Expected versus Realized Income Expectations: A Test of the Rational Expectations Hypothesis †

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Abstract

We analyze answers to household survey questions on whether the respondents' household income has changed in the past twelve months, and on whether the respondents expect their household income to change in the next twelve months. Both questions are answered on a discrete five points scale. The data are an unbalanced panel of ten consecutive annual waves.

Using cross-tabulations of expected and realized changes, we first test the "best-case" hypothesis. This hypothesis implies, under two different nonparametric assumptions on how respondents form their predictions, that respondents have rational expectations, that there are no common unexpected shocks, and that reported expectations are best predictions of future outcomes. We find that the best case hypothesis is rejected: for all years, too many respondents who predict an income fall, *ex post* report that their household income has not changed.

We then construct a bivariate ordered probit random effects panel data model, in which we explain both expectations and realizations from background variables such as age, education level, and labour market status, and from the one year lagged expectation and realization. We show that the hypothesis of rational expectations implies certain restrictions on the parameters in the two equations of this model. The model is estimated by simulated maximum likelihood using the Geweke-Hajivassilou-Keane (GHK) method. The hypothesis of rational expectations is rejected. The hypotheses that expectations are adaptive or naive can be tested in a similar way, and are also rejected.

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1 Introduction

How economic agents form their expectations is an important issue in many fields of economic theory. Common assumptions in the theoretical literature are rational expectations, adaptive expectations, or naive expectations. Empirical evidence on whether these theories provide a realistic description of actual behaviour, is less common. The most direct approach to this is to use survey information on what agents expect, and compare that with *ex post* realizations. Several studies have analyzed the issue using micro data from business surveys on whether output is expected to increase, decrease or remain the same in the next three months. The answers are then compared with the answers to a similar question asked three months later on what has actually happened to output. Ivaldi (1992) surveys various models used for this type of analysis. Using an errors-in-latent-variable model, he finds that the hypothesis of rational expectations (REH) is not always rejected for the French manufacturing industry. Nerlove and Schuermann (1995, 1997), on the other hand, using different latent variable models, unambiguously reject REH for Swiss and UK firms. They also reject the hypotheses of adaptive expectations (AEH) and naive expectations (NEH).

Empirical work on expectations of private households or individuals, is even more scarce. Still, expectations of future incomes, prices, labour market opportunities, play a major role in many life cycle models, in which households optimize some discounted value of utility in the current and in future periods. Expectations are thus important in dynamic structural models of savings, portfolio choice, consumption, investments in durable goods, labour supply, job search, fertility, etc. In most such models, REH or another hypothesis like AEH or NEH, are taken for granted. The fit of the model or significance of certain behavioral parameters are sometimes used as indirect evidence in favour or against one of these hypotheses, but this evidence is not very strong. If the wrong hypothesis is used, this may hamper the usefulness of the structural models for policy analysis.

It therefore seems important to investigate how private households or individuals form their expectations in a more direct way. The way to do this is to use survey questions on the household's future expectations on relevant economic phenomena, like prices and household income. Various household surveys contain questions on the changes in these variables expected by the respondents, and respondents' uncertainty in these predicted changes. Some studies using Italian and Dutch surveys have investigated whether the answers to such questions are related to the respondents' actual economic behaviour in a way that theory would predict. For example, Guiso, Japelli and Terlizzese (1996) show that income uncertainty has a negative impact on the household portfolio share of risky assets in Italy. Hochguertel (1998) finds a similar result for the Netherlands. On the other hand, Alessie and Lusardi (1997) do not find the expected negative relationship between savings and the predicted income change in data for the Netherlands.

In this paper, we focus on household inomce expectations. We will not look at the impact of expectations on economic behaviour like savings, portfolio choice, etc., but will focus on a direct analysis of expectations formation, by comparing expected and realized income changes. Our analysis is in line with the studies of Das, Dominitz and van Soest (1999) and Das and van Soest (1997, 1999). We use panel data on Dutch households covering the years 1984 until 1993. In each wave, heads of households have answered questions on whether the respondents' household income has changed in the past twelve months, and on whether they expect their household income to change in the next twelve months. Both questions are answered on a discrete five points scale.

First, we present the data, and replicate part of the study by Das, Dominitz and van Soest (1999), who looked at six panel waves. Using cross-tabulations of expected and realized changes, we nonparametrically test the "best-case" hypothesis, implying that respondents have rational expectations, that there are no common unexpected shocks, and that reported expectations are best predictions of future outcomes, under two different nonparametric assumptions on how respondents form their predictions. We find that the best case hypothesis is rejected: for all years, too many respondents who predict an income fall, ex post report that their household income has not changed. This shows that either people do not have rational expectations, or people are faced with positive macroeconomic shocks for a number of consecutive years. The latter explanation obviously becomes less plausible the more panel waves are used.

The next step is to find out for which groups of households REH cannot be confirmed, and to analyze how people form their expectations if they do not use rational expectations. Das and van Soest (1997, 1999) have used univariate models for the deviations between observed answers on expected and realized changes. This approach, however, is somewhat *ad hoc*, since it does not account for the conceptual difference between expectations and realizations questions: the former is a location measure of the respondent's subjective distribution of the income change, the latter is one draw from the actual income change distribution. Even if actual and subjective distribution coincide, the discrete nature of both variables implies that expectations and realizations are not necessarily the same. This is shown by Manski (1990) and taken into account by the nonparametric tests.

The main contribution of the current paper is that we set up and estimate a structural framework that takes the Manski (1990) critique into account. Observed categorical realizations and expectations are modeled as two separate ordered response variables. We introduce a bivariate ordered probit random effects panel data model, in which we explain both expectations and realizations from background variables such as age, education level, and labour market status, and from the one year lagged expectation and realization. Under the assumption that respondents' expectations reflect the mean or median of their subjective income change distribution, we show that the hypothesis of rational expectations implies certain restrictions on the parameters in the two equations of this model. The model extends the models used by Nerlove and Schuermann (1995, 1997), in the sense that it allows for background variables and the use of the complete ten waves panel instead of only two waves. The model, therefore, is not only used to test whether REH is valid on average, for the population as a whole, but can also be used to analyze deviations from REH for groups of households with certain characteristics. Moreover, while Nerlove and Schuermann (1995, 1997) cannot address the issue of macroeconomic shocks and test REH under the assumption that macroeconomic shocks do not play a role, we can distinguish macroeconomic shocks from violations of REH under assumption that macroeconomic shocks are not correlated to background characteristics.

The model is estimated by simulated maximum likelihood using the Geweke-Hajivassilou-Keane (GHK) method. The main conclusion is that the hypothesis of rational expectations is rejected. The hypotheses that expectations are adaptive or naive can be tested in a similar way, and are also rejected.

