Qualitative Expectational Data as Predictors of Income and Consumption Growth: Micro Evidence from the British Household Panel Survey

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Abstract

The putative ability of consumer sentiment or expectational data to predict movements in consumption and income growth data is exploited widely by policy-makers. But the informational content of these data has been little studied at the micro-level since they are often collected by cross-sectional rather than panel surveys and moreover are often published in aggregated form. This paper establishes at a micro-economic level whether expectational data are predictors of income and consumption growth, and whether they contain information additional to that already contained in past income and consumption data. This is conducted using panel structural vector autoregressive models, and exploits hitherto largely uninvestigated individual-level expectational data from the BHPS. We conclude that the predictive power of the expectational data disappears for consumption growth, but not income growth, when one controls for lagged income and consumption movements.

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1 Introduction

Consumer confidence data are collected in many countries and are widely reported as they are perceived by many to lead movements in consumption and income; e.g. see Carroll et al. (1994) and Ludvigson (2004). In addition they may influence policy-makers' decisions when setting interest rates. Therefore a coherent analysis of their information content is very important. However, often these data are collected by 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 published only as aggregated variables. Typically, given that the underlying survey data are qualitative, this is as the proportion of optimists less pessimists - the so-called balance of opinion. This has made it difficult to study the data in detail and to come to an informed view about their value.

In this paper we exploit the British Household Panel Survey (BHPS) from 1991 to 2003. The BHPS asks a nationally representative sample of more than 5000 households (comprising about 10,000 individual interviews) a range of socioeconomic questions. Importantly the BHPS offers direct observations on individuals' confidence or expectations. Specifically individuals are asked: "*How do you expect your financial position to change over the coming year?*". They are invited to reply with a categorical answer: *improve*, *stay the same* or *worsen*. While the wording of this question is somewhat vague, since it is unclear whether it refers to income, it is perhaps no less vague than similar questions in other surveys used widely by financial commentators and economic forecasters. While the BHPS, as an annual survey, cannot capture rapid shifts in expectations which less complete but more frequent consumer surveys might capture it has the advantage of supplementing direct observations on individuals' expectations with direct observations on the contents of individuals' information sets, such as their incomes and socioeconomic background.

We provide the first detailed empirical investigation into the power of these expectational data to predict income and consumption changes. Any link between sentiment data and consumption growth is probably of greater interest to policy makers than is a link between sentiment and income growth since it is consumption rather than income which affects the level of demand and thus inflationary pressures. In common with many others [e.g. see Hall & Mishkin (1982) and Guariglia & Rossi (2002)] we use data on food consumption, since the BHPS does not collect data on total individual or household consumption. Relationships between consumer confidence and income and consumption growth are estimated at a micro-economic level, specifically at the household level. While expectational data are available at the individual level, consumption and income data are available in the BHPS at the household-level only. Consequently we relate the head of household's expectations to income and consumption growth. This is carried out using a panel structural vector auto-regressive model, a tool more commonly used in applied macroeconomics which conveniently distinguishes between short and long run relations. We establish whether the expectational data are predictors of income and consumption changes and whether they contain information additional to that already contained in past income and consumption data. Thereby we provide evidence on whether households set their consumption patterns according to the rational expectations permanent income (RE-PIH) model whereby consumption is smoothed. A number of macroeconomic studies (e.g. see Campbell & Mankiw (1991) and Weale (1990)) suggest that, in contradiction to the joint implications of life-cycle optimisation and rational expectations, there is considerable consumption out of current rather than permanent income. To the extent that this is true it follows that, if the expectations terms have predictive power for income growth, they will probably also have predictive power for consumption growth. In addition, in the spirit of the macroeconomic analysis of Carroll et al. (1994), we use the micro data to test whether lagged confidence predicts current consumption growth only because it predicts current income growth. This is expected when, as suggested by Campbell & Mankiw (1991), some households consume as predicted by the RE-PIH while others do not and instead consume out of current income. In this case the confidence data should help predict consumption growth indirectly, via their ability to predict income growth, but not directly. Our work is also related to studies, primarily to US data-sets, which test the RE-PIH by testing whether there is excess sensitivity to predicted changes in income with the important distinction that we employ direct data on consumers' expectations rather than inferring them as the predicted values from an equation explaining income growth; e.g. see Hall & Mishkin (1982) and Garcia et al. (1997).

We find, consistent with previous work [see Brown & Taylor (2006)], that the expectational data predict both micro consumption and income growth when one does not condition on past income and consumption data. However, once one introduces a structural relationship between income and consumption, and controls for these lagged income and consumption data, the predictive power of the expectational data disappears for consumption growth but not income growth. This result is robust to whether we identify a structural relationship using the permanent income hypothesis or an *ad hoc* consumption out-of-current income model. In both cases we control for both lagged consumption and income growth and their lagged levels. This latter term, capturing any long-run effects, has not been considered in previous micro studies [e.g. Brown & Taylor (2006) and Guariglia & Rossi (2002)] which despite the overwhelming macroeconomic evidence [see Davidson et al. (1978) and Cochrane (1994)] estimate first differenced equations thereby excluding this possibility. The RE-PIH suggests that it is a long-run equilibrium [see Stock & West (1988)]. Campbell & Mankiw (1991) in fact attach a different interpretation to this error-correction term arguing that it does not represent any kind of disequilibrium but reflects, consistent with the RE-PIH, the savings ratio affecting income growth; see Campbell (1987). When there is consumption out of current as well as permanent income this error-correction term will also affect consumption growth.

