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Financial Expectations and Household Consumption: Does Middle Inflation Matter?*

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Abstract

Using British panel data, we explore the finding that households often expect their financial position to remain unchanged compared to other alternatives, using a generalised middle inflated ordered probit (*GMIOP*) model. In doing so we account for the tendency of individuals to choose 'neutral' responses when faced with attitudinal and opinion-based questions, which are a common feature of survey data. Our empirical analysis strongly supports the use of a *GMIOP* model to account for this response pattern. Expectations indices based on competing discrete choice models are then exploited to explore the role that financial expectations play in driving the consumption of different types of durable goods and the amount of expenditure undertaken. Whilst financial optimism is significantly associated with consumption, indices which fail to take into account middle-inflation are found to overestimate the impact of financial expectations.

JEL Classification: C12, C35

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1 Introduction and background

A common feature of survey data is the tendency for individuals to choose 'neutral' responses. This is particularly so for the case of attitudinal or opinion-based questions, where a sizable proportion of respondents are inclined to select middle options. Such choices may signal that the respondent does not know an answer, reflect an expectation that things will remain unchanged, or capture indifference towards the available alternative options.

This phenomenon extends to responses to questions relating to financial expectations. For example, a recurring feature of the *British Household Panel Survey* (BHPS) is respondents' predictions that their financial position will remain about the same the following year, rather than getting better or worse.[1] This is despite the observation that in practice, expected financial positions are seldom realised. The consequences of this disparity between expectations and realisations have been explored in a number of contributions, with a focus on evaluating the 'rationality' of households' financial expectations (Souleles 2004, Brown and Taylor 2006, Mitchell and Weale 2007). Such literature forms part of a more general body of work that sets out to determine whether survey expectations are 'rational': noteworthy contributions include work on expectations about future prices (Mankiw et al. 2004, Madeira and Zafar 2015); firms' demand conditions and inventories (Nerlove 1983, Boneva et al. 2020); and household-level expectations concerning income growth (Das and van Soest 1999, Das et al. 1999).[2]

However, limited attention has been paid to the distribution of households' categorical responses to expectations based questions, and in the context of this paper, why many households expect their financial position to remain unchanged compared to other alternatives. This paper fills this gap in the literature.[3] Our interest is with the BHPS survey question 'Looking ahead, how do you think you will be financially a year from now?',[4] where an overwhelming majority of respondents choose the neutral '*about the same*' category. This response pattern characterises all waves of the BHPS survey, which runs from 1991-2008 covering different points of the business cycle (See Figure A.1 in Appendix A).

[1] Other large scale surveys also report similar findings, such as the University of Michigan *Survey of Consumers*.

[2] Other relevant work includes Pesaran and Weale (2006), Manski (2004) and Pesaran (1987). The seminal contribution on rational expectations is Muth (1961).

[3] A number of the above papers comment on the tendency for expectations to be concentrated in a single category but do not explore the reasons for such a build-up (see for instance: Mitchell and Weale (2007); Pesaran and Weale (2006); Nerlove (1983) using firm level data; Mankiw et al. (2004) using inflation expectations data). Drawing on contributions from a number of number of different fields, an early discussion of the psychological drivers of expectations is Wärneryd (1995).

[4] This can be interpreted as capturing perceptions of the probability of financial distress.

Various reasons may explain this response. One possibility is that an '*about the same*' expectation reflects a genuine belief that the financial position will not worsen or improve in the near future, due to the realised financial position exhibiting considerable persistence over time. This may be attributable to the underlying, observed variables that drive expectations—household income, savings, GDP, and so on—being subject to such persistence. However, as survey participants may be subject to psychological influences (Tourangeau et al. 2000), other candidate mechanisms may drive neutral responses. For example, a middle alternative may be perceived as representing what is 'normal' (Price et al. 2017), or the safest choice, minimizing the potential for error.

Alternatively, some respondents may engage in 'satisficing' behaviour (Krosnick 1991), in which the minimum cognitive effort is used to produce a response perceived by the household to be acceptable to the interviewer (in this case, '*about the same*'). Here, perceived question complexity (Boxall et al. 2009) may also contribute to the presence of 'status quo' bias (Samuelson and Zeckhauser 1988), where individuals choose the option which implies that things will remain unchanged relative to the current period. Other explanations may entail choosing the neutral option as a face-saving exercise as in Bagozzi and Mukherjee (2012); 'unrealistic optimism' (Weinstein 1980, Jeffersona et al. 2017) which would imply that respondents expect their financial position to worsen in the future, but still report 'about no change';[5] or by contrast, a role for 'defensive pessimism' (Ben-Mansour et al. 2006), in which uncertainty about the future may induce households to 'expect the worst', or intentionally set lower expectations for themselves irrespective of past performance or evidence. The presence of the latter mechanism may clearly be relevant in situations where households have evidence that finances may improve, but which is disregarded until it is known that it will occur with absolute certainty.[6]

