The Rationality and Reliability of Expectations Reported by British Households: Micro Evidence from the British Household Panel Survey

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Abstract

This paper assesses the accuracy of individuals' expectations of their financial circumstances, as reported in the British Household Panel Survey, as predictors of outcomes and identifies what factors influence their reliability. As the data are qualitative bivariate ordered probit models, appropriately identified, are estimated to draw out the differential effect of information on expectations and realisations. Rationality is then tested and we seek to explain deviations of realisations from expectations at a micro-economic level, possibly with reference to macroeconomic shocks. A bivariate regime-switching ordered probit model, distinguishing between states of rationality and irrationality, is then estimated to identify whether individual characteristics affect the probability of an individual using some alternative model to rationality to form their expectations.

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1 Introduction

Despite the importance of expectations to macroeconomic behaviour, and their central role in economic models, there has been little empirical work, as Carroll (2003) explains, modelling individuals' expectations. This has made it difficult to understand expectation formation and to come to an informed view about the informational value of expectational or consumer confidence data. In part the paucity of direct data on individuals' expectations is responsible.[1] When collected, data often derive from cross-sectional surveys and it is impossible to monitor either how the views of particular respondents are changing over time or how they relate to actual economic experience. In addition, often the results of the surveys are qualitative and are published only as aggregated variables - typically as the proportion of optimists less pessimists, the so-called balance of opinion. But recently there has been an increased effort both to exploit available micro panel data sets and then study them with a view to understanding expectations and in particular expectational errors. This paper seeks to contribute to this small but growing literature which includes Souleles (2004), with an application to the Michigan Index of Consumer Sentiment. Related studies include Das & van Soest (1997) and Das & van Soest (1999) with applications using Dutch data and, most closely related to this paper, Brown & Taylor (2006) who studied British data. These studies, like ours, focus on expectations or forecasts of individual specific, rather than aggregate, variables. Crucially they exploit the panel aspect of the surveys to identify individual-level forecast errors from consecutive or matched surveys.

Specifically we provide a detailed empirical investigation into the formation and reliability of individual-level expectational data in Britain. Our data source is the British Household Panel Survey (BHPS) from 1991 to 2003 which is a nationally representative sample of more than 5000 households, comprising about 10,000 individual interviews. The BHPS asks individuals a range of questions including ones about the state of their household's finances this year and their expectations for next year. Responses to these two questions are ordered and categorical as they reply "improve", "stay the same" or "worsen". The relationship between these answers in successive years, capturing an individual's expectational error, forms the basis of our study. Unlike the Michigan Index

[1] As Carroll notes there are in fact long established data sets of expectations in the US such as the Michigan survey, the Survey of Professional Forecastsers and the Conference Board. For the UK, the focus of our empirical work, there are less sources particularly surveying more than a few dozen individuals or firms. For a review of survey expectations and their role in understanding expectation formation see Pesaran & Weale (2006).

of Consumer Sentiment, which provides at best just one forecast error per individual (cf. Souleles (2004)), the BHPS provides multiple forecast errors per individual.

We then seek to extend our understanding of the informational content of expectational data by identifying those factors which influence their reliability. This is achieved by drawing out the differential effect of information on expectations and realisations. We suggest the use of bivariate ordered probit models, appropriately identified, to identify those factors which determine consumers' expectations and the subsequent realisations. We explain how the models facilitate both testing rationality and understanding deviations of realisations from expectations at a micro-economic level, possibly with reference to macroeconomic shocks. In contrast previous work has relied on single equation models; see Das & van Soest (1999) and Souleles (2004).[2] These do not draw out the differential effect of information on expectations and realisations. In addition they do not accommodate the ordered nature of both expectational and realisation responses; they assume a single latent continuous random variable underlies the error rather than letting the error simply be the difference between two latent continuous random variables representing expected and realised income changes. Other work has extracted (latent) regression coefficients from the polychoric correlation matrix separately estimated for consecutive waves from the panel; see Horvath et al. (1992), Ivaldi (1992) and Nerlove & Schuermann (1995).[3] Accordingly this method tests for rationality contingent on the assumption of no macroeconomic shocks.[4]

We thereby determine whether individuals use information efficiently when forming their expectations and thus test whether expectational errors were rational ex ante. This is important since expectations can be rational ex ante but not look rational ex post, since macroeconomic shocks, for example, can cause a bias between expectations and the subsequent realisation. Ex post we then try to explain how and why individuals make

[2]Brown & Taylor (2006) also employ single equation methods although the form of their model is different. They seek to explain realisations (dependent variable) with respect to expectations (independent variable). In one specification like us they allow expectations to be endogenous. But, as explained below, this is achieved using generated expectational values and is therefore likely, in contrast to our simultaneous method, to suffer from generated variable bias. Their other method assumes expectations are exogenous. More worryingly in this case expectations are considered as an index with 0 denoting down, 1 the same and 2 better. Clearly this model is not identified up to scale.

[3]This methodology can be seen as a special case of two-stage, *structural equation modelling*, estimators more commonly employed in psychometrics; see Lee et al. (1992) and Moustaki (2001).

[4]Nonparametric rationality tests, again implicitly assuming no macroeconomic shocks, have also been developed; see Gourieroux & Pradel (1986). As indicated other tests of the reliability of expectational data have transformed the underlying micro-level responses, the focus of this paper, into aggregate (or at best sectoral) quantitative variables using some quantification method typically based on the proportions of optimists and pessimists and then tested rationality; e.g. see Lee (1994).

expectational errors; we investigate whether macroeconomic shocks occurring after the expectation was formed help to explain expectational errors. This overcomes problems previous work has had identifying whether deviations of expectations from realisations are failures of rationality or are explicable by common shocks hitting households after they made the forecast.

In common with much previous work [see Horvath et al. (1992); Das & van Soest (1999) and Nerlove & Schuermann (1995)], including work using the BHPS [see Brown & Taylor (2006)] we find rationality is rejected for the sample as a whole. Recent work has explained rejection of the rational expectations hypothesis in terms of the costs of forming rational expectations exceeding the benefits; e.g. see Carroll (2003) and Branch (2004). It can be optimal to form expectations using some alternative to rational expectations when there are costs to gathering information and forming rational expectations. To-date focus has been on identifying this alternative model of expectation formation. Our focus is slightly different. We exploit the broad array of information the BHPS contains on individuals' characteristics to identify statistically the characteristics of individuals for whom the costs of forming rational expectations apparently exceed the benefits. This is achieved using a bivariate regime-switching ordered probit model, distinguishing between states of rationality and irrationality. In particular we examine whether age and other background variables affect the probability of an individual using some alternative model to rationality to form their expectations. Given that we aim to establish stylised facts about the sort of people who are likely to form expectations using some alternative to rational expectations, the alternative model does not need to be specified structurally. Future work should distinguish between alternative explanations for irrational behaviour, perhaps by introducing additional states which distinguish between different models of expectation formation.

The plan of this paper is as follows. Section 2 introduces the BHPS. Given the categorical nature of the observed expectational data, Section 3 motivates the consideration of a continuous latent variable underlying the categorical responses as the preferred means of modelling these data. Respecting the categorical nature of the survey data, Section 4 then provides some descriptive statistics on expectations, including consideration of their reliability. Section 5 suggests the use of bivariate ordered probit models to examine formally the relationship between expectations and realisations. Section 6 explains how this model provides a ready means to test rationality. Section 7 details the modelling results. Section 8 then suggests the use of and then estimates a regime-switching bivariate probit model to identify what factors influence the probability of being rational. Section 9 concludes.