The plan of this paper is as follows. Section 2 sets out the modelling framework, while Section 3 introduces the BHPS and provides descriptive statistics summarising the relationship between micro level expectational data and consumption and income growth. Section 4 summarises the role of expectations in the structural models, and Section 5 presents the results from the vector auto-regressive models and Section 6 concludes.

2 Modelling Income and Food Consumption

Reflecting their co-determination, and to accommodate dynamics, log food consumption (c_{it}) and log income (y_{it}) for household i at time t ($i = 1, ..., N_t$), ($t = 1, ..., T$), are modelled simultaneously within a vector auto-regressive (VAR) framework. This framework has more commonly been used when modelling macroeconomic rather than microeconomic consumption and income behaviour. Expectations, as we explain below, enter the consumption and income growth equations as endogenous I(0) regressors. This seems appropriate since the BHPS explicitly asks individuals about their expectations of change or growth in their financial circumstances, Δy_{it}, rather than their level.

Use of VAR models also has the advantage of nesting many of the different specifications which have been used to study the relation between consumption and income in micro-based studies. These often serve as the basis of tests for excess sensitivity at a micro-economic level. For example, when modelling consumption growth Brown & Taylor (2006) and Benito & Mumtaz (2006), to take two recent applications to the BHPS, restrict attention to static single-equation representations in the growth rate of consumption.[1] Guariglia & Rossi (2002), also in an application to the BHPS, do allow consumption

[1]Restricted models also tend to be used in micro-applications beyond the BHPS. For example, in an application to the Michigan Index of Consumer Sentiment Souleles (2004) considers a static single-

growth to be autoregressive but do not consider error correction terms. But as Stock & West (1988) explain within the context of testing the permanent income hypothesis, and as Pesaran & Shin (1999) explain more generally, consideration of (unrestricted) distributed lag models has the advantage of rendering inference asymptotically valid even in the presence of unit roots. This contrasts models where the dynamics are restricted and the regressors cannot be rewritten in terms of I(0) variables. Indeed in time-series it has been argued that the use of ARDL models is an attractive means of modelling both short and long run behaviour as it obviates the need to pre-test for a unit root; see Pesaran & Shin (1999).

However, in our application to the BHPS the small T for many households means T is best considered fixed. This means I(1) variables do not change the asymptotics as they do when $T \to \infty$ [see Bond et al. (2005)]; but our use of distributed lag methods means that inference is valid irrespective of unit roots. This is convenient in our context where T, in any case, is too small even to enable use of panel based unit root tests which allow for heterogeneity.

The framework also distinguishes short and long run relations. By allowing for a long-run relationship between consumption and income we nest the model used by Guariglia & Rossi (2002) in our framework. We might expect a long-run relationship since under the permanent income model if (total) log consumption and log income are I(1) we should expect them to be cointegrated with cointegrating vector (1,-1); this implies the log savings ratio, which according to the model equals the negative of expected labour income growth, is I(0). Reflecting the fact that the BHPS provides data on food, rather than total, consumption we allow c_{it} and y_{it} to follow a long-run relationship of the form: $c_{it} = \theta y_{it}$, where θ is the income elasticity of food expenditure. Nevertheless, for convenience we continue to refer to the error-correction term as the (log) savings ratio.

Write the vector autoregressive model of lag order p in $\mathbf{z}_{it} = (c_{it}, y_{it})'$ in its error-correction form

$$\Delta c_{it} = a_i^c + a_t^c + \mathbf{\Pi}_c \mathbf{z}_{t-1}^* + \sum_{j=1}^{p-1} \mathbf{\Gamma}_{cj} \Delta \mathbf{z}_{it-j} + u_{it}^c \quad \text{and} \tag{1}$$

$$\Delta y_{it} = a_i^y + a_t^y + \mathbf{\Pi}_y \mathbf{z}_{t-1}^* + \sum_{j=1}^{p-1} \mathbf{\Gamma}_{yj} \Delta \mathbf{z}_{it-j} + u_{it}^y \ , \tag{2}$$

where a_i^c and a_i^y are fixed or stochastic individual-specific time invariant effects allowing

equation model for consumption growth.

for heterogeneity in the means of $\Delta\mathbf{z}_{it}$, and u_{it}^c and u_{it}^y are mean zero disturbances, uncorrelated across i and t, where $Var(u_{it}^c) = \sigma_c^2$, $Var(u_{it}^y) = \sigma_y^2$ and $E(u_{it}^c u_{it}^y) = \sigma_{cy}$. a_t^c and a_t^y are modelled as time dummies and are included to capture cross-sectional dependence explained by common (macroeconomic) shocks.