We account for the tendency to expect no-change in a household's financial position by using the recently developed *generalised middle-inflated ordered probit* (*GMIOP*) model of Brown et al. (2017).[7] This modelling strategy is applicable to situations where a large

[5] The quintessential definition of unrealistic optimism can be found in Weinstein (1980): 'According to popular belief, people tend to think they are invulnerable. They expect others to be victims of misfortune, not themselves. Such ideas imply not merely a hopeful outlook on life, but an error in judgment that can be labeled *unrealistic optimism*.' (p.806)

[6] The notion of 'unrealistic optimism' is most often used in the context of risk decisions where an individual sees themselves as less likely to experience a negative event than other people (such as smokers thinking the negative health effects will hit other people, but not them).

[7] These authors revisit the work of Harris and Zhao (2007), the original paper on the so-called zero-inflated ordered probit (*ZIOP*) model—which explores smoking behaviour using data from the Australian *National Drug Strategy Household Survey*—and Bagozzi and Mukherjee (2012), who use a middle-inflated ordered probit (*MIOP*) to model the presence of 'face-saving' middle-category responses in a commonly studied *Eurobarometer* survey question. Specification tests reject both these models in favor of the nesting

proportion of empirical observations fall into a single choice category, which in the context of our application, is the middle one. In accordance with previous findings in this growing literature, failing to account for middle-category inflation can lead to model mis-specification, parameter bias, and incorrect inference (Harris and Zhao 2007, Brown et al. 2017). From this analysis we are able to obtain a linear prediction of financial expectations which is *purged* (i.e. net) of the effects of inflation.

As well as considering expectations formation and inflation in the '*about the same*' category, we also investigate how financial expectations are associated with both the likelihood of consumption of different types of durable goods and the amount of expenditure undertaken. Browning et al. (2016) use the BHPS to investigate the life-cycle demand patterns for services from household durable goods, specifically white goods or appliances and consumer electronics. We follow Brown and Taylor (2006) by investigating the relationship between financial expectations and consumption behaviour, and in line with Browning et al. (2016) focus on durable goods decomposing overall expenditure into white goods and electronic purchases. The BHPS is a rich dataset which contains a number of variables that can be plausibly assumed to affect reporting behaviour but not financial expectations, arguably enabling us to evaluate the causal effect of sentiment (after adjusting for inflation) on household spending behaviour at both the intensive and extensive margins. The results reveal that specifications which do not *purge* the financial expectations index of inflation tend to overestimate the effect of sentiment on both the likelihood of undertaking expenditure and the overall amount spent. These findings highlight the importance of modelling financial expectations appropriately when the distribution of subject responses is characterised by middle-category inflation. Expectations play a key role in our understanding of business cycles and the design of policy institutions,[8] if policy makers are able to influence beliefs through monetary or fiscal policy then economic activity can be manipulated accordingly. Our work is the first to show the importance of modelling financial expectations appropriately by allowing for middle-category inflation otherwise the effects on economic activity are overestimated.

generalised versions proposed in Brown et al. (2017), which preserve the ordering of outcomes.

[8] Previous research for Europe and the US has shown that consumer sentiment is a pro-cyclical indicator which can predict the probability of a recession, i.e. key turning points in the business cycle, as well as quantitatively forecast GDP and its constituent components such as consumer expenditure (Ludvigson 2004, Taylor and McNabb 2007, Christiansen et al. 2014). The role of expectations in forecasting economic activity is an effect over and above other potential leading indicators.

2 Modelling middle-inflation

Recent advances in discrete choice modelling have witnessed the emergence of statistical techniques that are able to account for an 'excess' of observations corresponding to a middle category in an ordered setting. Bagozzi and Mukherjee (2012) address this issue by using a middle-inflated ordered probit (*MIOP*) model. Brown et al. (2017) demonstrate that under certain parameter restrictions, the *MIOP* can be nested in a more flexible modelling framework which they call a generalised middle inflated ordered probit (*GMIOP*) model. We estimate both models, and show that a generalised estimation strategy is favourable. This has implications for our approach to accounting for the determinants of consumption, as analysed in Section 4.