The structure of the remainder of this paper is as follows. In Section 2 we briefly describe the data. In Section 3, we discuss the nonparametric tests of Das, Dominitz and van Soest (1999). In Section 4, we present the bivariate model for expectations and realizations, and explain how REH, AEH and NEH can be tested in this framework. In Section 5, we discuss the results. Section 6 concludes.

2 Data

The data we use in the analysis are taken from the Dutch Socio-Economic Panel (SEP), which is administered by Statistics Netherlands. This panel runs since April 1984. Until 1989 households were interviewed twice a year: in April and in October. Since 1990, information is gathered in May only.

We focus on subjective questions concerning household income growth. These questions are:

1: Did your household's income increase, decrease, or remain unchanged during the past twelve months?
Possible answers: stong decrease (1); decrease (2); no change (3); increase (4); strong increase (5).

2: What will happen to your household's income in the next twelve months?
Possible answers: see 1.

To get an as smooth as possible transition from the change in the timing of the interviews, we use the April waves from 1984 till 1989, and the May waves from 1990 onwards (till 1993). A disadvantage of using the April waves is that we cannot use information on actual income. Between 1984 and 1989, information on monthly income is collected in all the October waves but not in all April waves. Moreover, in 1990 the questions concerning actual income from the main sources such as earnings, changed completely, so that comparable data on actual income for the whole time period of 10 years are not available. We will not use actual income variables, and will use variables like education level and age to proxy the actual income level.

The SEP is an unbalanced panel. Each year households leave the panel, and new households enter. The total number of (heads of) households per wave are presented in Table 1. We removed some households from the sample because of missing answers to the subjective questions concerning income change, or because information on household charateristics or charateristics of the head of household was missing. Table 1 displays the number of removed observations for these two categories. The table shows that the 1990 wave has substantial item nonresponse on the subjective income change questions. An explanation is that the questions in this wave are asked to either the head of household or the partner. In all other waves, the answers were given by both the head of household and the partner. The rather high number of observations which are removed because of missing characteristics in 1991, is mainly due to lack of information on the education level.

In the model which will be introduced in Section 4, we will use the pooled dataset for all waves. This pooled data set is an unbalanced panel which originally contains 9325 observations. However, we will only use observations that remain in the panel for at least three consecutive years. As a consequence, the number of observations drops to 5755[1].

[1] There were 1913 households with complete information for only one wave and 1657 households with information in only two waves.

Slightly less than half of this number is present in more than five waves; 656 households are observed in all ten waves.

Table 1. Number of observations per wave.

	wave									
	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993
number of households:										
	3980	3458	4692	4611	5036	5119	5212	4821	5347	5184
removed because of:										
1) item nonresponse on subjective income change questions:										
	144	91	177	138	145	154	1875	35	61	41
2) missing characteristics:										
	35	35	97	100	306	73	9	591	37	31
used for estimation in pooled dataset:										
	2380	2570	3770	3934	4139	4193	3007	2985	2776	2545

The final row of Table 1 presents the actual number of observations per wave that is used in the estimation of the model. Obviously, new households that have entered the panel in the final years are removed because they cannot be observed for at least three consecutive waves. Therefore the number of observations declines towards the end.

In the remainder of the paper, we will assume that sample selection, item nonresponse on the income change variables, and attrition, are random conditional on the background characteristics included in the regressors. The small nonresponse rates on the income change variables – except for the year 1990, where nonresponse is due to the construction of the questionnaire – gives some confidence that this assumption is reasonable.

3 Nonparametric tests

In this section we apply the methodology that is described in Das, Dominitz and van Soest (1999) to compare predictions and outcomes. We test the best case scenario hypothesis, which implies REH together with some additional assumptions. Section 3.1 briefly summarizes the framework and presents the bounds on features of the empirical distribution of realized outcomes under the best case scenario hypothesis In Section 3.2 we replicate the empirical analysis of Das et al. While Das et al. used the October waves of 1984 till 1989, we will use the April waves of 1984 till 1989 and the May waves of 1990 till 1993.

3.1 Methodology

The survey questions ask respondents to choose among a selection of (ordered) response categories. The categorical nature of the data complicates the comparison between predictions and outcomes in the sense that the data bind but do not identify the probability of each possible outcome. In Das et al. (1999) bounds on these probabilities are derived, extending previous work by Manski (1990) on binary data. It turns out that, for the ordered response case, the bounds depend on the assumed model of how respondents form their "best prediction" when they are asked to choose among (ordered) categories. Here, we discuss the bounds in case of the modal and the median category assumption. The category containing the mean assumption can only be used if exact quantitative data on realized income changes are available, and this is not the case in the current paper. For more details, we refer to Das et al. (1999).

The null hypothesis which is tested in this framework, involves more than just REH. It is the joint null hypothesis that: 1) respondents have rational expectations, i.e. their subjective income change distribution coincides with the actual distribution from which the realized income change is drawn; 2) observations are independent, implying that there are no macroeconomic shocks; 3) respondents have the same income concept and the same category bounds in mind when answering the questions on predicted and realized income change; and 4) the respondents' predicted income changes reflect the modal category or the median category of their subjective income distribution. Rejecting the null hypothesis can therefore be interpreted as rejecting REH if the other three assumptions are maintained.

Modal category assumption

When respondents choose the category with the highest probability, bounds on the conditional probabilities of the (categorical) realization r given the (categorical) prediction p are

$$\mathrm{P}\{r = k|p = k\} \geq \mathrm{P}\{r = j|p = k\}, \quad j = 1, \ldots, K, \tag{1}$$

where K is the total number of (ordered) categories ($K = 5$, in our case). The inequality can be tested for each $j \neq k$; it can be tested for the sample as a whole, or for specific subgroups. Das et al. (1999) perform the test for each pair of consecutive waves separately.

The test based on the modal category assumption does not make use of the ordered nature of our data. The same inequalities have also been used for testing REH on the basis of business surveys, without explicitly discussing the framework and the complete null hypothesis. Ivaldi (1992) refers to it as a weak, nonparametric, test of REH.

Median category assumption

The assumption is equivalent to the assumption that respondents predict the category containing the median of their subjective income distribution. It explicitly makes use of the fact that the reponse categories are ordered. Das et al. (1999) derive the following bounds on the conditional probabilities.

$$\mathrm{P}\{r > k|p = k\} \leq \frac{1}{2} \tag{2}$$

and

$$\mathrm{P}\{r < k|p = k\} \leq \frac{1}{2}. \tag{3}$$

The inequalities under both assumptions can be tested using the asymptotic distribution of the sample fractions which are the sample analogues of the population fractions in the inequalities. This distribution is only valid if the observed realized income changes are independent, implying that the null hypothesis includes the assumption that there are no common shocks.