$\mathbf{\Pi}_c$ and $\mathbf{\Pi}_y$ characterise the long-run or levels relationship between c_{it} and y_{it}. The long-run is characterised by the restriction that $\mathbf{\Pi}_c = \alpha_c\beta'$ and $\mathbf{\Pi}_y = \alpha_y\beta'$ where $\beta = (1, -\theta)$. This ensures c_{it} and y_{it} are cointegrated $(1, -\theta)$ when c_{it} and y_{it} are I(1). α_c and α_c represent the speeds of adjustment to the common long-run. When $\alpha_c = -1$ adjustment to the long-run is instantaneous, and when $\alpha_c = 0$ there is no long-run. Note we expect α_y to have an opposite sign to α_c given the cointegrating vector remains $(c_{it} - \theta y_{it})$.

Households' expectations (Δy_{it}^e) of their financial circumstances in year t, which they form in year $(t-1)$, enter both (1)-(2) as micro-level dummy explanatory variables; specifically two dummies are included for improving and deteriorating confidence.[2] This simple approach, used frequently with discrete-choice models [see Heckman (1978)], has the advantage of letting the effect of confidence on income and consumption vary according to whether confidence is improving or deteriorating. Δy_{it}^e are allowed to be endogenous and correlated with present and past shocks, but are assumed uncorrelated with future shocks u_{it+1}^c. This assumption therefore permits the likely measurement error caused by use of the two dummies as proxies for true but unknown quantitative expectations of financial situation as well as reflecting the likely endogeneity of expectations. This means, conveniently, that a separate model governing the determination of Δy_{it}^e does not need to be postulated in order to estimate the parameters in (1)-(2) consistently. Specifically, it is assumed that Δy_{it}^e are "weakly exogenous" with respect to the matrix of long run multipliers, $\mathbf{\Pi}_c$, meaning they are not affected by the error-correction term, $\mathbf{z}_{t-1}^*$. This implies y_{it}^e is a so-called "long run forcing" variable for $c_{it,}y_{it}$ as there is no feedback from the *level* of $c_{it,}y_{it}$; see Pesaran & Shin (1999). However, in the short run $c_{it,}y_{it}$ can still be "Granger-causal" for y_{it}^e. See Mitchell & Weale (2007) for further discussion on expectation formation.

Assuming $(u_{it}^c, u_{it}^y)'$ is distributed bivariate Gaussian, u_{it}^y is expressed conditionally in terms of u_{it}^c as

$$u_{it}^y = \left(\sigma_{cy}/\sigma_c^2\right) u_{it}^c + e_{it}, \tag{3}$$

where $e_{it} \sim IN(0, \sigma_e^2)$, $\sigma_e^2 = \sigma_c^2 - (\sigma_{cy}^2/\sigma_y^2)$ and e_{it} is independent of u_{it}^c. Substitute (3)

[2] Alternative methods of modelling with ordered categorical explanatory variables have been considered; see Breslaw & McIntosh (1998).

into (1). The conditional model for Δy_{it} is then given by

$$\Delta y_{it} = a_i^{y*} + \left(\sigma_{cy}/\sigma_c^2\right) \Delta c_{it} + \sum_{i=1}^{p-1} \mathbf{\Gamma}_{yj}^{*} \Delta \mathbf{z}_{t-i} + \mathbf{\Pi}_y^{*} \mathbf{z}_{t-1}^{*} + e_{it} \ , \tag{4}$$

where $a_i^{y*} = a_i^y - (\sigma_{cy}/\sigma_c^2)\, a_i^c$, $\mathbf{\Gamma}_{yj}^{*} = \mathbf{\Gamma}_{yj} - (\sigma_{cy}/\sigma_c^2)\, \mathbf{\Gamma}_{cj}$, $j = 1, ..., p-1$, and $\mathbf{\Pi}_y^{*} = \mathbf{\Pi}_y - (\sigma_{cy}/\sigma_c^2)\, \mathbf{\Pi}_c$.

Therefore Δc_{it} is assumed weakly exogenous by construction. For robustness, given its likely endogeneity in the presence of measurement error, below we experiment with instrumenting Δc_{it}.

Equations (1) and (4) effectively deliver a structural VAR model where e_{it} can be interpreted as a "temporary" shock and u_{it}^c as a "permanent" shock; see Cochrane (1994).[3] This follows since, under the RE-PIH, shocks to income holding consumption constant mean consumers believe the shock is temporary; only when consumption changes do they believe a shock to be permanent. The reduced-form (total) shock to income growth, u_{it}^y, therefore comprises both a permanent and a transitory component.

The RE-PIH suggests $\mathbf{\Gamma}_{cj} = \mathbf{\Pi}_c = 0$ ($j = 1, ..., p-1$). That is, consumption growth should be orthogonal to lagged information, including Δy_{it}^e, and follow a random-walk. RE-PIH also suggests that $\mathbf{\Pi}_y^{*} \neq 0$ since the lagged savings ratio should help predict future output changes; see Campbell (1987). We might expect $\mathbf{\Pi}_c \neq 0$ if some households behave according to the life-cycle rational expectations model while others consume out of current rather than permanent income; see Carroll et al. (1994). Under this model since the savings ratio affects income growth, and because a fraction of consumers consume from current rather than permanent income, any variable which predicts Δy_{it} also predicts Δc_{it}.