In our application, the interviewer asks each individual i a question on financial expectations, which assumes the form of 'Looking ahead, how do you think you will be financially a year from now?' Respondents provide one of three possible answers, which have a natural ordering: that they will be *worse off*, *about the same*, or *better off*. These responses are observed by the econometrician and are respectively coded -1, 0, and 1, to create a financial expectations index ($\widetilde{y}_i$). The choice set available to the respondent is thus given by $\widetilde{y}_i = \{-1, 0, 1\}$. Here, we emphasize that when the distribution of responses across all individuals is observed, the middle category of $\widetilde{y}_i = 0$ appears 'inflated'. As is shown in Figure A.1 in Appendix A, the *about the same* response dominates all other categories. The *GMIOP* approach assumes that when three response categories are observed, the $\widetilde{y}_i$ are generated by three distinct data generation processes (DGPs), which are all unobserved. These assume the form of a single ordered probit (OP) equation and two 'splitting equations', which take the form of binary probits.

The OP equation is captured by a latent variable y_i^*, and specified as a linear in parameters function of a vector of observed characteristics $\mathbf{z}_i$, with unknown weights $\boldsymbol{\gamma}$ and a random normal disturbance term ε_{yi}:

$$y_i^* = \mathbf{z}_i'\boldsymbol{\gamma} + \varepsilon_{yi}. \tag{1}$$

Expression (1) is defined by

$$y_i = \begin{cases} -1 & if \quad y_i^* \leq \mu_0 \\ 0 & if \quad \mu_0 \leq y_i^* \leq \mu_1 \\ 1 & if \quad \mu_1 \leq y_i^* \end{cases} \tag{2}$$

where μ_0 and μ_1 are threshold parameters to be estimated such that $\mu_0 < \mu_1$, and correspond to an underlying propensity to select the observed responses of *worse off*, *about the same*, or *better off*. Outcome probabilities for y_i are determined by the model in expressions (1) and (2) *viz.*,

$$\Pr(y_i) = \begin{cases} -1 & = & \Phi(\mu_0 - \mathbf{z}_i'\boldsymbol{\gamma}) \\ 0 & = & [\Phi(\mu_1 - \mathbf{z}_i'\boldsymbol{\gamma}) - \Phi(\mu_0 - \mathbf{z}_i'\boldsymbol{\gamma})] \\ 1 & = & [1 - \Phi(\mu_1 - \mathbf{z}_i'\boldsymbol{\gamma})] \end{cases} \tag{3}$$

where $\Phi(\cdot)$ denotes the cumulative distribution function (CDF) of the normal distribution.

To allow for the observed build-up of *about the same* responses, we allow for the propensities to select the *better off* or *worse off* responses in y^* to be 'tempered' by the two splitting equations. These latent equations have the effect of pushing respondents away from selecting *better off* or *worse off* in expression (1) towards the middle outcome. In this way, the observed *about the same* category $\widetilde{y}_i = 0$ is inflated. These two latent variables are specified as

$$w_i^* = \mathbf{x}_i'\boldsymbol{\beta}_w + \varepsilon_{iw}; \;\; b_i^* = \mathbf{x}_i'\boldsymbol{\beta}_b + \varepsilon_{ib}, \tag{4}$$

where $\mathbf{x}_i$ is a vector of observed characteristics, $\boldsymbol{\beta}_w$ and $\boldsymbol{\beta}_b$ are parameter vectors, and ε_{iw} and ε_{ib} are random normal disturbances. Conditional on having a propensity to select *worse off* in y_i^*, a value of $w_i = 1$ entails that the respondent chooses *worse off* over the *about the same* category, which is assigned a value of $w_i = 0$. Similarly, conditional on having a propensity to select *better off* in y_i^*, a value of $b_i = 1$ entails that the respondent chooses *better off* over the *about the same* category, which is assigned a value of $b_i = 0$. The probabilities that a respondent is steered away from selecting *worse off* or *better off* responses towards the *about the same* outcome are given, respectively, by

$$\Pr(w_i = 0) = \Phi(-\mathbf{x}_i'\boldsymbol{\beta}_w); \;\; \Pr(b_i = 0) = \Phi(-\mathbf{x}_i'\boldsymbol{\beta}_b). \tag{5}$$

Our assumption is that the same block of variables $\mathbf{x}_i$ drives each of these splitting equations.[9]

As the y_i^* and w_i^* equations relate to the same set of individuals, as do the y_i^* and b_i^* equations, it is very likely that the unobservables in these equations will be correlated, with correlation coefficients ρ_{yw} and ρ_{yb}, respectively.[10] The overall probabilities of individual i having financial expectations that are *worse off*, *about the same* and *better off* are given by