2 The BHPS: Data Description

The BHPS has been conducted since 1991 collecting nationally representative data annually from a panel of originally five thousand households comprising about ten thousand individuals. The same individuals have been re-interviewed in successive years and if they form a new household, all adults in the new household are thereafter included in the survey. The data collected include information on the incomes of individual members of the households and a wide range of socioeconomic data such as age, sex and educational background. We consider thirteen waves of the BHPS, covering the years 1991 to 2003. This covers a period of recession and recovery.

Of central concern are the responses the BHPS provides to the questions: "*Has your financial position improved, stayed the same or worsened over the past year?*" and "*How do you expect your financial position to change over the coming year?*" with the second question inviting the same categorical answers.

The actual wording of these questions in the BHPS is not specified clearly enough to be sure they are referring to income growth.[5] But, to interpret the difference between the retrospective and lagged prospective questions as a forecasting error, we do assume respondents have the same concept in mind when replying to each question. These data have been used as explanatory variables when seeking to explain consumption, income and savings behaviour (see Guariglia (2001) and Guariglia & Rossi (2002)) but have been largely ignored as a source of information in their own right.

The BHPS starts interviews in a given year in September. The majority of interviews are completed by the end of December although some interviewing continues through to the end of April. Matching the expectational and realisation data reduces the time-series dimension of the panel at our disposal from 13 to 12 years. Moreover, in the econometric work we exploit data the BHPS has on the change in households' objective incomes. This further reduces the time dimension, to 11 years. For consistency throughout we restrict attention to these 11 years, but note that the descriptive statistics given below are little affected when the 12 year window is considered.

While the BHPS, as an annual survey, cannot capture rapid shifts in expectations

[5] There is, however, a statistically significant and positive correlation between individuals' financial position and income growth in their household (adjusted for household size using an equivalence scale); information on households' income is also provided in the BHPS. The polyserial correlation (Olsson et al. (1982)) between the retrospective financial position question (which is qualitative) and objective income growth (as reported quantitatively) pooled across individuals and time has a t-value of 17.31. This drops to 9.54 for the expectational financial position question.

which less complete but more frequent consumer surveys might capture it has the advantage of supplementing direct observations on individuals' expectations and realisations with direct observations on the contents of individuals' information sets, such as their incomes and socioeconomic background. In contrast previous micro-level studies into the nature of expectation formation in the UK have relied on data-sets like the Confederation of British Industry's survey of around 1000 firms each quarter; see Horvath et al. (1992) and Nerlove & Schuermann (1995). While this survey does provide, albeit unpublished, micro-level qualitative expectational and realisation data, little is known, certainly in a quantitative form, about the contents of firms' information sets, such as their income (turnover) and profits. This has prevented analysis moving beyond tests of rationality, or specific alternatives such as naive expectations, constructed from the contingency table of qualitative responses and the polychoric correlation matrix.[6] In contrast we seek both descriptively and econometrically to determine whether factors like age are associated with an increased propensity to form rational expectations.

3 Latent Variable Testing of the Reliability of Expectations

In common with others (e.g. see Ivaldi (1992), Horvath et al. (1992) and Nerlove & Schuermann (1995)) we assume that individuals' survey responses are determined by an individual-specific unobserved continuous random variable as it crosses thresholds.

Consider a survey that asks a sample of N_t individuals at year t both a retrospective question, namely whether their financial circumstances, for example, have improved, not changed or worsened over the past year and a prospective question, namely whether they expect their financial circumstances to improve, not change or worsen over the next year.

Let y_{it} denote the latent variable characterising the actual financial situation of individual i at time t, y_{it}, $\{i = 1, 2, ..., N_t; t = 1, ..., T\}$. At the end of period $(t-1)$ individual i makes a prediction, y^*_{it}, of y_{it} based on information available to it, the information set $\Omega_{i,t-1}$.

$$y^*_{it} = \mathsf{E}\{y_{it}|\Omega_{i,t-1}\}. \tag{1}$$

The retrospective and prospective survey data provide two pieces of categorical information on the individual-specific random variable y_{it}:

[6] Ivaldi (1992) applies a related methodology to Finnish data.

1. a prediction of y_{it} made at the end of period $(t-1)$. The prediction is denoted by the discrete random variable $y^p_{it,j}$, $j = 1,2,3$ (corresponding to "improve", u^*, "stay the same", s^*, and "worsen", d^*, respectively), where

$$y^p_{it,j} = 1 \text{ if } a_{j-1,it} < y^*_{it} \leq a_{j,it}; 0 \text{ otherwise}$$

2. the actual outcome in period t. The outcome is denoted by the discrete random variable $y^r_{it,j}$, $j = 1,2,3$, or u, s and d, where

$$y^r_{it,j} = 1 \text{ if } b_{j-1,it} < y_{it} \leq b_{j,it} \text{ ; } 0 \text{ otherwise} \tag{2}$$

We follow convention and assume $\{a_{0,it}, b_{0,it}\} = -\infty$ and $\{a_{3,it}, b_{3,it}\} = \infty$.

4 Descriptive Statistics on Expectations and their Reliability

The probability distribution characterising $y^p_{it,j}$ and $y^r_{it,j}$ is summarised by a 3×3 contingency table. Table 1 lists these tables separately for each wave in the BHPS, while Figure 1 draws out specific information contained in the contingency tables. U, S and D denote the proportion of individuals who reply u, s and d, with asterisks referring to the expectational question.

4.1 People are perennially too optimistic

Table 1 and Figure 1 reveal that more individuals realised a worsening in their financial circumstances than expected it. People, on average, appear to have been too optimistic. Alternatively they may have got their forecasts right but, which seems unlikely across 11 years, have been subject to a series of negative shocks unforeseen at the time they formed their expectations. However, there is an asymmetry since in contrast to when they are pessimistic individuals' optimism appears to be borne out, in the sense that a similar proportion of individuals reported an improvement in their financial circumstances to expected it.[7] This raises the possibility that positive and negative economic shocks are

[7]Interestingly, as Michael Bryan kindly pointed out to us, a similar picture emerges for the US when studying the Michigan survey and comparing responses to the perceptions and expectations of "financial condition" question. Summarising, US individuals also appear to have been overly optimistic since while

asymmetric; the results are consistent with the view that good luck is more predictable than bad luck

Table 1: Contingency Tables of Realisations and Expectations from the BHPS

	$P(u\|u^*)$	$P(s\|u^*)$	$P(d\|u^*)$	$P(u\|s^*)$	$P(s\|s^*)$	$P(d\|s^*)$	$P(u\|d^*)$	$P(s\|d^*)$	$P(d\|d^*)$
1993	0.105	0.071	0.053	0.106	0.300	0.148	0.029	0.069	0.120
1994	0.115	0.079	0.056	0.107	0.286	0.149	0.024	0.069	0.115
1995	0.122	0.079	0.059	0.114	0.322	0.141	0.021	0.055	0.087
1996	0.139	0.087	0.052	0.128	0.343	0.115	0.021	0.045	0.069
1997	0.154	0.083	0.050	0.136	0.351	0.112	0.019	0.040	0.056
1998	0.147	0.086	0.058	0.136	0.358	0.116	0.016	0.032	0.050
1999	0.149	0.100	0.050	0.123	0.371	0.112	0.015	0.031	0.049
2000	0.150	0.090	0.055	0.129	0.370	0.114	0.016	0.030	0.047
2001	0.144	0.098	0.049	0.139	0.383	0.102	0.016	0.030	0.040
2002	0.133	0.092	0.050	0.132	0.394	0.112	0.014	0.030	0.043
2003	0.119	0.095	0.041	0.120	0.440	0.106	0.010	0.026	0.043

Notes: $P(.|.^*)$ denotes the proportion of individuals in the BHPS who reported an improvement (u), no change (s) or worsening (d) in their financial circumstances, conditional on having expected an improvement (u^*), no change (s^*) or worsening (d^*).