3.2 Results of the test

Table 2 presents estimates of the conditional probabilities of the realizations given the predictions. These estimates are used to test for significant violations of the modal category assumption, i.e. of one of the inequalities in (1).[2] For $k = 1$ (strong decrease predicted), the inequality (1) is not satisfied for 1986-1987, 1988-1989, and 1989-1990. For 1986-1987 this result is significant. For $k = 2$, the test results are unanimous: for all (combinations of) years, the estimate of $P\{r = 3|p = 2\}$ significantly exceeds the estimate of $P\{r = 2|p = 2\}$, implying that the null hypothesis is rejected. For $k > 2$, no significant violations of (1) are found. Thus the conclusion of Das et al. (1999) is confirmed for this longer time span: in all years, too many of those who expect their incomes to fall, *ex post* report no change. The long time span for which this is the case, makes it implausible that this is due to macroeconomic shocks, and suggests that at least some respondents do not have rational expectations.

Table 3 shows 90% confidence intervals for the cumulative probabilities that can be used to test the best case scenario under the median category assumption. For $k = 1$, inequality (3) is significantly violated in 7 years and for $k = 2$, inequality (2) is violated in all 10 years. For $k = 3$ and $k = 4$, no violations of either (2) or (3) are found. For $k = 5$, we find that (2) is rejected in 5 out of 10 years, suggesting that too many of those who predict a large income increase, report a smaller increase or no increase at all. Together with the result for $k = 1$, this suggests that too many people give predictions in the extreme categories. That we find this with the median category assumption only is explained by the fact that the modal category assumption always requires a plurality of probability mass in the predicted category, whereas the median category requires a majority when either the lowest or highest category is predicted. For $k = 2$, however, the results of median and modal category are completely in line with each other: the best case scenario is rejected for all years.

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[2] See Das et al. (1999) for details.

Table 2. Estimates of $P\{r = j|p = k\}$ (in percentages), where k stands for *predicted* category and j for *realized* category of future income change ($n = \#\{i : p_i = k\}$).

		$j = 1$	$j = 2$	$j = 3$	$j = 4$	$j = 5$	n
$k = 1$: strong decrease	'84 - '85	36.3	28.8	25.9	7.6	1.4	212
	'85 - '86	41.2	21.7	22.7	10.3	4.1	97
	'86 - '87	25.8	16.7	43.9	9.1	4.6	66
	'87 - '88	36.8	19.1	30.9	8.8	4.4	68
	'88 - '89	32.5	15.6	35.1	10.4	6.5	77
	'89 - '90	22.9	28.6	28.6	14.3	5.7	35
	'90 - '91	41.5	19.5	19.5	12.2	7.3	41
	'91 - '92	39.7	18.0	20.5	18.0	3.9	78
	'92 - '93	45.6	21.5	19.0	10.1	3.8	79
	'93 - '94	46.4	17.5	23.7	9.3	3.1	97
$k = 2$: decrease	'84 - '85	14.2	26.7	45.2	11.3	2.7	1237
	'85 - '86	6.9	19.9	55.1	16.0	2.1	682
	'86 - '87	10.0	20.1	54.7	13.2	2.1	583
	'87 - '88	12.0	22.8	52.1	10.7	2.4	457
	'88 - '89	11.2	20.8	50.1	14.3	3.6	475
	'89 - '90	11.7	20.0	33.2	27.9	7.2	265
	'90 - '91	16.8	23.3	36.2	16.4	7.3	232
	'91 - '92	17.2	22.3	41.1	15.5	3.9	489
	'92 - '93	12.8	23.9	42.2	17.3	3.9	510
	'93 - '94	14.9	27.6	40.2	14.7	2.6	619
$k = 3$: no change	'84 - '85	4.9	14.5	58.0	19.0	3.6	1350
	'85 - '86	2.8	8.7	60.4	24.3	3.8	1676
	'86 - '87	2.9	9.3	64.8	19.7	3.2	2747
	'87 - '88	2.3	8.3	67.0	19.2	3.2	3009
	'88 - '89	2.1	5.7	61.9	26.4	4.1	3065
	'89 - '90	2.6	6.6	45.7	37.8	7.2	2112
	'90 - '91	3.8	9.2	53.5	26.6	7.0	1915
	'91 - '92	4.6	9.9	53.3	27.7	4.6	2460
	'92 - '93	4.5	10.2	55.8	26.2	3.4	2730
	'93 - '94	3.8	11.7	59.5	22.3	2.7	2829

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$k = 4$: increase	'84 - '85	3.4	8.3	37.5	38.8	12.0	291
	'85 - '86	4.0	3.7	30.5	49.2	12.6	374
	'86 - '87	1.9	4.8	34.6	43.1	15.7	703
	'87 - '88	1.8	4.6	35.3	44.6	13.7	762
	'88 - '89	2.3	4.0	24.3	52.9	16.6	832
	'89 - '90	2.0	4.1	14.8	55.7	23.4	560
	'90 - '91	3.4	4.4	23.6	46.3	22.3	681
	'91 - '92	3.9	8.3	24.3	46.3	17.1	1196
	'92 - '93	2.6	6.9	27.3	50.6	12.6	1250
	'93 - '94	3.5	8.1	29.0	49.2	10.3	984
$k = 5$: strong increase	'84 - '85	0.0	9.1	45.5	36.4	9.1	11
	'85 - '86	6.7	13.3	20.0	13.3	46.7	15
	'86 - '87	10.3	0.0	13.8	44.8	31.0	29
	'87 - '88	2.2	6.7	22.2	31.1	37.8	45
	'88 - '89	2.6	2.6	13.2	21.1	60.5	38
	'89 - '90	0.0	0.0	15.4	26.9	57.7	26
	'90 - '91	0.0	5.9	17.7	26.5	50.0	34
	'91 - '92	6.1	3.7	19.5	35.4	35.4	82
	'92 - '93	5.9	3.4	12.5	27.3	51.1	88
	'93 - '94	10.5	14.9	11.9	25.4	37.3	67

Table 3. 90% confidence intervals for the (cumulative) probabilities (in percentages; $n = \#\{i : p_i = k\}$)