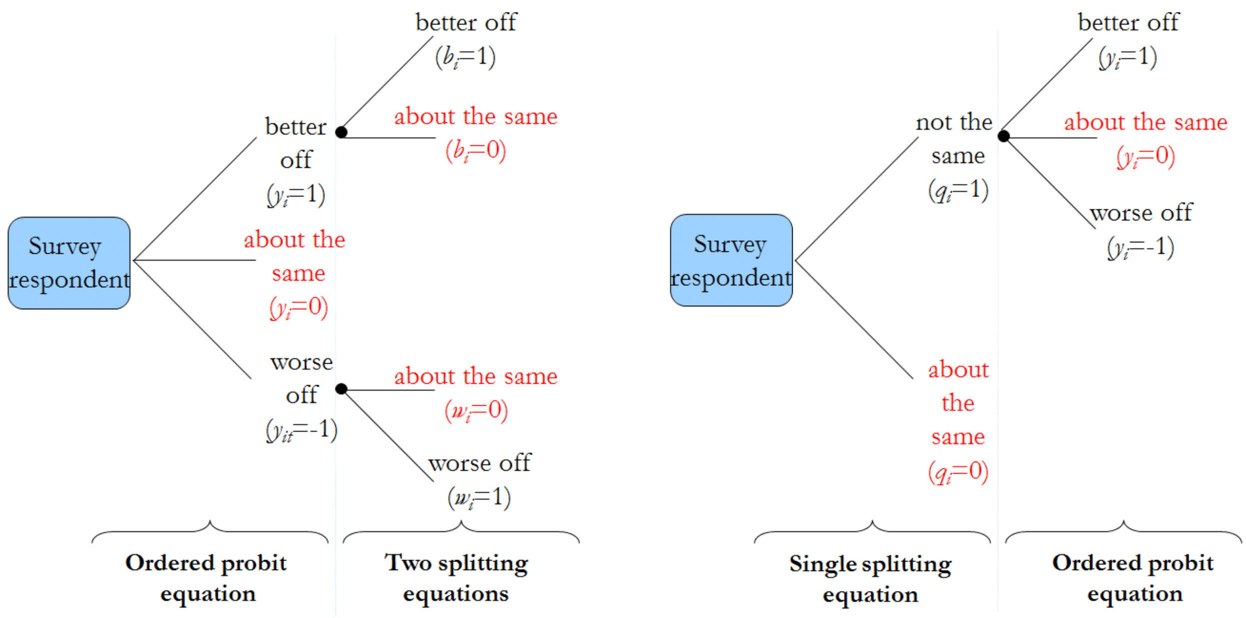
$$\Pr(\widetilde{y}_i) = \begin{cases} \Pr(\widetilde{y}_i = -1 \,|\mathbf{z}_i, \mathbf{x}_i) & = & \Phi_2\left(\mu_0 - \mathbf{z}_i'\boldsymbol{\gamma}, \mathbf{x}_i'\boldsymbol{\beta}_w; -\rho_{yw}\right) \\ \Pr(\widetilde{y}_i = 0 \,|\mathbf{z}_i, \mathbf{x}_i) & = & \begin{cases} [\Phi(\mu_1 - \mathbf{z}_i'\boldsymbol{\gamma}) - \Phi(\mu_0 - \mathbf{z}_i'\boldsymbol{\gamma})] \\ +\Phi_2\left(\mu_0 - \mathbf{z}_i'\boldsymbol{\gamma}, -\mathbf{x}_i'\boldsymbol{\beta}_w; \rho_{yw}\right) \\ +\Phi_2\left(\mathbf{z}_i'\boldsymbol{\gamma} - \mu_1, -\mathbf{x}_i'\boldsymbol{\beta}_b; -\rho_{yb}\right) \end{cases} \\ \Pr(\widetilde{y}_i = 1 \,|\mathbf{z}_i, \mathbf{x}_i) & = & \Phi_2\left(\mathbf{z}_i'\boldsymbol{\gamma} - \mu_1, \mathbf{x}_i'\boldsymbol{\beta}_b; \rho_{yb}\right) \end{cases} \tag{6}$$