As we should expect if individuals form expectations rationally the top panel in Figure 1 also shows greater dispersion in realisations than expectations.[8] A striking aspect is the number of individuals who expect no change in their financial circumstances. This is consistent with Nerlove (1983) who in a study of firm-level output growth comments on the fact that prospective output growth is much more concentrated on "no change" than are reports about what has (retrospectively) happened to output. This is obviously consistent with a situation where substantial deviations from the initial expectation are the result of shocks which were not forecast.

The middle panel of Figure 1 plots the probability of an expectational error, estimated as the proportion of non-diagonal elements on the contingency table. The probability of an error declines slightly over the sample-period. This is consistent with macroeconomic evidence that suggests volatility (in GDP growth or the business cycle) has declined over the last 15 years; e.g. see Sensier & van Dijk (2004). Consistent with the evidence

the proportion of individuals who were optimists is similar for perceptions and expectations, a higher proportion of individuals perceived a worsening in their financial expectation than expected it.

[8]This is a common finding with qualitative data on realisations and expectations; e.g. for an application to Holland see Das & van Soest (1999).

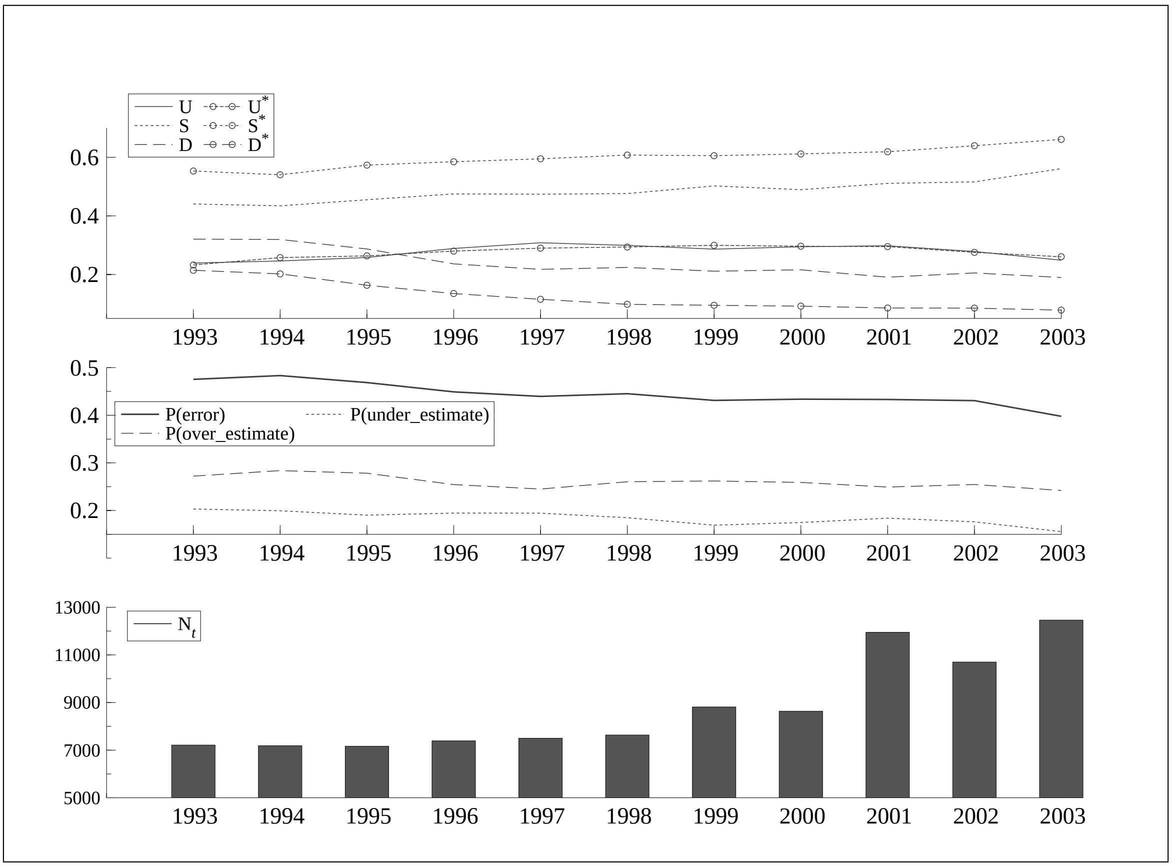

Figure 1: The proportion of optimists and pessimists in the BHPS

in the top panel of Figure 1, suggesting that people are too optimistic when looking ahead, the middle panel in Figure 1 confirms that more individuals over-estimate (i.e. the reported realisation turns out lower than expected) than under-estimate (i.e. the reported realisation turns out more than expected).

It can also be observed from Table 1 that we cannot reject the Gourieroux & Pradel (1986) [GP] nonparametric test for rationality. Under GP, rationality is satisfied if and only if $p_{kk} \geq \max_{j \neq k} p_{jk}$; $k = 1, ..., K$,, where p_{jk} denotes the probability of observing realisation j and expectation k. But this test is valid only under the assumption that individuals' *ex ante* and *ex post* probability density functions characterising behaviour are equivalent. This implies that no macroeconomic shocks hit the economy after the expectation is formed, but before the realisation is stated.

4.2 The accuracy of individual-level expectations

To indicate quantitatively, at the micro-level, the accuracy of individuals' qualitative forecasts of their financial situation we estimate by maximum likelihood the polychoric correlation between their expectations and the subsequent realisation which they report.[9] Assuming y_{it} and y^*_{it} follow a standardised bivariate normal distribution the polychoric correlation between the variables is defined as the off-diagonal element from their covariance (correlation) matrix; see Olsson (1979). Our panel data set allows us to compute the polychoric correlation across time ($t = 1, \ldots, T$) and separately across individuals ($i = 1, \ldots, N$). Expressed alternatively, the contingency table can be constructed both across i and t. This proves important in detecting heterogeneity between individuals and over time.

Figure 2 plots the polychoric correlation between expectations and realisations, along with the associated 95% confidence intervals, across time. Realisations and expectations are positively correlated and in a statistically significant manner. However, there is some volatility across time in the strength of their relationship, with a tendency towards decreased correlation.