		$P\{r < k \mid p = k\}$		$P\{r > k \mid p = k\}$		n
		lower	upper	lower	upper	
$k = 1$: strong decrease	'84 - '85	–	–	58.2	69.1	212
	'85 - '86	–	–	50.5	67.0	97
	'86 - '87	–	–	65.4	83.1	66
	'87 - '88	–	–	56.3	72.9	68
	'88 - '89	–	–	58.8	76.3	77
	'89 - '90	–	–	65.5	88.8	35
	'90 - '91	–	–	45.9	71.2	41
	'91 - '92	–	–	51.1	69.4	78
	'92 - '93	–	–	45.2	63.6	79
	'93 - '94	–	–	45.3	61.9	97
$k = 2$: decrease	'84 - '85	12.5	15.8	56.9	61.5	1237
	'85 - '86	5.3	8.5	70.4	76.0	682
	'86 - '87	7.9	12.0	66.9	73.1	583
	'87 - '88	9.5	14.5	61.5	68.9	457
	'88 - '89	8.8	13.5	64.5	71.5	475
	'89 - '90	8.5	14.9	63.6	73.0	265
	'90 - '91	12.8	20.8	54.6	65.2	232
	'91 - '92	14.4	20.0	56.9	64.2	489
	'92 - '93	10.3	15.2	59.8	66.8	510
	'93 - '94	12.5	17.2	54.2	60.8	619
$k = 3$: no change	'84 - '85	17.6	21.2	20.7	24.5	1350
	'85 - '86	10.2	12.7	26.4	30.0	1676
	'86 - '87	11.2	13.3	21.7	24.3	2747
	'87 - '88	9.6	11.5	21.2	23.7	3009
	'88 - '89	6.9	8.5	29.0	31.8	3065
	'89 - '90	8.2	10.3	43.3	46.9	2112
	'90 - '91	11.7	14.2	31.8	35.4	1915
	'91 - '92	13.3	15.6	30.7	33.8	2460
	'92 - '93	13.5	15.8	28.2	31.0	2730
	'93 - '94	14.3	16.6	23.7	26.4	2829

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$k = 4$:	'84 - '85	44.3	54.0	8.9	15.2	291
increase	'85 - '86	34.1	42.4	9.7	15.4	374
	'86 - '87	38.2	44.3	13.4	17.9	703
	'87 - '88	38.8	44.7	11.6	15.7	762
	'88 - '89	27.9	33.2	14.5	18.7	832
	'89 - '90	18.1	23.7	20.5	26.3	560
	'90 - '91	28.5	34.4	19.7	24.9	681
	'91 - '92	34.2	38.8	15.3	18.9	1196
	'92 - '93	34.5	39.0	11.1	14.2	1250
	'93 - '94	38.0	43.1	8.7	11.9	984
$k = 5$:	'84 - '85	76.7	100.0	–	–	11
strong increase	'85 - '86	32.1	74.5	–	–	15
	'86 - '87	54.8	83.1	–	–	29
	'87 - '88	50.3	74.1	–	–	45
	'88 - '89	26.4	52.5	–	–	38
	'89 - '90	26.4	58.2	–	–	26
	'90 - '91	35.9	64.1	–	–	34
	'91 - '92	55.9	73.3	–	–	82
	'92 - '93	40.1	57.6	–	–	88
	'93 - '94	53.0	72.4	–	–	67

4 Model

The results in the previous section imply that the joint hypothesis of no macro-economic shocks, rational expectations, and questions on expected and realized income changes are answered in the same way, is rejected for all time periods we consider. In this section we will impose more structure and formulate an econometric model to investigate why this joint hypothesis is rejected. Can we reject rational expectations, and, if so, can we indicate which groups of people typically have non-rational expectations, or can we explain the results from macroeconomic shocks? We introduce a bivariate model explaining the answers to the predicted as well as the realized income change questions, which generalizes the models used by Nerlove and Schermann (1995, 1997).

Realized income changes

We allow for an unbalanced panel, but will only use respondents i who participate in at least three consecutive waves. N_i is defined as the number of consecutive waves in which respondent i is observed and index t corresponds to the different waves (ranging from -1 to N_i-2, where the wave with index -1 is used for the explanatory variables in the initial condition equation. See below.).

The answer to the realized income change question given in wave t of the survey by respondent i is denoted by y_{it}. This is an ordered variable, with five possible answers coded from 1 (strong decrease) to 5 (strong increase). Like in a standard ordered response model, we assume that it relates to an underlying continuous latent variable y_{it}^* as follows:

$$y_{it} = j \text{ if } m_{j-1}^y < y_{it}^* \leq m_j^y \quad (j = 1, \ldots, 5).$$

The category boundaries $-\infty = m_0^y < m_1^y < \ldots < m_4^y < m_5^y = \infty$ are assumed to be constant across individuals and across time; m_1^y, m_2^y, m_3^y and m_4^y are parameters to be estimated.[3]

The underlying latent variable is modelled using the following dynamic random effects panel data equation.

$$y_{it}^* = X_{i,t-1}'\beta_1 + \rho y_{i,t-1}^* + \lambda_t + \alpha_{iy} + \epsilon_{it} \quad (t = 1, \ldots, N_i - 2), \tag{4}$$

where $X_{i,t-1}$ is a vector of background variables reflecting, for example, age, education level, and labour market status of the respondent. The reason for including $X_{i,t-1}$ rather than X_{it} is that this is necessary to make it possible to compare the equations for predictions and realizations (see below). Note that we have included the latent lagged variable $y_{i,t-1}^*$ and not the latent observed variable $y_{i,t-1}$. This reflects the notion that the observed

[3]Some of them will be normalized.

variable is discrete due to the way it is measured only, while the underlying continuous latent variable is the magnitude of economic relevance. The parameter α_{iy} is an individual specific (random) effect, included to allow for unobserved heterogeneity across respondents; ϵ_{it} is an idiosyncratic error term. Time dummies λ_t are included to allow for macro-economic shocks. These macro-economic shocks are thus assumed to be common for all respondents, and not to vary with $X_{i,t-1}$ or $y^*_{i,t-1}$.

Since the equation contains the lagged income change, it cannot be used for $t = 0$. Due to the latent variable nature of the model, simply ignoring $t = 0$ leads to inconsistent estimates (see Heckman, 1981a). Following Heckman (1981b), we solve this problem by adding a linearized reduced form static equation for y^*_{i0}:

$$y^*_{i0} = X'_{i,-1}\beta_0 + \phi_y \alpha_{iy} + \epsilon_{i0}.$$

The presence of $X_{i,-1}$ in the above equation explains why we only use observations who are present in at least three consecutive waves. Only from the third wave onwards ($t = 1$), the observations help for estimating the parameters in the dynamic equation.[4]

Predictions of income changes

The answer to the expected income change question given in wave t of the survey by respondent i is denoted by p_{it}. This is an ordered response variable. Analogously to y_{it}, we model it using an underlying continuous latent variable p^*_{it}:

$$p_{it} = j \text{ if } m^p_{j-1} < p^*_{it} \leq m^p_j \ \ (j = 1, \ldots, 5).$$

We make the same assumptions on the category boundaries m^p_j as on m^y_j. It seems natural that m^y_j and m^p_j are identical, but, apart from some necessary normalizations to identify the model (see below), this is something we can test, and we will not impose it *a priori.*

We specify the following latent variable equation for p^*_{it}:

[4] Some efficiency gain could be achieved by using the observations which are in the panel for two waves, since these do provide information for estimating the auxiliary parameters in the reduced form equation. Moreover, an alternative which avoids the loss of the first observation ($t = -1$) would be to include $X_{i,0}$ instead of $X_{i,-1}$ in the equation for $t = 0$. This would drive a larger wedge between static reduced form and dynamic equations, however.

$$p_{it}^* = X_{it}'\gamma_1 + \theta_1 y_{it}^* + \theta_2 p_{i,t-1}^* + \nu_t + \alpha_{ip} + \omega_{it} \ \ (t = 1, \ldots, N_i - 1). \tag{5}$$

The parameter α_{ip} is an individual specific (random) effect, included to allow for unobserved heterogeneity across respondents. This will probably be correlated with α_{iy}. ω_{it} is an idiosyncratic error term. Time dummies ν_t in this equation are included to allow for predicted macro-economic effects.