In addition to (1) and (4) we consider an alternative structural model, albeit one that is ad hoc but consistent with the idea that some households consume out of current income. This is inconsistent with the RE-PIH, unless income follows a random walk [e.g. see Nelson (1987) and Banerjee & Dolado (1988)]. Nevertheless this alternative structural model is also consistent with the reduced-form (1)-(2). Indeed since both structural models are exactly identified, imposing two identifying restrictions (a zero restriction on the matrix of contemporaneous relations and orthogonality of the structural errors), they cannot be distinguished from each other statistically. But the economic interpretation differs. The

[3] Equivalently this structural VAR model could be identified from the reduced-form VAR, (1)-(2), by orthogonalising the shocks with c_{it} ordered first. In addition, under the RE-PIH, Cochrane (1994) proved that Blanchard-Quah type restrictions on the matrix of long-run multipliers are equivalent to the restrictions we impose, in (1) and (4), on the contemporaneous multipliers.

alternative model reverses the "back to front" appearance of (1) and (4), by letting current income growth determine current consumption growth rather than the other way round. This ad hoc consumption out of current income model comprises (2) and

$$\Delta c_{it} = a_i^{c*} + \left(\sigma_{cy}/\sigma_y^2\right)\Delta y_{it} + \sum_{i=1}^{p-1} \mathbf{\Gamma}_{cj}^{*} \Delta \mathbf{z}_{t-i} + \mathbf{\Pi}_c^{*} \mathbf{z}_{t-1}^{*} + e_{it}^{c} \ , \tag{5}$$

where $u_{it}^c = \left(\sigma_{cy}/\sigma_y^2\right) u_{it}^y + e_{it}^c,\ a_i^{c*} = a_i^c - \left(\sigma_{cy}/\sigma_y^2\right) a_i^y,\ \mathbf{\Gamma}_{cj}^{*} = \mathbf{\Gamma}_{cj} - \left(\sigma_{cy}/\sigma_y^2\right)\mathbf{\Gamma}_{yj},\ j = 1, ..., p-1$, and $\mathbf{\Pi}_c^{*} = \mathbf{\Pi}_c - \left(\sigma_{cy}/\sigma_y^2\right)\mathbf{\Pi}_y$.

Given the dynamics, and the consequent bias of OLS estimators due to the individual effects a_i^c and a_i^c, both sets of structural equations are estimated using Arellano-Bond (GMM) estimators; see Bond (2002) for a review.[4] These are designed to accommodate small T and large N data and are therefore a natural choice when examining the BHPS. Asymptotics rely on $N \to \infty$ with T fixed. The model specification is tested using the Hansen-Sargan test for overidentifying restrictions and (m2) tests for second-order serial correlation are presented.

3 The BHPS and consumer confidence

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 thereafter are 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. In particular the BHPS provides direct, albeit categorical, information on individuals' expectations since individuals are asked "*How do you expect your financial position to change over the coming year?*". They are invited to reply with a categorical answer: *improve*, *stay the same* or *worsen*.

We consider the log of household annual income data y_{it} in real terms and adjusted for changes in household size using equivalence scales following Bardasi & Jenkins (2004). The log of total consumption c_{it} is proxied, as in Guariglia & Rossi (2002), by households'

[4] T is too small to enable consumption and income growth equations to be estimated separately for each individual, i. Accordingly, we apply panel-data estimators which impose (slope) homogeneity restrictions across i.

total weekly food and grocery bill. These data are available only on an interval scale from wave two. There are 12 intervals breaking consumption down into intervals of 10 or 20 pounds. Consistent with others [e.g. see Guariglia & Rossi (2002)] we use the mid-points. The data are also deflated and equivalised at a household level based on the ratio of annual real household income to its real and equivalised counterpart. In estimation instruments overcome any measurement error induced by use of the midpoints. These income and consumption data are related to the head of households' expectations of their financial position.

Before estimating (1) and (4), and (2) and (5), and seeking to understand whether expectational data predict income and consumption changes, specifically when controlling for past income and consumption data, we provide some descriptive evidence about how the expectational data relate to consumption and income.

Figure 1 plots the polyserial correlation coefficient, and associated 95% confidence interval, of the expectational data against consumption and income growth for each year in the panel. Polyserial correlation accounts for the categorical nature of the micro-level expectational data by assuming households' responses are triggered by a latent continuous normally distributed random variable as it crosses thresholds; see Olsson et al. (1982). Figure 1 shows that while the correlation of the expectational data with consumption growth is in general statistically insignificant, switching between positive and negative correlation over time, the correlation with income growth is positive and statistically significant.