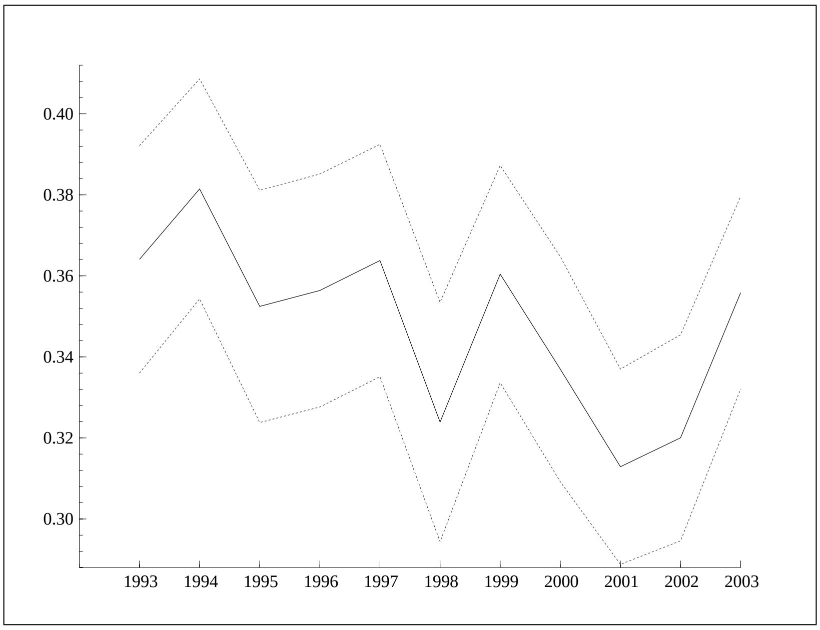

Figure 2: Financial Circumstances in the BHPS: Polychoric Correlation Between Realisations and Expectations and the associated 95% confidence interval

[9]While the Pearson (product moment) correlation coefficient can be computed for polychotomous observations, it is known to be misleading; see Mislevy (1986).

To begin to establish whether certain types of individual are more likely to form accurate expectations than others we estimate the polychoric correlation between expectations and realisations for men and women separately, for those of different ages, for those with A-level qualifications or above and for those who are employed (either as an employee or self-employed). We consider this issue more systematically in section 8 when regime switching bivariate probit models are estimated which both let us identify what proportion of the sample are rational and study whether there are any systematic patterns in terms of who is rational.

Table 2 lists the polychoric correlation between realisations and expectations for these sub-groups. The most striking finding is that older people appear to form more accurate expectations ex post, in that the estimated correlation coefficient rises with age. This is consistent with the view that older people forecast better as their incomes are easier to predict; their incomes are subject to less unpredictable noise (lower variance). Below in Section 8 we examine whether this increased correlation translates into an increased tendency to be rational in old age. Table 2 also shows some evidence to support the view that those educated to A-level or above form more accurate expectations ex post.

5 Bivariate Probit Modelling Framework

To examine formally the reliability of households' expectations and determine what factors influence their reliability we consider a bivariate model which allows expectations and realisations to be determined simultaneously:

$$y_{it} = \alpha + \beta z_{it-1} + z_t + \varepsilon_{it} \tag{3}$$

$$y^*_{it} = \alpha^* + \beta^* z_{it-1} + z^*_t + \varepsilon^*_{it} \tag{4}$$

where the disturbances ε_{it} and ε^*_{it} follow a bivariate normal distribution:

$$\begin{bmatrix} \varepsilon_{it} \\ \varepsilon^*_{it} \end{bmatrix} \sim \text{i.i.d.N}\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma^2_\varepsilon & \rho \\ \rho & \sigma^2_{\varepsilon^*} \end{bmatrix} \right), \tag{5}$$

and z_{it-1} is realised income growth in year $(t-1)$, relative to year $(t-2)$, for individual i's household as reported quantitatively (objectively) in the BHPS. The household income data are in real terms and adjusted for changes in household size using equivalence scales following Bardasi & Jenkins (2004). z_{it-1} is assumed to be in an individual's information

Table 2: Polychoric correlations between individual-level realisations and expectations for selected groupings

		Polychoric corr.	NT
Total	All individuals	0.353 (0.004)	96665
Age	<20	0.279 (0.016)	5978
	20-30	0.289 (0.009)	17807
	30-40	0.283 (0.008)	22273
	40-50	0.303 (0.009)	19358
	50-60	0.347 (0.011)	15752
	60>	0.408 (0.010)	23583
Sex	Female	0.343 (0.006)	52641
	Male	0.363 (0.006)	44024
Educ	O-levels or below	0.346 (0.006)	51695
	A-levels or above	0.349 (0.006)	43912
Job Status	Employed	0.330 (0.005)	57074
	Other	0.349 (0.067)	39566

Notes: Estimation using the BHPS from 1991 to 2003. Estimated standard errors in parentheses

set when she forms her expectations. z_t are time dummies designed to capture macroeconomic shocks observed after individuals form their expectations but before they reply to the realisation question, such that $z_t^* = E(z_t | \Omega_{t-1})$. $(z_t - z_t^*)$ can therefore be interpreted as a macroeconomic shock. Use of dummies is, in a sense, convenient as it obviates the need to identify and estimate the macroeconomic shocks per se. Below we compare the estimated dummies with a time-series of macroeconomic shocks computed as deviations of GDP growth from forecasts published in real-time by HM Treasury.

Equations (3)-(4) accommodate measurement error in the underlying continuous random variables y_{it} and y_{it}^* by treating them as dependent variables. This does, however, assume the measurement error is uncorrelated with the explanatory variables; see Bertrand

& Mullainathan (2001). Crucially (3)-(4) allows expectations y^*_{it} to be endogenous essentially tackling simultaneity bias in a similar manner to a vector autoregression by assigning any contemporaneous dependence ρ to the disturbance terms. In contrast previous work such as Horvath et al. (1992) has assumed expectations are exogenous; this is inconsistent with the plausible view that common factors influence both expectations and realisations.

To account for the ordinal nature of the available data $y^p_{it,j}$ and $y^r_{it,j}$, (3)-(4) is estimated as an ordered bivariate probit panel-data model. We consider a pooled model; but importantly parameter estimates remain consistent with the inclusion of random effects and their standard errors are consistent when a corrected covariance matrix is used; see Guilkey & Murphy (1993).[10] In fact, the homogeneity restrictions (across i) imposed on the coefficients in (3)-(4) are driven by the properties of the BHPS data. Since T is small, ranging from 1 to 11 across individuals, (3)-(4) cannot be estimated separately for each individual. But to draw out heterogeneity below the model is estimated separately for men and women. In addition, in section 8 we let individuals switch between a rational and irrational state according to a wider set of background characteristics.

Equations (3)-(4) can be seen to generalise Souleles (2004) whose model amalgamates (3)-(4) into a single equation explaining the forecast error $(y_{it} - y^*_{it})$. A related approach is adopted by Das & van Soest (1997) and Das & van Soest (1999) when examining Dutch households. Given the available data (i.e. $y^p_{it,j}$ and $y^r_{it,j}$) ordered probit estimation, with five categories of error, can then proceed only on the assumption that errors are cardinal; i.e. two places off the diagonal on the contingency table is twice as bad as being one place off. Additionally use of a single equation does not let one draw out the differential affect of information on expectations and realisations.

As well as identifying those factors which determine consumers' expectations and making comparisons with the realisations, as we now explain a test for whether consumers make efficient use of available information when forming their forecasts or expectations of the future can be formulated using (3)-(4).

[10]In fact experimentation in both Gauss and in gllamm (see Skrondal & Rabe-Hesketh (2004)) could not overcome the computational burden associated with the estimation of bivariate ordered random effects models, with a large sample.

6 Testing rationality

Under rationality and quadratic loss

$$\mathsf{E}(y_{it} - y_{it}^*|\Omega_{it-1}) = 0. \tag{6}$$

This also implies that the expectational errors have zero means and are serially uncorrelated. To test this hypothesis in a meaningful manner attention must be paid to how equations (3)-(4) are identified.