The income change prediction p_{it}^* given in wave t refers to the income change in the next twelve months. It is allowed to depend on the realized income change y_{it}^* which the respondent has experienced during the past twelve months. p_{it}^* is a prediction of $y_{i,t+1}^*$, so this effect may reflect a genuine economic process which leads to correlation between y_{it}^* and $y_{i,t+1}^*$. It may also, however, reflect a psychological effect of past income changes on future expectations. The two will be disentangled below, in the context of testing for rational expectations. Finally, we also allow the prediction in year t to depend on the prediction in year $t-1$. Such a relation might be interpreted in an adaptive expectations framework, as we will show below. Earlier work on a univariate model suggested that such an effect is significant though quantitatively not very important (see Das and van Soest, 1999).

For the same reason as for the equation for the realized income change, a separate linearized reduced form equation is used for the first time period:

$$p_{i0}^* = X_{i0}'\gamma_0 + \theta_0 y_{i0}^* + \phi_p \alpha_{ip} + \omega_{i0}.$$

Distributional assumptions

We assume that the idiosyncratic error terms $(\epsilon_{it}, \omega_{it})$ are independent over time, and independent of regressors X_{it} and individual effects α_{iy} and α_{ip}. We allow for correlation between ϵ_{it} and ω_{it}. More specifically, we assume that $(\epsilon_{it}, \omega_{it})$ is bivariate normal with mean zero, variances σ_ϵ^2 and σ_ω^2 and covariance $\sigma_{\epsilon,\omega}$ for $t > 0$, and variances $\sigma_{\epsilon,0}^2$ and $\sigma_{\omega,0}^2$ and covariance $\sigma_{\epsilon,\omega,0}$ for $t = 0$.

The individual effects $(\alpha_{iy}, \alpha_{ip})$ are treated as random effects, assumed to be independent of the X_{it}. Fixed effects models are not considered. First, many of the regressors of interest such as age and education level variables do not vary over time or vary over time in a systematic way, and their effects would not be identified in a fixed effects context. Second, due to the discrete bivariate nature of the model, estimation techniques allowing for fixed effects are, to our knowledge, not available. We allow for correlation between α_{iy} and α_{ip}. More specifically, we assume that $(\alpha_{iy}, \alpha_{ip})$ is bivariate normal with mean zero, variances $\sigma^2_{\alpha_y}$ and $\sigma^2_{\alpha_p}$, and covariance $\sigma_{\alpha_y,\alpha_p}$.

Rational expectations

In the model introduced above, the relation between predictions and realizations is very flexible. We will now show that rational expectations implies restrictions on the parameters in the two dynamic equations which can be tested.

We assume that the predictions p^*_{it} reflect some location measure of the individual's subjective distribution of the underlying continuous income change variable y^*_{it}. Under the assumption that the conditional distribution of y^*_{it} is symmetric around zero, the conditional mean and the conditional median of y^*_{it} are the same, so it does not make any difference which of the two we location measures we use. The assumption that p^*_{it} reflects the median of the conditional distribution of y^*_{it} is in line with the median category assumption in the previous section, since the median category is the same as the category containing the median of the underlying continuous latent variable. It is not in line with the modal category assumption, since the modal category is not necessarily the category containing the mode of the continuous variable.

Rational expectations implies that the realized income change $y^*_{i,t+1}$ is drawn from this same distribution. If the respondent's information set at the time of the interview in wave t is denoted by I_{it}, and if the location measure used by the respondent is the conditional mean, we get

$$p^*_{it} = E\{y^*_{i,t+1}|I_{it}\}.$$

Since the respondent's information set will contain the lagged variables and the exogenous variables X_{it}, the model and the law of iterated expectations now imply

$$X'_{it}\gamma_1 + \theta_1 y^*_{it} + \theta_2 p^*_{i,t-1} + \nu_t = X'_{i,t}\beta_1 + \rho y^*_{i,t} + E_t\{\lambda_{t+1}\} \ \ (t = 1, \ldots, T_i - 1).$$

Here E_t denotes the expected value given all information available to the econometrician at time t. $E_t\{\lambda_{t+1}\}$ is unknown but depends on time only, not on i (and thus not on $X_{i,t}$ or $y^*_{i,t}$). If we would have used the median instead of the mean, the same result would have been obtained due to the symmetry of the error terms and the individual effects, except that $E_t\{\lambda_{t+1}\}$ would be replaced by $Median_t\{\lambda_{t+1}\}$.

Rational expectations thus implies the following equality restrictions on the parameters in the two dynamic equations.

$$\gamma_1 = \beta_1; \ \ \theta_1 = \rho; \ \ \theta_2 = 0. \tag{6}$$

We will estimate the model with and without imposing these restrictions. A likelihood ratio test will then show whether the hypothesis of rational expectations can be rejected or not.[5]

The restrictions to be tested do not involve the time dummies ν_t and λ_{t+1}. The reason is that REH implies $\nu_t = E_t\{\lambda_{t+1}\}$ or $\nu_t = Median_t\{\lambda_{t+1}\}$, but not $\nu_t = \lambda_{t+1}$. Without imposing REH or additional assumptions, we cannot consistently estimate $E_t\{\lambda_{t+1}\}$ or $Median_t\{\lambda_{t+1}\}$; we can only estimate λ_{t+1} itself. On the other hand, if we do impose REH, we can interpret the estimates of ν_t in the restricted model (imposing (6)) as estimates of $E_t\{\lambda_{t+1}\}$ or $Median_t\{\lambda_{t+1}\}$. The differences between the estimates of the realized macroeconomic effects λ_{t+1} and the estimates of ν_t can then be interpreted as estimates of the realizations of unanticipated macroeconomic effects.

The test for REH thus allows for unanticipated macro-economic effects, and is in this sense more general than the tests used by Nerlove and Schuermann (1995, 1997).

[5] In principle, a similar set of restrictions could be tested for the static equations for $t = 0$. Since these are considered as auxiliary equations, however, we chose not to consider such restrictions.