To provide a descriptive indication of the capacity of the expectational data to predict income growth to different time horizons (often described as h-step ahead predictors) we estimate the polyserial correlation coefficient between income growth and various lags of the expectational data by maximum likelihood. Table 1 indicates that the forecasting power of the expectational data becomes weaker as the horizon increases, becoming insignificant more than two years ahead.

Finally, as is common when qualitative survey data are used to forecast macroeconomic aggregates [see Pesaran & Weale (2006) for a review], the aggregate findings from the BHPS are related to aggregate (economy-wide) consumption growth. The BHPS is quantified and aggregated simply by computing the proportion of respondents in each of the three categories at a given point in time (let U denote the proportion of optimists, S the proportion expecting no change and D the proportion of pessimists). Figure 2 shows that over 50% of respondents indicate that they do not expect their financial situation to improve or deteriorate. This proportion has increased slightly since 1991. Figure 2 also reveals that there are more optimists than pessimists, and that collectively respondents became more gloomy in 1992, a time when the UK economy was in recession.

Figure 2 also plots the 'balance of opinion' (BAL), defined as the proportion of optimists less pessimists. This is used widely by forecasters as an indicator of future tendencies. Accordingly the balance is related to year ahead official aggregate annual consumption growth data in the bottom panel of Figure 2. The balance statistic, extracted from the BHPS, is smoother than the subsequent outturn for consumption growth but does a good job at tracking its general tendency. Correlation is positive and quite strong at 0.64. The strength of this relationship is in line with that found using other qualitative surveys more commonly used when forecasting; e.g. see Mitchell et al. (2002) for consideration of Confederation of British Industry's (CBI) survey. In contrast correlation with annual GDP growth is negligible at 0.03. The strong macroeconomic correlation with income growth contrasts the lower correlation found at the microeconomic level in Figure 1. This is explained by the considerable heterogeneity across households.

Table 1: Polyserial correlation between micro-level expectational data and income growth, with estimated t-ratios in parentheses

	Δy_{it}
1-year ahead	0.046 (9.548)
2-year ahead	0.027 (4.896)
3-year ahead	0.008 (1.208)

4 The Role of Expectations in the Structural Models

With either of these identifying assumptions, the role of expectational variables is to provide information on the error terms. Using the permanent income hypothesis to identify the model consumption is the driver of income. If the intervals between time periods were very short, then lagged consumption should be a sufficient statistic for current consumption, with no further role for expectations. However, the question in the survey asks about "weekly spending" with no indication over what period the average should be calculated while, as noted above, the question on expectations refers to the coming year. Thus it is perfectly possible for expectations to have changed since the start of the period to which average spending relates and, as a consequence, it is perfectly possible