Conditioning ε_{it} on ε_{it}^* we can write

$$\varepsilon_{it} = (\rho/\sigma_{\varepsilon^*}^2)\varepsilon_{it}^* + \eta_{it} \tag{7}$$

where η_{it} is an i.i.d. error such that $\mathsf{E}(\eta_{it}\varepsilon_{it}^*) = 0$. To ensure $\mathsf{Var}(y_{it}) \geq \mathsf{Var}(y_{it}^*)$, which must hold under rationality, for identification we assume $\sigma_\varepsilon^2 = 1$ but let $\sigma_{\varepsilon^*}^2 \leq \sigma_\varepsilon^2$ be freely estimated. Identification is then achieved by assuming common thresholds for the expectations and realisations: $a_{jt} = b_{jt} = a_j$ $(j = 1, 2)$. In other words, consumers are assumed to use the same "yardstick" when evaluating *ex ante* and *ex post* movements in their financial circumstances.[11] Similarly Horvath et al. (1992), in contradistinction to Ivaldi (1992), impose this restriction to identify a regression relationship between y_{it} and y_{it}^*. This differs from polychoric (LISREL) correlation when for identification it is assumed instead that $\sigma_\varepsilon^2 = \sigma_{\varepsilon^*}^2 = 1$. As discussed, this restriction is inappropriate when testing rationality; it is therefore preferable to assume common thresholds instead. Conveniently we also bypass any complications [see Cudeck (1989)] that may arise from inferring a structural model from correlation rather than covariance matrices, complications ignored by Horvath et al. (1992), Ivaldi (1992) and Nerlove & Schuermann (1995). $\mathsf{Var}(y_{it}) \geq \mathsf{Var}(y_{it}^*)$ explains our empirical finding that there is a concentration of expectations in the no change category (see Figure 1). Identification is completed by assuming, as is usual in discrete choice models since no threshold parameters are set to zero, $\alpha = \alpha^* = 0$.

We can clearly identify the restrictions which rationality, see (6), imposes on equations (3)-(4) by considering the conditional linear model[12]

$$y_{it} = (\alpha - \rho\alpha^*) + (\beta - \rho\beta^*)z_{it-1} + (z_t - \rho z_t^*) + \rho y_{it}^* + \eta_{it} \tag{8}$$

[11] This restriction has been employed elsewhere; e.g. see Wren-Lewis (1986).

[12] Our use of the joint density is also motivated by the fact that efficiency is lost in estimation if the conditional rather than joint distribution is considered even when $\mathsf{E}(y_{it}^*\eta_{it}) = 0$; see Ronning & Kukuk (1996).

which implies that the expectational error is determined by the following process

$$(y_{it} - y_{it}^*) = (\alpha - \rho\alpha^*) + (\beta - \rho\beta^*)z_{it-1} + (z_t - \rho z_t^*) + (\rho - 1)y_{it}^* + \eta_{it} \quad (9)$$

which is familiar to us as the standard (Mincer-Zarnowitz) framework to test rationality.

It is of methodological interest that when testing rationality Brown & Taylor (2006) arrive at a reduced-form equation similar to (8). In their first specification Brown and Taylor assume expectations are exogenous. In addition they do not account appropriately for the categorical nature of the expectational data from the BHPS since they appear simply to explain realisations with respect to expectations considered in the form of an index like $y_{it,j}^p$. Clearly one can always re-scale $y_{it,j}^p$ to ensure $\rho = 1$, their hypothesis of interest. Secondly, Brown and Taylor allow y_{it}^* to be endogenous; at a first-step expectations are modelled and at a second step (8) is estimated using predicted values for y_{it}^*. Our approach has the advantage of being one-step and does not suffer from use of generated variables which, as Brown & Taylor (2006) explain, is likely to induce bias. In addition we make clear the identification restrictions employed.

Therefore for rationality the following three restrictions need to hold:

1. $\alpha = \alpha^*$
2. $\beta = \beta^*$
3. $\rho = 1$

These restrictions ensure orthogonality of $y_{it} - y_{it}^*$ with respect to Ω_{it-1}. Decomposing Ω_{it-1} into sub-components is helpful in letting us determine with respect to what each restriction imposes orthogonality. We can see that (i) $\mathsf{E}((y_{it} - y_{it}^*|y_{it}^*) = 0$ when $(\rho - 1) = 0 \Rightarrow \rho = 1$; (ii) $\mathsf{E}((y_{it} - y_{it}^*)|z_{it-1}) = 0$ when $\beta = \rho\beta^*$; (iii) $\mathsf{E}((y_{it} - y_{it}^*)|1) = 0$, which is unbiasedness, when $\alpha = \rho\alpha^*$. Therefore $\mathsf{E}((y_{it} - y_{it}^*)\Omega_{it-1}) = 0$ requires $\rho = 1$, $\beta = \beta^*$ and $\alpha = \alpha^*$. A Wald test can therefore be constructed to test (6). The test for rationality, as indicated, is a joint test of the identifying restrictions and these three testable assumptions implied by rationality.

Under rationality micro-level expectational errors are explicable only with respect to macroeconomic shocks

$$y_{it} - y_{it}^* = (z_t - z_t^*) + \eta_{it}. \quad (10)$$

Therefore testing the three restrictions, in effect, is an application of the conventional orthogonality test (of z_{it-1}) to the analysis of qualitative data. But from (10) we can see that rationality, even under the maintained assumption of quadratic loss, in the presence of macroeconomic shocks need not imply expectations are unbiased ex post. In addition given the categorical nature of the expectational data and the ensuing use of discrete choice models, rather than the classical linear regression, even if the macroeconomic effects are assumed orthogonal to the other explanatory variables we should not expect the parameter estimates in (9) to be consistent when they are omitted; for related discussion for single equation discrete choice models see Wooldridge (2002) [p. 470].

7 Estimation Results

Equations (3)-(4) are estimated separately for men and women.[13] This sample split was motivated by the practical desire to speed up estimation of what, with a large sample, is quite an involved model. It will also establish whether heterogeneity is present, although it is unclear what economic theory would suggest gender helps determine rationality. Table 3 reports the results while Figure 3 plots the estimated dummy variables, which were all highly significant statistically.

Table 3: Explaining realisations and expectations using a bivariate ordered probit model

	Female	Male
$a_1 = b_1$: lower threshold	-0.789	-0.769
	(-147.79)	(-129.13)
$a_2 = b_2$: upper threshold	0.606	0.480
	(125.27)	(99.70)
β : coeff on income in realis eqn	0.010	0.018
	(2.77)	(4.46)
β^* : coeff on income in expec eqn	0.014	0.017
	(5.08)	(5.31)
ρ	0.337	0.357
	(60.10)	(57.55)
$\sigma^2_{\varepsilon^*}$	0.732	0.749
	(47.79)	(37.71)
NT	52641	44024
N	10434	8847
LogL	-97988	-85760
H_0 : REH (p-value)	0.000	0.000
$H_0 : \beta = \beta^*$ (p-value)	0.122	0.330

Notes: Estimation using the BHPS from 1991 to 2003. Estimated t-values in parentheses.

[13] Those individuals still at school are dropped from the panel.

From Table 3 we can see that there are no clear differences between men and women, beyond slight evidence that men react more strongly to realised changes in their lagged income. Across men and women we can draw out several common findings.