On the other hand, the restrictions in (6) clearly rely on the assumption that macro-economic effects are uncorrelated with the right hand side variables $X_{i,t}$, $y^*_{i,t}$ and $p^*_{i,t-1}$. This maintained assumption can be relaxed by testing fewer restrictions. For example, a test on $\theta_1 = \rho$ and $\theta_2 = 0$ can be seen as a test of REH allowing for macro-economic shocks which can be correlated with $X_{i,t-1}$ but (conditional on $X_{i,t-1}$) not with $y^*_{i,t-1}$ or $p^*_{i,t-1}$. Perhaps the weakest test is a simple test on whether θ_2 is nonzero, since there does not seem any reason why macro-economic shocks should be correlated to past predictions, conditional on everything else. As we will show later, a significant value of θ_2 can point at (partly) adaptive expectations.

Normalizations

The issue of normalization slightly complicates comparing the restricted model (imposing (6)) and the unrestricted model. In the unrestricted model, we need separate scale and location normalizations for the latent variables reflecting expected and realized incomes. This is achieved through the category boundaries: $m_1^y = m_1^p = -2$, and $m_4^y = m_4^p = 2$. In the restricted model, the equality of slope coefficients in the two dynamic equations implies that normalizing restrictions need to be imposed in one of the two equations only; the other equation is then identified due to the restrictions. Thus in the restricted model, we impose $m_1^y = -2$, and $m_4^y = 2$, but we estimate m_1^p and m_4^p. This implies that the number of degrees of freedom for the likelihood ratio test is reduced by 2.[6]

Adaptive and Naive Expectations

Although this is probably less relevant than REH, the framework can also be used to test the hypotheses of adaptive expectations (AEH) and naive expectations (NEH). These cases are nested in the general two equations model. AEH implies (see Nerlove and Schuermann, 1995, equation (2.8)):

[6] Using a different normalization would avoid this problem, but would make the estimation results less transparent.

$$p^*_{it} - p^*_{i,t-1} = \delta[y^*_{it} - p^*_{i,t-1}] + u_t$$

for some parameter $\delta > 0$, where u_t is some white noise error term. This implies the following restrictions on the parameters of the two dynamic equations:

$$\gamma_1 = 0; \quad \theta_1 + \theta_2 = 1 \tag{7}$$

Naive expectations would imply that the (latent) prediction is given by the current realization plus noise (see Nerlove and Schuermann, 1995, equation (2.9)):

$$p^*_{it} = y^*_{it} + u_t$$

This is the special case of AEH with $\delta = 1$, and thus implies the following restrictions on the parameters of the general model.

$$\gamma_1 = 0; \quad \theta_1 = 1; \quad \theta_2 = 0 \tag{8}$$

Like REH, both AEH and NEH can be tested using likelihood ratio tests or Wald tests on parameter restrictions in the general two equations model.

Obviously, AEH and REH could also be combined. For example, it is possible to test the hypothesis that expectations are a convex combinations of REH and AEH expectations:

$$p^*_{it} = \alpha E\{y^*_{i,t+1}|I_{it}\} + (1-\alpha)\{\delta y^*_{it} + (1-\delta)p^*_{i,t-1}]\}$$

for some $\alpha \in [0, 1]$. Eliminating α en δ, it is straighforward to show that this implies the following non-linear set of parameter restrictions.

$$(1-\rho)\gamma_1 \;=\; (1-\theta_1-\theta_2)\beta_1 \tag{9}$$

These restrictions can be tested for using a likelihood ratio test, for example, appropriately accounting for a similar normalization as in the REH test.

Estimation

The complete bivariate model for all waves is a recursive system of ordered response equations. Due to the normality assumptions on idiosyncratic errors and random individual effects, all the errors are jointly normal, with some covariance matrix depending on the parameters. The likelihood contribution of one individual can therefore be written as a multivariate normal probability. Exact computation of the likelihood would require high dimensional numerical integration and is therefore infeasible in practice. This is a typical case for smooth maximum likelihood, where the exact likelihood contributions are replaced by approximations based upon a number (R, say) of independent random draws for each individual. See Hajivassiliou and Ruud (1994), for example. If R tends to infinity, the approximating likelihood becomes an accurate approximation of the exact likelihood, and the estimator based upon maximizing the approximate likelihood will be similar to the maximum likelihood estimator. Under appropriate regularity conditions, if draws are independent across individuals, and if R tends to infinity faster than $\sqrt{n}$, the simulated maximum likelihood estimator and the exact maximum likelihood estimator are asymptotically equivalent, and standard errors etc. can be computed in the same way as for the exact ML–estimator.

The remaining issue is how to draw and how to use the draws to approximate the exact likelihood. The crude frequency simulator – based upon draws of all the errors, yielding a zero or a one for each replication – is the intuitively most obious procedure, but it leads to a non–differentiable approximation of the likelihood, making it hard to find the maximum. A much better alternative here is the so-called GHK (Geweke, Hajivassiliou and Keane), which is specifically designed for the type of multivariate normal probabilities we are dealing with, and which has been applied succesfully to similar types models. See Hajivassiliou and Ruud (1994) or Keane (1993) for a description and further references. The idea is that the multivariate probability in the likelihood is first written recursively as a product of univariate conditional normal probabilities, where the conditions are inequalities. Independent draws from the uniform distribution on [0,1] are then recursively transformed into draws from a truncated normal, where truncation is based upon the same inequality conditions. The conditional probabilities given the inequalities are then replaced by the conditional probabilities given the previous draws. The latter are univariate normal probabilities and therefore easy to work with. The likelihood contribution is then replaced by an average over R approximations based upon R such sequences of draws.

All the estimates presented in the next sections are based upon an approximation with $R = 25$ draws for each individual, and upon independent draws across individuals. In a sensitivity analysis, we didn't find evidence that the results were sensitive to increasing R.

5 Results

Table 4 presents the estimation results of the parameters in the dynamic equations (4) and (5) in the unrestricted model.[7]. The first two columns refer to the realization y^* and the last two columns correspond to the prediction p^*. We see that all slope coefficients in the equations for y^* (β_1) and p^* (γ_1) are significant at the 5% level except the dummy for a retired head of household. The signs of the coefficients in γ_1 and β_1 always correspond.

A female head of household, on average, predicts and experiences a lower income change than a male head of household, *ceteris paribus*. Realized and predicted income changes are, on average, lower when the head of household is older. This decreasing pattern holds until the retirement age. After that people often live from some predetermined retirement benefits. The results for the dummies for education level are as expected. On average, those with higher eduation level predict and experience higher changes in income. This is in line with the stylized fact that life cycle income patterns are steeper for

[7]Estimation results for the parameters in the auxiliary initial condition equations are presented in Appendix A.

the higher educated. The effect of education level on the predictions seems smaller than the effect on the realizations. The dummies referring to the labor market status indicate that unemployed and disabled heads of households experience and predict lower income growth compared to others (working and retired heads). Similarly, income changes for two earner households are lower than for one earner households.