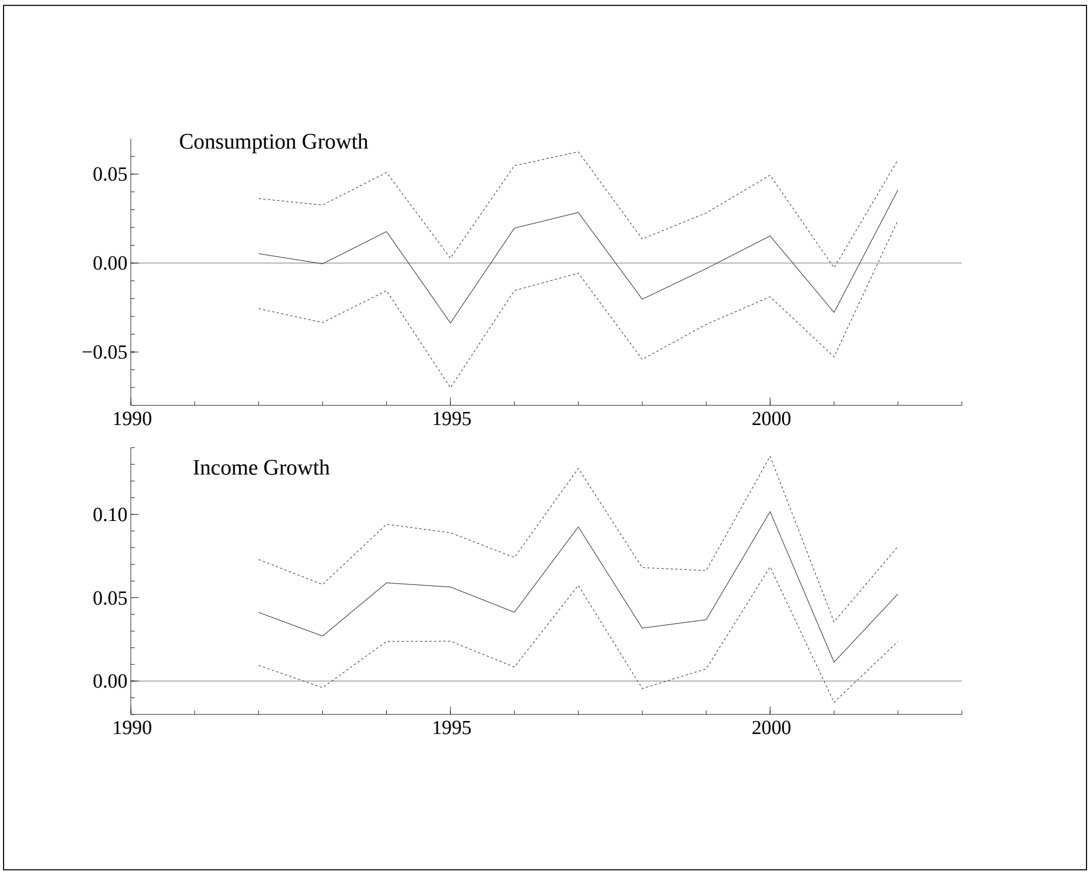

Figure 1: The forecasting power of micro-level expectational data: polyserial correlation of the expectational data against consumption and income growth with 95% confidence intervals

for expectations to play a role in equation (1). In equation (4) the expectational term may provide information on e_{it}.

With the consumption out of income model there is no reason to believe that past income and consumption should be sufficient statistics for current income; it is natural to look for a role of expectations in equation (2). Similarly, the nature of the model means that one can look for a role for expectations as providing information on e^c_{it} in (5). Nevertheless, if such a role is statistically significant, it would mean that the hypothesis that consumption is driven by current and past income alone would be rejected.

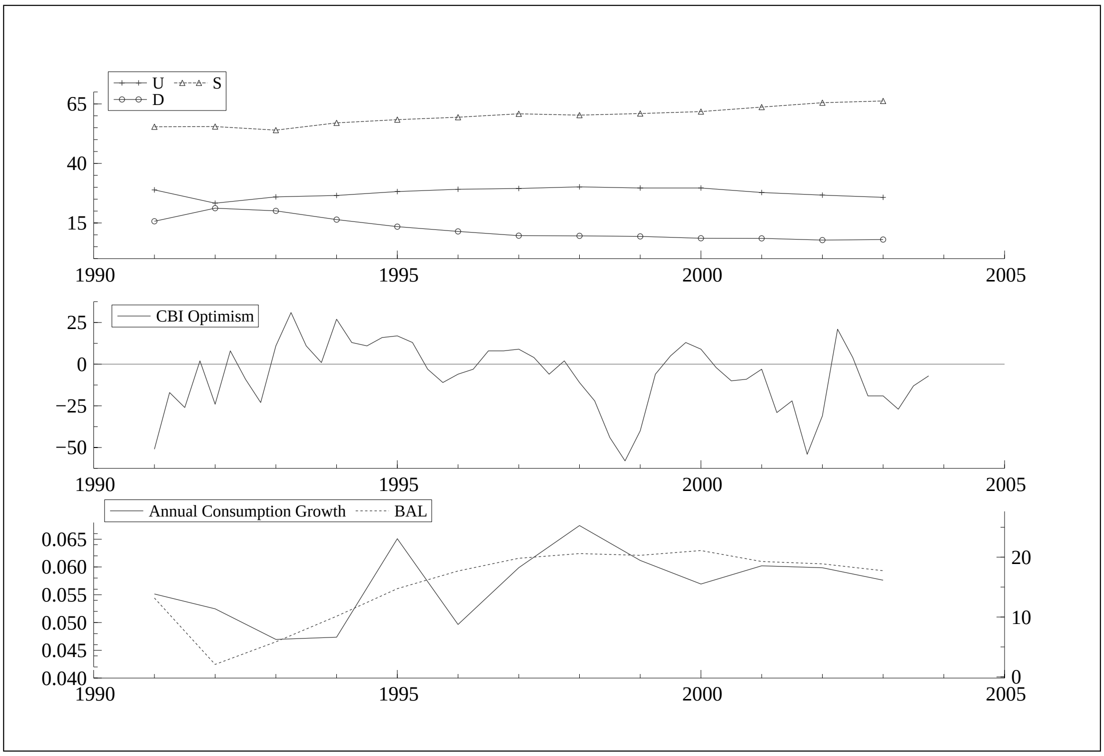

Figure 2: Relating the proportions of optimists and pessimists in the BHPS to the macroeconomy and alternative confidence measures (from the CBI survey)

5 Results: the predictive power of consumer confidence

Table 2 provides the estimation results for both equations (1) and (4) and the ad hoc consumption out of current income model, (2) and (5).[5] These are based on estimation of an ARDL(2,2) model in the log levels of consumption and income, in other words a first differenced model with one lag of consumption and income growth. While lags of consumption and income growth are sometimes found to be individually insignificant, the m2 test for serial correlation often indicates gains to introducing the extra dynamic terms. At the expense of efficiency, rather than consistency, we focus on results using these more general models. The GMM results in Table 2 appear to be based on well specified models according to the goodness-of-fit tests (the m2 test for serial correlation and the

[5]As Browning & Lusardi (1996) review (see their Table 5.1) control variables, so-called taste shifters, are commonly included in consumption growth (Euler) equations estimated from micro-data. Typically the controls are age and family size. Given we have already accounted for family size by using equivalised consumption and income data we include age and its square as additional regressors.