Consistent with rationality individuals appear to react similarly to observed income changes both when forming expectations and when reporting their realisations. As we might expect, a rise in lagged objective income is associated with increased confidence and higher reported subjective income. This is consistent with evidence for other countries. For example, using the Dutch Socio-economic Panel, Alessie & Lusardi (1997) and Das & van Soest (1999) find that expectations are positively affected by realised income changes in the past. This confirms the impression that individuals have in mind their own income growth, at least among other things, when replying to subjective expectational questions.

A positive and statistically significant correlation, ρ, indicates that consistent with the descriptive evidence in Figure 2 there is a positive and significant relationship between expectations and realisations. Comparison with Table 2 reveals little difference relative to the unconditional polychoric correlation coefficient; in Table 2 the correlation between expectations and realisations, across all individuals, was estimated to be 0.353 which is very similar to the values for $\widehat{\rho}$ seen in Table 3. But $\widehat{\rho} < 1$ implies that this relationship is not as close as rationality demands. In particular, it implies that while statistically significant macroeconomic shocks occurring after the forecast was made do not explain all of the forecasting error. This suggests individuals' expectations are not rational ex ante, since they can be explained with reference to lagged income growth and that the expectational error can be forecast in part with reference to expectations themselves. Unsurprisingly rationality is therefore rejected via a Wald test, with p-values of 0.00. Indeed the cause of the irrationality appears to be $\rho < 1$ rather than $\beta_i' \neq \beta_i'^*$, since one cannot reject the hypothesis that $\beta = \beta^*$.

Expectational errors therefore appear to have a systematic component that varies across individuals. Since $\widehat{\rho}\widehat{\beta}_i^* < \widehat{\beta}_i$ a fall (rise) in realised income means an individual over (under) estimates her future income. Individuals whose income increased in the last year tend to be too pessimistic when forecasting the future. Conversely individuals whose incomes decreased in the last year tend to be too optimistic when forming their expectations. This is consistent with the view that expectations are too smooth and under rationality should react more strongly to observed income changes. This kind of regressive expectation might be explained by the value function in the prospect theory of Kahneman & Tversky (1979) which implies that the risk attitude of individuals will depend on whether they are in a win or a loss situation relative to their reference point. Individuals become risk lovers (and perhaps optimistic) in loss situations (when their realised income declined last year) and risk averse (and perhaps pessimistic) in win situations (when their realised income increased last year).

Figure 3 plots the estimated time dummies for the realisation and expectational equations. These time dummies are statistically significant implying that there is a relationship between micro and macro forecasting errors. This, of course, constitutes no violation of rationality ex ante. The top panel indicates that the expectations dummies are smoother, with the realisation dummies exhibiting a little more volatility. This smoothness casts doubt on the value of expectational data for short term forecasting since it suggests they are unable to pick up short term fluctuations.

The remaining panels of Figure 3 plot the macroeconomic shock, identified as the difference between z_t and z_t^*, alongside a time-series of 'known' macroeconomic shocks. These are computed as deviations of actual GDP growth from consensus forecasts published in real-time by HM Treasury.[14] Inspecting the difference between the dummy variables, which we interpret as a shock, we see that people are continually subject to negative shocks. This helps to explain the excessive optimism which, we found above, individuals have when forming expectations. Across households financial circumstances routinely turn out worse than expected. Figure 3 also shows that the bias in individuals' expectations varies over time and appears to follow a cyclical pattern. Nevertheless, accounting for macroeconomic shocks does not explain individuals' irrationality.

Relating these shocks with the HMT shock we can identify whether individuals collectively react to something we can agree was a genuine shock or whether they were collectively deluded and reacted to perceived rather than realised macroeconomic shocks. The greatest negative shocks occur at times when the macroeconomy exceeded HMT's expectations. Indeed the micro and macro shocks are correlated -0.45, implying that the shocks that affect individuals are different from those that affect forecasters at HM Treasury.

8 Rational versus Irrational States: a regime-switching bivariate probit model

To determine statistically those individuals, and those types of people, for whom the net benefit of forming rational expectations is apparently positive we extend the bivariate

[14] We consider HMT forecasts made in December for the (calendar) year ahead.

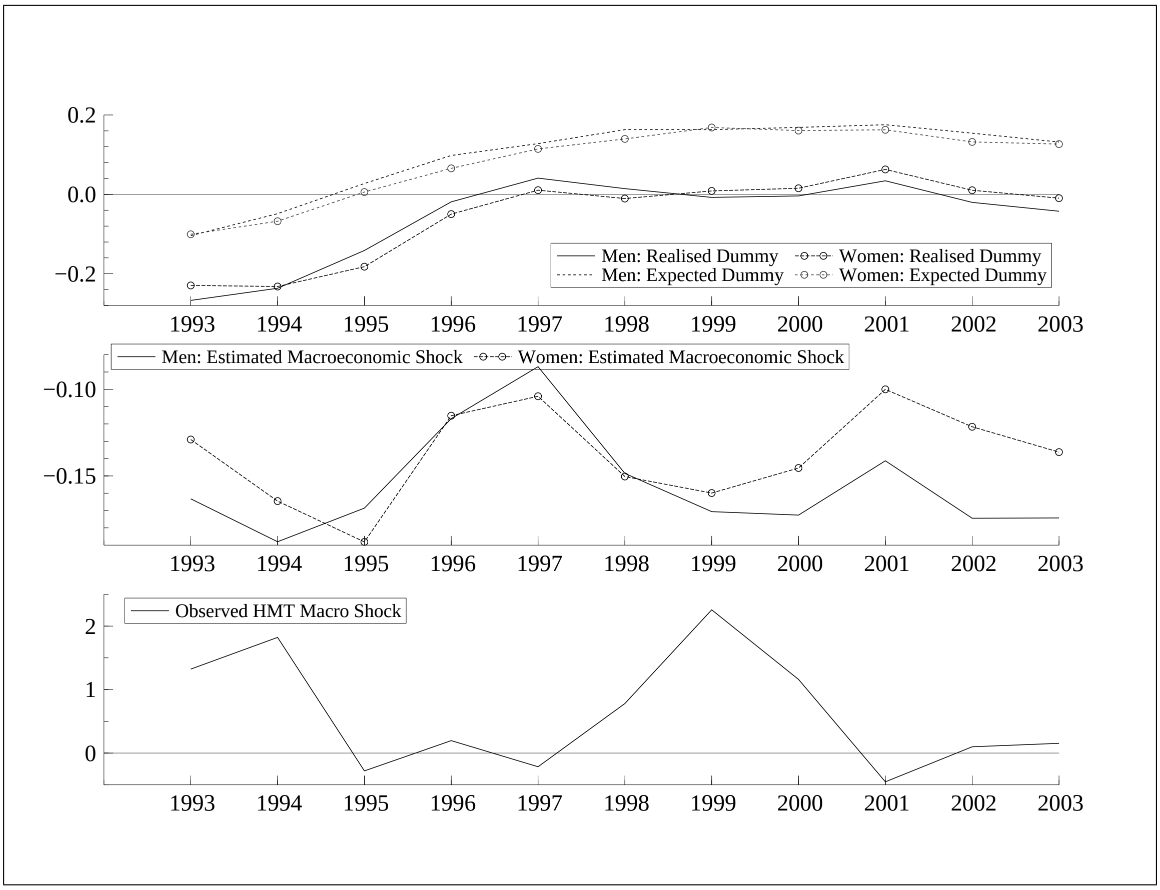

Figure 3: Macroeconomic Shocks: Relating the macroeconomic shocks for men and women from the BHPS to known macroeconomic shocks based on HM Treasury forecasts of GDP growth

ordered probit model, (3)-(4), to categorize individuals as rational or irrational in each year. Consistent with the fact that the net benefit of forming rational expectations can vary for a given individual over time, each individual can switch between 'rationality' and 'irrationality' over time. Individuals can then be classified into one of these two categories, if significant statistically, according to which one is more likely. The function that determines the probability of a switch could be interpreted as the reduced-form of the cost-benefit function. Individuals who form rational expectations could be presumed to have concluded that the net benefit of forming rational expectations is positive.