Table 4. Estimates of the parameters in the unrestricted model.

Realization (y)			Prediction (p)		
variable	estimate	t-value	variable	estimate	t-value
constant	1.40	11.20	constant	1.13	9.72
gender	-0.17	-6.46	gender	-0.13	-6.31
age/10	-0.32	-7.22	age/10	-0.38	-10.37
$(\text{age}/10)^2$	0.018	3.73	$(\text{age}/10)^2$	0.025	6.99
d_edu2	0.071	2.14	d_edu2	0.050	2.02
d_edu3	0.12	3.98	d_edu3	0.097	4.25
d_edu4	0.26	7.38	d_edu4	0.17	5.80
d_edu5	0.39	8.37	d_edu5	0.19	5.09
d_unem	-0.17	-3.18	d_unem	-0.20	-5.90
d_ret	-0.054	-1.26	d_ret	-0.034	-1.15
d_dis	-0.18	-4.60	d_dis	-0.24	-8.49
d_two	-0.098	-4.64	d_two	-0.083	-5.34
ρ	0.12	12.20	θ_1	0.070	1.50
			θ_2	0.093	8.62
λ_{1986}	0		ν_{1986}	0	
λ_{1987}	-0.19	-3.43	ν_{1987}	0.030	0.74
λ_{1988}	-0.11	-2.03	ν_{1988}	0.069	1.74
λ_{1989}	-0.085	-1.53	ν_{1989}	0.10	2.57
λ_{1990}	0.0060	0.11	ν_{1990}	0.14	3.35
λ_{1991}	0.20	3.45	ν_{1991}	0.14	3.04
λ_{1992}	-0.013	-0.22	ν_{1992}	0.16	3.58
λ_{1993}	-0.13	-2.06	ν_{1993}	0.16	3.39
m_1^y	-2		m_1^p	-2	
m_2^y	-1.25	-108.60	m_2^p	-1.12	-90.61
m_3^y	0.56	50.23	m_3^p	0.63	45.85
m_4^y	2		m_4^p	2	
σ_ϵ	1.11	163.52	σ_ω	0.75	143.10
σ_{α_y}	0.32	19.91	σ_{α_p}	0.20	8.38
$\sigma_{\alpha_y,\alpha_p}$	0.088	10.63			
$\sigma_{\epsilon,\omega}$	-0.015	-0.26			
log likelihood: -54572 (number of observations = 5755)					

When we look at the parameters that reflect the dynamics of the model we see that past actual income growth positively relates to current actual income growth. Still, since ρ is (far) less than one, the effect of changes in income in the past on current income growth vanishes quite rapidly.

The estimates of θ_1 and θ_2 indicate that current realized income growth and past predictions have a positive impact on predicted income growth in the next twelve months. The effect of current realized income growth, however, is not significant, and the magnitude of both effects is rather small.[8] As explained in the previous section, an interpretation of the significant positive effect of the past prediction could be that people imperfectly adapt their expectations (and thus do not have completely rational expectations).

The estimated covariance structure of the random effects and the idiosyncratic error terms is largely in line with what we would expect. The variance of the prediction errors (σ_ω^2) is smaller than the variance of the error terms in the realizations (σ_ϵ^2). This is in line with the fact that the former is a location measure and the latter a drawn realization. The variance of the individual effect is also smaller for the predictions than for the realizations, suggesting that respondents do not use the complete knowledge of their individual effect in forming their predictions (either since this is not in their information set, or because they do not have rational expectations). The two individual effects have a significant but rather small positive correlation. The covariance between the two idiosyncratic errors is insignificant.

Testing the expectations hypotheses

The implication of rational expectations on the parameters in the dynamic equations is summarized in (6). We re-estimated the model under these restrictions and used a likelihood ratio test to test them.[9] The outcome of the test statistic is equal to 104, by far

[8] The fact that current income growth does not matter for the prediction of next year's growth is different from our previous findings in Das and van Soest (1997, 1999). This difference is due to including the past prediction.

[9] Estimation results for the restricted model are presented in Appendix B.

exceeding the critical value of $\chi^2_{12;0.05} = 21$. We therefore conclude that REH is rejected.

One reason for this is that REH implies $\theta_2 = 0$, and we already saw that this is rejected. As a consequence, REH would still be rejected if we would weaken the null hypothesis and allow for correlation between macro-economic shocks and respondent or family characteristics X_t or even the lagged income change y_t^*. Even then we would still expect that deviations between predictions and realizations are uncorrelated to past predictions p_t^* (conditional on X_t and y_t^*) and this is rejected by the data.

Table 5 displays estimates of the differences between γ_1 and β_1 and ρ and θ_1 in the unrestricted model, and thus gives insight in each of the REH restrictions in (6). We see that all differences are insignificant except the ones related to eduation level. Table 5 also indicates that we cannot conclude that past income growth influences realized and predicted income growth in the next twelve months in a different way: the difference between the estimates of the coefficients of the lagged income change (ρ and θ_1) is not significant.

The higher educated have, on average, a larger tendency to underpredict and a smaller tendency to overpredict their future income change than the lower educated. Since we have allowed for macro-economic shocks – which are assumed to be independent of education level –, we cannot (yet) unambiguously conclude whether the high educated have rational expectations and the lower educated tend to overpredict, or whether the low educated have rational expectations and the high educated tend to underpredict. The tables in Section 3, however, suggest that the former is more likely than the latter.

Table 4 already shows that many parameters in γ_1 are significant, and that the sum of θ_1 and θ_2 is much smaller than 1. Thus many of the the restrictions on the parameters under adaptive expectations (7) are separately rejected, and a formal test on joint significance confirms that AEH is rejected. Since naive expectations are a special case of adaptive expectations, naive expectations (NEH, restrictions (8)) is also rejected. Thus resondents' income change expectations are neither rational, nor adaptive or naive.

Finally, we have also tested the hypothesis that expectations are a combination of REH and AEH, leading to restrictions (9). These restrictions are strongly rejected by a likelihood ratio test. Moreover, imposing the restrictions leads to a negative implied estimate of the speed of partial adjustment parameter δ, and thus does not lead to interpretible results. We therefore do not present these result in detail.

Table 5. Estimates of the differences between β_1 and γ_1 and ρ and θ_1.