Hansen-Sargan test for overidentifying restrictions).

Two error-correction terms are considered for each estimator. These reflect alternative assumptions about the long run income elasticity for food consumption. Given our use of food rather than total consumption data a unity long run income elasticity is inappropriate so we allow the long-run elasticity to be estimated freely by including both c_{it-1} and y_{it-1} instead of an error-correction term with an imposed long-run elasticity. We denote this model U_{RE} for Cochrane's specification and U_{IN} for the consumption out of income model, with the income and consumption equation in a given VAR model denoted by a superscript; e.g. U^y_{RE} or U^c_{RE}. The implied long-run elasticity, θ, in this case is presented in Table 2. This does not appear well determined; estimates vary from -0.045 to a nonsensical 8.01. We therefore also present results for a second case where a long run elasticity of 0.3 is imposed, denoting this restricted model R_{RE} and R_{IN}. Such a value is more consistent with what we might expect. For example, the US Department of Agriculture estimate the long-run income elasticity for food, beverages and tobacco to be 0.3 in the UK.[6] We also consider a third, parsimonious, model denoted $R_{RE}*$ and $R_{IN}*$ respectively. While there are two equations in each of the U and R models, indicated by the superscripts y and c, there is only one in each of the R^* models since the other equation is already reported since it is not restricted further. With Cochrane's specification, consumption drives income but fluctuations in income do not drive fluctuations in consumption. Thus the $R_{RE}*$ model allows consumption to affect income. By contrast, with the consumption out of income model, income is assumed to drive consumption, but not to be driven by it and thus in the $R_{IN}*$ model current income is allowed to affect consumption.

Our findings are as follows. First of all, the results confirm that, on their own, the expectational terms have predictive power for both consumption and income. The expectation of an improvement to financial circumstances is a significant predictor of an increase in consumption, while the expectation of a fall is of no statistical significance. Both the expectation of an improvement and the expectation of a worsening are significant predictors of changes in income. However, the question we are interested in is whether the expectational variables provide additional information over and above what can be learned from the past history of income and consumption. Looking at the Cochrane model, once we take account of the role of past consumption as a predictor of changes to

[6] At the time of writing, these international data on the income elasticity for broad consumption groups are available from the US Department of Agriculture's web-site: http://www.ers.usda.gov/Data/InternationalFoodDemand/StandardReports/Incomeelasticitygroups.xls

current consumption, we find that expectational effects are no longer statistically significant (model U^c_{RE}). The restriction that both they and previous income is insignificant is easily accepted ($\chi^2_3 = 0.55$). In the unrestricted income equation we find that the expectation of a worsening in circumstances remains a significant predictor of a decline in income in the unrestricted equation (model U^y_{RE}). The lags in the consumption equation point to utility function with the sort of habit formation present discussed by Fuhrer (2000) However this model also has an income elasticity of expenditure on food of 3.7. When we impose the restriction that this elasticity is 0.3, which is just accepted at a 5% level ($\chi^2_1 = 3.76, P = 5.2\%$) the expectational terms lose their statistical significance (model R^y_{RE}). Nevertheless, a joint test for the absence of the expectational terms and an elasticity of 0.3 is strongly rejected ($\chi^2_3 = 13.9, P = 0.3\%$). Our preferred model is therefore that shown as $R^y_{RE}*$ with the elasticity restricted to 0.3 and the term in the expectation of a rise in income restricted to zero.

If we identify the model using the consumption out of income assumption, the expectational terms turn out to be slightly more important. They have no significant role in the consumption equation whether estimated freely or with a long-run elasticity of 0.3 imposed ($\chi^2_1 = 3.13, P = 7.7\%$ - model R^c_{IN}). Our preferred consumption equation, with these terms absent is shown as $R^C_{IN}*$.The income equation is rather different. In its unrestricted form the expectation of a worsening in the economic situation is a predictor of a fall in income (model U^y_{IN}). The long-term relationship between consumption and income is not a significant predictor of future income growth and is removed in model R^y_{IN}. However, the expectation of a worsening in circumstances also remains significant in this equation.

Our overall conclusion is therefore that the expectation of a worsening of economic circumstances is a predictor of a decline in income, but the expectation of an improvement in circumstances is not a significant predictor of an increase in income. Expectations terms have no direct influence on consumption whether we identify the consumption/income relationship using the permanent income hypothesis or the consumption out of income model.

6 Concluding Comments

Given the importance to policy-makers of anticipating developments in the economy, there is an understandable interest in direct measures of expectations. The British Household

Panel Survey provides a micro-economic data set with which to explore whether they are statistically significant as indicators of future changes in the variables to which they relate. We find, in common with earlier work, that taken on their own they do indeed predict movements in both household income and household consumption. However, once one introduces a structural relationship between income and consumption the situation is much less clear.