The two categories are distinguished from each other by allowing the individual to switch between (3)-(4), with the rationality restrictions imposed, and a freely estimated version of (3)-(4). The latter could be seen as the reduced-form of various models of irrational behaviour. We let individuals switch according to an unobserved random variable

$\{s_{it}\}$, where $s_{it} = 1$ when individual i at time t is in state 1 (rationality) and $s_{it} = 2$ when they are in state 2 (irrationality).[15] Let $\mathsf{P}(s_{it} = l; \theta) = p_j$ $(l = 1, 2)$, where θ is a vector of parameters, denote the probability that individual i at time t is in state 1 or 2. Specifically we use a probit model to establish the probability in each year that an individual is rational or irrational, with the probability depending on a function of individual-level characteristics such as age, job market status, education, whether the level of their income is above the median level and income growth. These were factors identified in Table 2 as of importance in explaining expectational errors. Effectively we let $\mathrm{P}(s_{it} = j; \theta) = \Phi(-\beta x_{it-1})$ where Φ is the cdf of the normal distribution and x_{it-1} is a vector of explanatory variables which include income growth z_{it-1}.

The regime-switching bivariate ordered probit model is estimated by maximum-likelihood. The joint unconditional probability of $\{y_{it}, y^*_{it}\}$, $f(y_{it}, y^*_{it}; \theta)$, is the weighted sum of the two bivariate conditional densities $f(y_{it}, y^*_{it}|s_{it} = l; \theta)$, with the weights equal to p_1 and $(1 - p_1)$.

Conditional on estimates for θ

$$P(s_{it} = l|y_{it}, y^*_{it}, \theta) = \frac{p_j f(y_{it}, y^*_{it}|s_{it} = l; \theta)}{f(y_{it}, y^*_{it}; \theta)}. \tag{11}$$

(11) can then be used to calculate for each individual $\{y_{it}, y^*_{it}\}$ the probability that they are from each state. When $P(s_{it} = l|y_{it}, y^*_{it}, \theta) > 0.5$ we classify individual i at time t as being in state l.

8.1 Switching results

Table 4 presents the results of the switching model. These are designed to help us understand statistically what if any factors contribute to behaviour more consistent with rationality. The estimated dummy variables are not reported but are very similar, in both states, to those presented in Figure 3.

Table 4 shows clearly that for both men and women age is highly statistically significant in the probability/switching equation. This suggests that the old might be more likely to find the net benefit of forming rational expectations to be positive. Accordingly they form expectations according to the rational expectations hypothesis. The less educated, whether male or female, are also more likely to form rational expectations. This is consistent with the view that the highly educated, because of their better prospects,

[15]For related discussion and references see Garcia et al. (1997). Similarly they used a switching regression to classify individuals as liquidity constrained.

have higher (opportunity) costs to forming rational expectations and/or derive less benefit from their formation, perhaps because they find it easier to correct expectational mistakes although we do not explore this formally. Interestingly although testing rationality via its implications for consumption behaviour, Benito & Mumtaz (2006) using the BHPS also find that the probability of excess sensitivity (irrationality) is higher for the young and those with a degree. Table 4 also shows that women with a job are less likely to form rational expectations, but men albeit not in a statistically significant manner are more likely. An individual's income, whether measured as growth over the last year or via a dummy variable equal to unity if higher than the median income level, appears to matter only for women, with the richer more likely to form rational expectations. We have no explanation for the differences between men and women. But we might imagine that the poor are less affected by their expectations, and hence have less incentive to form them rationally, since state benefits limit downside risk and on the upside credit constraints mean they cannot act upon their optimism. In any case, Table 4 shows that the incentives to form rational expectations vary across individuals according to their situation.[16]

While rationality was rejected for the sample as a whole in Table 3, from the results of the switching model presented in Table 4 we can compute the proportion of individuals who, in fact, form expectations consistent with rationality. Using (11) we calculate over the sample as a whole the proportion of individuals whose predicted probability of being in the rational state exceeds 0.5. This is taken as a measure of the proportion of the sample who are rational. For men we find that 40% are rational, and for women 42%. Similarly the mean probability of being rational is 0.38 and 0.36, for men and women, respectively. These estimates again can be related to those of Benito & Mumtaz (2006), who also using the BHPS, estimated that 20%-40% of UK households display excess sensitivity with the remaining larger group smoothing their consumption to the degree predicted by the joint implications of rationality and the permanent income hypothesis.

9 Concluding Comments

This paper complements the US-based work of Souleles (2004) by modelling and then testing the rationality of individual-level expectational data in Britain. In so doing it provides useful insight into the validity of standard economic assumptions about expectations formation. In addition, when expectational data are qualitative, as they are in

[16] Relatedly, in the context of forecasting inflation, Bryan & Palmqvist (2005) use survey data to test whether the incentive to form rational expectations increases with the level of inflation.

the application to the BHPS, it suggests the use of bivariate ordered probit models, appropriately identified, as a vehicle both to understand expectation formation and to test rationality in the presence of macroeconomic shocks.

It is found that the British are more optimistic/pessimistic about the future when they have recently seen their households' income growth rise/fall. But since lagged movements in their income growth can also help explain individuals' expectational errors, we reject the hypothesis that they form their expectations rationally. But when forming their expectations individuals do appear to react to lagged movements in their household's income consistent with rationality, suggesting a systematic and purposeful component to expectations. However, the correlation between expectations and realisations, even after controlling for macroeconomic shocks, is weak and we find that expectations are excessively smooth and appear regressive. We suggest that this might be explained by prospect theory (cf. Kahneman & Tversky (1979)), whereby individuals become risk lovers (optimistic) in loss situations (when their realised income declined last year) and risk averse (pessimistic) in win situations (when their realised income increased last year). Under rationality individuals should react more strongly to observed income changes. We also find that individuals appear to be overly optimistic about their financial circumstances. This is consistent with the view that good luck is more predictable than bad luck.

A regime-switching model is then estimated to determine statistically the types of people who are more likely than not to form rational expectations. We find that around 40% of individuals form expectations consistent with rationality. We also find that the probabilities are different for different types of people. In particular, we find that the propensity to form rational expectations increases with experience (i.e. age) rather than education. The young and highly educated are presumed to have concluded that the net benefits of forming rational expectations are negative. In future work we aim to build on these stylised facts and distinguish statistically between alternative models of irrational behaviour.

