)**	111.013(4.217)**
Prob. of living to 85	1.443(0.282)**	3.571(0.337)**
Smoking	0.371(0.211)*	2.479(0.284)**
Inverse Mills' Ratio	-	-31.512(2.789)**
Economic factors at time t		
Net Worth (in $100,000)	-0.02(0.015)	0.010(0.015)
Respondent Income (in $1,000)	-0.002(0.001)	-0.019(0.002)**
No Health Insurance	1.893(0.385)**	6.578(0.562)**
Private Health Insurance	0.526(0.220)	1.233(0.227)**
Self-employed	1.107(0.282)**	0.778(0.284)**
Pension	-1.47(0.214)**	-9.953(0.783)**
Financially Knowledgeable	0.527(0.193)**	-0.114(0.200)
Health factors at time t		
Health limitation	0.116(0.237)	0.346(0.237)
Good-V.Good-Exc. Health	-0.19(0.285)	-2.004(0.327)**
Doctor visits	-0.01(0.012)	-0.018(0.013)
High blood pressure	0.461(0.217)**	-0.337(0.229)
Diabetes	0.256(0.391)	1.295(0.404)**
Cancer	-0.51(1.007)	0.287(1.014)
Stroke	-2.74(1.778)	-4.506(1.861)**
Heart Problems	0.121(0.348)	0.266(0.350)
Arthritis	0.101(0.203)	-0.880(0.222)**
Diff. walking multiple blocks	-0.02(0.357)	-1.169(0.373)**
Difficulty climbing stairs	0.044(0.471)	-0.407(0.473)
Demographic factors at time t		
White	0.802(0.215)**	0.828(0.215)**
Male	1.348(0.182)**	-1.500(0.315)**
Bachelor's Degree	-0.03(0.223)	-0.120(0.223)
Professional Degree	-0.21(0.297)	-3.856(0.436)**
Married	-1.40(0.234)**	-1.305(0.234)**
Wave 1-2	-0.68(0.201)**	0.419(0.223)*
Wave 2-3	-0.34(0.221)	-2.279(0.280)**
Adj. R^2	0.0719	0.098
Test of Weak Instruments	F(2,4696)=14.20	F(2, 4605)=68.10
Number of Observations	4,724	4,634

Table A.4. Selection Equation Results NLSY79

Variables	Probit	Marginal Effects
Economics 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	-0.016(0.022)	0.0005
Male	0.127(0.118)	0.004
Black	0.273(0.178)	0.007
Hispanic	0.113(0.185)	0.003
Number of Siblings	0.047(0.028)*	0.001
Highest Grade Completed	0.496(0.067)**	0.016
Labor Market Experience	0.168(0.098)*	0.005
Northeastern Residence	0.418(0.150)**	0.010
North-Central Residence	0.893(0.187)**	0.019
Southern Residence	1.122(0.182)**	0.031
Rural Residence	0.387(0.191)**	0.010
Local Unemployment Rate	0.148(0.071)**	0.005
Religious Affiliation		
Protestant	-0.049(0.237)	-0.001
Baptist	-0.028(0.173)	-0.001
Catholic	0.430(0.165)**	0.012
Constant	-4.704(0.725)**	-
Predicted Probability	0.988	
Log Likelihood	-262.90	
Pseudo-R^2	0.243	
Number of Observations	2,395	2,395

Table A.5. First Stage Results for Weak RE Test using IV. NSLY79

Variables	1st Stage of IV	1st Stage of Corrected IV
Constant	10.838(0.170)**	11.168(1.522)**
Mother's Education	0.109(0.020)**	0.082(0.019)**
Father's Education	0.153(0.016)**	0.113(0.015)**
Inverse Mills Ratio	-	-1.821(0.870)**
Economics Factors at time t		
Avg. Family Income ($1,000)	-	0.008(0.003)**
Demographic Factors at time t		
Age	-	-0.447(0.090)**
Male	-	-0.027(0.082)
Black	-	0.297(0.109)**
Hispanic	-	0.470(0.135)**
Number of Siblings	-	-0.031(0.018)*
Highest Grade Completed	-	0.834(0.072)**
Labor Market Experience	-	-0.033(0.064)
Northeastern Residence	-	-0.082(0.151)
North-Central Residence	-	-0.152(0.165)
Southern Residence	-	-0.148(0.172)
Rural Residence	-	-0.497(0.107)**
Local Unemployment Rate	-	-0.091(0.046)**
Adj. R^2	0.128	0.263
Test of Weak Instruments	F(2,2313)=171.38	F(15,2299)=47.59
Number of Observations	2,316	2,316

Table A.6. First Stage Results for Strong RE Test using IV. NLSY79

Variables	1^{st} Stage of IV	1^{st} Stage of Corrected IV
Constant	10.013(1.419)**	11.168(1.522)**
Mother's Education	0.086(0.019)**	0.082(0.019)**
Father's Education	0.111(0.016)**	0.113(0.016)**
Inverse Mills Ratio	-	-1.821(0.869)**
Economics Factors at time t		
Avg. Family Income ($1,000)	0.009(0.003)**	0.008(0.003)**
Demographic Factors at time t		
Age	-0.467(0.090)**	-0.446(0.090)**
Male	0.001(0.081)	-0.027(0.082)
Black	0.332(0.107)**	0.297(0.109)**
Hispanic	0.549(0.130)**	0.470(0.135)**
Number of Siblings	-0.024(0.018)	-0.031(0.018)*
Highest Grade Completed	0.936(0.053)**	0.834(0.072)**
Labor Market Experience	-0.004(0.062)	-0.033(0.064)
Northeastern Residence	0.061(0.135)	-0.082(0.165)
North-Central Residence	0.058(0.131)	-0.152(0.165)
Southern Residence	0.094(0.127)	-0.148(0.172)
Rural Residence	-0.444(0.104)**	-0.497(0.107)**
Local Unemployment Rate	-0.065(0.045)	-0.091(0.047)**
Adj. R^2	0.262	0.267
Test of Weak Instruments	F(2,2300)=72.59	F(2,2299)=72.28
Number of Observations	2,316	2,316