The relationship between income and consumption requires a theoretical framework in which to identify it. We consider alternative identifying assumptions for the consumption/income relationship. With both of these we find that expectations influence income but not consumption. Thus the general conclusion is that policy-makers who are concerned about the short-term evolution of demand need not pay attention to expectational terms. Users of models with backward-looking consumption functions will find the expectational effects helpful in predicting household income growth as a driver of household consumption; while with forward-looking models the variable simply sheds light on how income adjusts to the fundamental driver which is consumption.

	Benchmark		Cochrane RE-PIH model					Consumption out-of-income model				
	OLS	OLS	GMM	GMM	GMM	GMM	GMM	GMM	GMM	GMM	GMM	GMM
Model			U^c_{RE}	R^c_{RE}	U^y_{RE}	R^y_{RE}	$R^y_{RE}*$	U^c_{IN}	R^c_{IN}	$R^C_{IN}*$	U^y_{IN}	R^y_{IN}
Dep.var	Δc_{it}	Δy_{it}	Δc_{it}	Δc_{it}	Δy_{it}	Δy_{it}	Δy_{it}	Δc_{it}	Δc_{it}	Δc_{it}	Δy_{it}	Δy_{it}
Indep. var												
Δy_{it}	-	-	-	-	-	-	-	0.125	0.216	0.212	-	-
								(1.65)	(3.66)	(3.60)		
Δc_{it}	-	-	-	-	0.163	0.531	0.531	-	-	-	-	-
					(1.84)	(4.44)	(4.45)					
Δy_{it-1}	-	-	-0.015	-	-0.084	-0.044	-0.045	-0.003	0.007	0.006	-0.078	-0.082
			(-0.62)		(-2.35)	(-0.84)	(-0.87)	(-0.17)	(0.29)	(0.28)	(-2.23)	(-2.32)
Δc_{it-1}	-	-	-0.067	-0.067	0.004	0.085	0.085	-0.065	-0.06	-0.060	-0.009	-
			(-3.19)	(-3.23)	(0.19)	(2.51)	(2.52)	(-3.17)	(-2.91)	(-2.92)	(-0.45)	
c_{it-1}	-	-	-0.720	-0.724	0.234	-	-	-0.734	-	-	0.106	-
			(-9.25)	(-9.66)	(2.02)			(-9.59)			(1.20)	
y_{it-1}	-	-	-0.032	-	-0.869	-	-	0.077	-	-	-0.853	-0.856
			(-0.49)		(-11.54)			(0.95)			(-11.23)	(-12.02)
$c_{it-1} - 0.3y_{it-1}$	-	-	-	-	-	0.749	0.747	-	-0.721	-0.711	-	-
						(4.73)	(4.74)		(-9.38)	(-9.26)		
$\Delta y^e_{it} : U$	0.017	0.026	-0.028	-	0.044	0.077	-	-0.032	-0.033	-	0.07	-
	(3.19)	(4.87)	(-0.24)		(0.43)	(0.52)		(-0.29)	(-0.30)		(0.68)	
$\Delta y^e_{it} : D$	0.007	-0.046	-0.004	-	-0.445	-0.262	-0.277	0.051	0.109	-	-0.434	-0.436
	(1.23)	(-5.49)	(-0.03)		(-3.13)	(-1.36)	(-1.44)	(0.39)	(0.85)		(-3.00)	(-3.03)
Hansen			0.221	0.233	0.077	0.100	0.100	0.265	0.316	0.355	0.068	0.066
m2			0.975	0.939	0.098	0.057	0.059	0.941	0.730	0.666	0.156	0.110
NT	42633	42633	26238	26238	26238	26238	26238	26238	26238	26238	26461	26750
N	8926	8926	5403	5403	5403	5403	5433	5403	5403	5403	5433	5470
θ			0.045		-3.714	-0.3	-0.3	-0.105	-0.3	-0.3	-8.01	
			(-0.49)		(-2.11)	(na)	(na)	(-0.96)	(na)	(na)	(-1.24)	
χ^2				χ^2_1= 0.55		χ^2_1 =3.76	χ^2_2=4.26		χ^2_1=3.13	χ^2_2=3.95		χ^2_3=2.17
P>χ^2				0.9683		0.0524	0.1188		0.0767	0.2673		0.5379

Estimation using the BHPS from 1991 to 2003. t-values in parentheses. Time dummies are included in each column but not reported, and also included in the list of instruments. Age and age squared are also included as additional explanatory variables. Δc_{it} denotes consumption growth, Δy_{it} income growth and $\Delta y^e_{it} : U$ and $\Delta y^e_{it} : D$ refer to the dummies on optimistic and pessimistic expectational responses. The instruments used in GMM are lags dated (t-3) or higher of the consumption and income data. Hansen is the p-value for a test of the over identifying restrictions. m2 is the p-value for a test of second order serial correlation in the first differenced residuals. θ is the estimated long-run income elasticity for food consumption. U and R denote unrestricted and restricted models, with χ^2 indicating the value of the chi-squared statistic testing the restrictions in R relative to U. P>χ^2 is the p-value associated with the chi-squared test. $R*$ denotes the model with additional restrictions imposed on R. Again χ^2 and P>χ^2 test for these restrictions relative to U

Table 2: Estimation results

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