Table 4: The probability of an individual using some alternative model to rationality to form their expectations. Rational versus irrational states: a regime switching approach

	Female		Male	
	Irrationality	Rationality	Irrationality	Rationality
$a_1 = b_1$: lower threshold	-0.742 (-75.250)	-0.646 (-65.259)	-0.806 (-80.905)	-0.415 (-58.006)
$a_2 = b_2$: upper threshold	0.242 (24.085)	0.837 (80.519)	0.129 (12.965)	0.781 (78.114)
β : coeff on income in realis eqn	0.003 (0.292)	0.011 (0.995)	0.025 (2.509)	0.001 (0.066)
β^* : coeff on income in expec eqn	0.010 (1.794)	−	0.025 (2.480)	−
ρ	0.455 (21.630)	1	0.434 (19.588)	1
$\sigma^2_{\varepsilon^*}$	0.769 (25.107)	0.399 (91.800)	0.821 (19.709)	0.744 (29.60)
Switching coefficients				
age/100	3.778 (377.79)		4.243 (423.602)	
education	-0.269 (-26.372)		-0.236 (-23.551)	
job status	-0.110 (-10.399)		0.015 (1.579)	
median income	0.056 (5.513)		-0.002 (-0.225)	
income growth (z_{it-1})	-0.008 (-0.845)		0.002 (1.528)	
constant	-1.832 (-183.209)		-2.204 (-220.432)	
NT	52641		44024	
N	10434		8847	
LogL	-93129		-81294	

Notes: Estimation using the BHPS from 1991 to 2003. Estimated t-values in parentheses. Education is a dummy variable equal to unity when educated to A-level or above. Similarly job status equals unity for an individual with a job and zero otherwise. Median income equals unity for those individuals whose household's income is above the median level and zero otherwise.

References

Alessie, R. & Lusardi, A. (1997), 'Saving and income smoothing: evidence from panel data', *European Economic Review* **41**, 1251–1279.

Bardasi, E. & Jenkins, S. P. (2004), Documentation for derived current and annual net household income variables, BHPS waves 1-12. University of Essex. Institute for Social and Economic Research.

Benito, A. & Mumtaz, H. (2006), Consumption excess sensitivity, liquidity constraints and the collateral role of housing. Bank of England Working Paper no. 306.

Bertrand, M. & Mullainathan, S. (2001), 'Do people mean what they say? Implications for subjective survey data', *American Economic Review (Papers and Proceedings)* **91**, 67–72.

Branch, W. (2004), 'The Theory of Rationally Heterogeneous Expectations: Evidence from Survey Data on Inflation Expectations', *Economic Journal* **114**, 592–621.

Brown, S. & Taylor, K. (2006), 'Financial expectations, consumption and saving: a microeconomic analysis', *Fiscal Studies* **27**.

Bryan, M. & Palmqvist, S. (2005), Testing near-rationality using detailed survey data. Federal Reserve Bank of Cleveland Working Paper no. 05/02.

Carroll, C. (2003), 'Macro-economic Expectations of Households and Professional Forecasters', *Quarterly Journal of Economics* **CXVIII**, 269–298.

Cudeck, R. (1989), 'Analysis of correlation matrices using covariance structure models', *Psychological Bulletin* **105**, 317–327.

Das, M. & van Soest, A. (1997), 'Expected and Realized income changes: evidence from the Dutch Socio-Economic Panel', *Journal of Economic Behaviour and Organization* **32**, 137–154.

Das, M. & van Soest, A. (1999), 'A panel data model for subjective information on household income growth', *Journal of Economic Behaviour and Organization* **40**, 409–426.

Garcia, R., Lusardi, L. & Ng, S. (1997), 'Excess sensitivity and asymmetries in consumption: an empirical investigation', *Journal of Money, Credit and Banking* **29**, 154–176.

Gourieroux, C. & Pradel, J. (1986), 'Direct Tests of the Rational Expecation Hypothesis', *European Economic Review* **30**, 265–284.

Guariglia, A. (2001), 'Saving behaviour and earnings uncertainty: evidence from the British Household Panel Survey', *Journal of Population Economics* **14**, 619–634.

Guariglia, A. & Rossi, M. (2002), 'Consumption, habit formation, and precautionary saving: evidence from the British Household Panel Survey', *Oxford Economic Papers* **54**, 1–19.

Guilkey, D. K. & Murphy, J. L. (1993), 'Estimation and testing in the random effects probit model', *Journal of Econometrics* **59**, 301–3170.

Horvath, B., Nerlove, M. & Wilson, D. (1992), A Reinterpretation of Direct Tests of Forecast Rationality using Business Survey Data, *in* K. Oppenländer & G. Poser, eds, 'Business Cycle Anlaysis by Means of Economic Surveys, Part I', Avebury, Aldershot, pp. 131–152.

Ivaldi, M. (1992), 'Survey Evidence on the Rationality of Expectations', *Journal of Applied Econometrics* **7**, 225–241.

Kahneman, D. & Tversky, A. (1979), 'Prospect theory: an analysis of decision under risk', *Econometrica* **47**, 263–292.

Lee, K. (1994), 'Formation of Price and Cost Inflation Expectations in British Manufacturing: a Multisectoral Anlaysis', *Economic Journal* **104**, 372–386.

Lee, S.-Y., Poon, W.-Y. & M., B. P. (1992), 'Structural equation models with continuous and polytomous variables', *Psychometrika* **57**, 89–105.

Mislevy, R. J. (1986), 'Recent developments in the factor analysis of categorical variables', *Journal of Educational Statistics* **11**, 3–31.

Moustaki, I. (2001), A review of exploratory factor analysis for ordinal categorical data, *in* R. Cudeck, S. Du Toit & D. Sorbom, eds, 'Structural equation modeling: present and future. A festschrift in honor of Karl Joreskog', Scientific Science International, pp. 461–476.

Nerlove, M. (1983), 'Expectations Plans and Realisations in Theory and Practice', *Econometrica* **51**, 1251–1279.

Nerlove, M. & Schuermann, T. (1995), Expectations: are they rational, adaptive, or naive? An essay in simulation-based inference, *in* G. Maddala, P. Phillips & T. Srinivasan, eds, 'Advances in Econometrics and Quantitive Economics', Basil Blackwell, Oxford, pp. 354–381.

Olsson, U. (1979), 'Maximum likelihood estimation of the polychoric correlation coefficient', *Psychometrika* **44**, 443–460.

Olsson, U., Drasgow, F. & Dorans, N. J. (1982), 'The polyserial correlation coefficient', *Psychometrika* **47**, 337–347.

Pesaran, M. H. & Weale, M. R. (2006), Survey Expectations, *in* G. Elliott, C. W. J. Granger & A. Timmermann, eds, 'Handbook of Economic Forecasting Volume 1', North-Holland, pp. 715–776.

Ronning, G. & Kukuk, M. (1996), 'Efficient estimation of ordered probit models', *Journal of the American Statistical Association* **91**, 1120–1129.

Sensier, M. & van Dijk, D. (2004), 'Testing for volatility changes in U.S. macroeconomic time series', *Review of Economics and Statistics* **86**, 833–839.

Skrondal, A. & Rabe-Hesketh, S. (2004), *Generalized latent variable modeling: multilevel, longitudinal, and structural equation models*, Chapman and Hall/CRC.

Souleles, N. S. (2004), 'Expectations, Heterogeneous Forecast Errors and Consumption: Micro Evdience from the Michagan Consumer Sentiment Surveys', *Journal of Money, Credit and Banking* **36**, 39–72.

Wooldridge, J. M. (2002), *Econometric analysis of cross section and panel data*, MIT Press, Cambridge, Massachusetts.

Wren-Lewis, S. (1986), ' An Econometric Model of U.K. Manufacturing Employment Using Survey Data on Expected Output', *Journal of Applied Econometrics* **1**, 297–316.