$\gamma_1 - \beta_1$:	estimate	t-value
constant	0.27	1.77
gender	-0.044	-1.56
age/10	0.057	1.12
$(\text{age}/10)^2$	-0.0070	-1.32
d_edu2	0.021	0.58
d_edu3	0.021	0.62
d_edu4	0.093	2.26
d_edu5	0.20	3.62
d_unem	0.032	0.54
d_ret	-0.020	-0.39
d_dis	0.058	1.26
d_two	-0.015	-0.62
$\rho - \theta_1$	0.047	1.00

6 Conclusions

Using panel data on expectations and realizations of income changes, we have addressed whether heads of household have rational expectations. First, we have used the nonparametric framework of Manski (1990) to test the best case scenario of rational expectations and absence of macro-economic shocks, combined with two different assumptions on which location measure of their income change distribution respondents use to form their predictions. Both lead to the conclusion that the best case scenario is rejected for each of the ten years we consider, since too many people who expect an income fall experience no change.

Next, we have formulated a bivariate dynamic latent variable model for predictions and realizations of income changes. The model is consistent with the Manski framework combined with the notion that people's predictions reflect the mean or median of their subjective income change distribution. The model extends the models used by Nerlove and Schuermann (1995, 1997) for testing REH and AEH of businesses. Unlike these authors and unlike Manski, our model allows for a better distinction between macro-economic shocks and violations of rational expectations. Our main conclusion here is that REH is rejected under various assumptions on the macro-economic shocks, even if these macro-economic shocks are allowed to be correlated to household characteristics and income changes in the past. We find that predicted changes for the next year are correlated to last year's predictions, conditional on household characteristics and last year's actual change. This is inconsistent with REH. Although it would be in line with adaptive expectations, we also reject a model which combines REH and AEH.

Our results are based upon ten years of data for one country only. Obviously, whether the results we find are specific to the country and the time period we consider remains to be seen. Still, our results suggest that alternative theories of expectations formation are needed to explain our data. This remains the challenge for future research.

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Appendix A

Table A1. Estimates of the parameters in the initial condition equations in the unrestricted model.

Realization (y)			Prediction (p)		
variable	estimate	t-value	variable	estimate	t-value
constant_0	1.63	8.55	constant_0	0.74	3.56
gender_0	-0.13	-2.60	gender_0	-0.097	-2.62
$\text{age}/10_0$	-0.62	-7.48	$\text{age}/10_0$	-0.31	-3.62
$(\text{age}/10)_0^2$	0.047	4.82	$(\text{age}/10)_0^2$	0.023	2.71
d_edu2_0	0.12	2.07	d_edu2_0	0.075	1.55
d_edu3_0	0.19	3.42	d_edu3_0	0.096	2.07
d_edu4_0	0.34	5.21	d_edu4_0	0.18	3.16
d_edu5_0	0.38	4.03	d_edu5_0	0.25	3.29
d_unem_0	-0.34	-4.14	d_unem_0	-0.20	-3.01
d_ret_0	0.036	0.37	d_ret_0	-0.065	-0.93
d_dis_0	-0.71	-9.09	d_dis_0	-0.39	-4.90
d_two_0	-0.16	-3.89	d_two_0	-0.062	-2.01
			θ_0	0.24	2.67
ϕ_y	1.21	12.80	ϕ_p	1.59	7.48
$\sigma_{\epsilon,0}$	1.19	78.17	$\sigma_{\omega,0}$	0.80	39.27
$\sigma_{\epsilon,\omega,0}$	-0.19	-1.47			

Appendix B

Table B1. Estimates of the parameters in the restricted model (restrictions: $\beta_1 = \gamma_1, \theta_1 = \rho, \theta_2 = 0$).

Realization (y)			Prediction (p)		
variable	estimate	t-value	variable	estimate	t-value
constant_0	1.63	8.55	constant_0	0.96	4.04
gender_0	-0.13	-2.60	gender_0	-0.10	-2.53
$\text{age}/10_0$	-0.61	-7.50	$\text{age}/10_0$	-0.33	-3.43
$(\text{age}/10)_0^2$	0.047	4.83	$(\text{age}/10)_0^2$	0.025	2.62
d_edu2$_0$	0.13	2.10	d_edu2$_0$	0.083	1.56
d_edu3$_0$	0.19	3.44	d_edu3$_0$	0.10	1.94
d_edu4$_0$	0.34	5.25	d_edu4$_0$	0.19	2.89
d_edu5$_0$	0.39	4.07	d_edu5$_0$	0.26	3.07
d_unem$_0$	-0.34	-4.13	d_unem$_0$	-0.22	-3.03
d_ret$_0$	0.034	0.35	d_ret$_0$	-0.068	-0.89
d_dis$_0$	-0.70	-9.01	d_dis$_0$	-0.41	-4.58
d_two$_0$	-0.16	-3.85	d_two$_0$	-0.064	-1.87
constant	1.40	16.61			
gender	-0.16	-8.07			
age/10	-0.40	-12.45			
$(\text{age}/10)^2$	0.026	7.71			
d_edu2	0.064	2.75			
d_edu3	0.12	5.55			
d_edu4	0.22	8.49			
d_edu5	0.29	9.09			
d_unem	-0.21	-6.57			
d_ret	-0.049	-1.85			
d_dis	-0.25	-9.42			
d_two	-0.095	-6.70			
ρ	0.11	12.05	θ_0	0.28	2.59
λ_{1986}	0		ν_{1986}	0	0
λ_{1987}	0.081	3.23	ν_{1987}	0.053	2.63
λ_{1988}	0.11	3.77	ν_{1988}	0.093	4.26
λ_{1989}	0.20	6.66	ν_{1989}	0.14	5.47
λ_{1990}	0.39	11.18	ν_{1990}	0.13	4.25
λ_{1991}	0.18	4.62	ν_{1991}	0.16	5.04
λ_{1992}	0.060	1.25	ν_{1992}	0.18	4.42
λ_{1993}	0.19	3.55	ν_{1993}	-0.0092	-0.22

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continue of table B1					
variable	estimate	t-value	variable	estimate	t-value
m_1^y	-2		m_1^p	-2.03	-25.60
m_2^y	-1.24	-108.95	m_2^p	-1.07	-22.78
m_3^y	0.57	50.83	m_3^p	0.85	26.19
m_4^y	2		m_4^p	2.35	30.36
ϕ_y	1.19	13.86	ϕ_p	1.28	7.97
$\sigma_{\epsilon,0}$	1.19	79.36	$\sigma_{\omega,0}$	0.87	22.10
σ_{ϵ}	1.11	164.64	σ_{ω}	0.81	29.98
σ_{α_y}	0.33	20.90	σ_{α_p}	0.30	20.35
$\sigma_{\alpha_y,\alpha_p}$	0.11	16.54			
$\sigma_{\epsilon,\omega,0}$	-0.21	-1.43			
$\sigma_{\epsilon,\omega}$	-0.057	-4.00			
log likelihood: -54624 (number of observations = 5755)					