where $\Phi_2(a, b; \rho)$ represents the standardised bivariate normal cumulative distribution function. We refer to the model in expression (6) as *GMIOPC*; the model under independent errors (i.e., setting $\rho_{yw} = \rho_{yb} = 0$) is denoted *GMIOP*. The probability of an *about the same* response comprises three distinct terms in the $\widetilde{y}_i = 0$ category: the probability of an *about the same* expectation arising in the *OP* equation, as captured by the term $[\Phi(\mu_1 - \mathbf{z}_i'\boldsymbol{\gamma}) - \Phi(\mu_0 - \mathbf{z}_i'\boldsymbol{\gamma})]$; and the probabilities arising as a result of being steered away from the $y_i = -1$ (*worse off*) and $y_i = 1$ (*better off*) outcomes in (1), which are respectively given by $\Phi_2\left(\mu_0 - \mathbf{z}_i'\boldsymbol{\gamma}, -\mathbf{x}_i'\boldsymbol{\beta}_w; \rho_{yw}\right)$ and $\Phi_2\left(\mathbf{z}_i'\boldsymbol{\gamma} - \mu_1, -\mathbf{x}_i'\boldsymbol{\beta}_b; -\rho_{yb}\right)$. The variables entering $\mathbf{x}_i$ and $\mathbf{z}_i$ are discussed below. The log likelihood function for the *GMIOP* model is shown in the Appendix B.

To shape intuition, Figure 1(a) depicts the *GMIOP* model. An interpretation of this figure is that during each interview, respondents are faced with choosing *worse off*, *about the same*, or *better off* when asked about their financial expectations. Clearly, one approach to modelling this decision is to employ a standard *OP* specification as in expressions (1)–(3). However, such a modelling strategy neglects the possibility that decisions to select an *about the same* response may derive from more than a single data generating process, thereby giving rise to the presence of the splitting equations in (4), also depicted in Figure 1(a). The impact of these equations is to allow respondents to be steered away from choosing *worse off*

[9] It would be possible to allow different variables to affect the tempering on the *better off* and *worse off* propensities in y_i^*, but this seems difficult to justify on *a priori* grounds.

[10] This is not the case for the w_i^* and b_i^* equations: these instead relate to two distinct sets of individuals, namely those in *worse* and *better* propensities, respectively.



(a) *GMIOP* model **(b) *MIOP* model**

Figure 1: The Generalised Middle-Inflated Ordered Probit model (*GMIOP*) and its nested variant (*MIOP*)

or *better off* towards selecting *about the same.*[11] In this sense, the expressions in (4) could also be termed 'inflation equations', due to their role in inflating the middle category. As a counterpoint to the *GMIOP*, the *MIOP* framework of Bagozzi and Mukherjee (2012) is illustrated in Figure 1(b). A *MIOP* model has a single splitting equation which captures the propensity of households to choose an *about the same* response over all other alternatives (*worse off*, *better off*).[12] This latent equation, which takes the form of a binary probit, is given by

$$q_i^* = \mathbf{x}_i'\boldsymbol{\beta} + \varepsilon_{iq}, \tag{7}$$

where $\mathbf{x}_i$ is the same vector of observed characteristics in (4), $\boldsymbol{\beta}$ is a parameter vector, and ε_{iq} is a random normal disturbance.[13] Expression (7) is estimated simultaneously with an *OP*

[11] Whether or not respondents are steered towards the *about the same* outcome is identified by the data, rather than being imposed by the modelling approach.

[12] A principal difference between the *MIOP* and *GMIOP* models is therefore that the former framework is driven by two DGPs, the latter model is characterised by three: that is, in addition to an *about the same* response emanating from the *OP* equation, it can arise from the tempered equations for *better off* or *worse off*, respectively. This type of observational equivalence is also depicted in Figure 1. We stress here that whilst both models have a single *OP* equation, a key difference between the *GMIOP* and *MIOP* is that the former has J–1 splitting equations when the model has J outcomes, whereas the *MIOP* has a single splitting equation.

[13] Harris and Zhao (2007) refer to this type of latent variable as a 'splitting' equation which is assumed to be a linear in parameters ($\boldsymbol{\beta}$) function of a vector of observed characteristics $\mathbf{x}$ and a random error term.

equation identical to that used in the *GMIOP* framework, as described by expressions (1)–(3). Relaxing the assumption that the error terms are independent leads to the correlated variant of the *MIOP*, which following Bagozzi and Mukherjee (2012), is termed *MIOPC*. For observations in regime $q_i = 0$, the inflated *about the same* outcome is observed; but for those in $q_i = 1$ any of the possible responses in our choice set {*worse off*, *about the same*, *better off*} are feasible. Membership of either regime ($q_i = 0, q_i = 1$) is not directly observed, and this relationship is identified during estimation by the data.

The model depicted in Figure 1(a) can nest the non-generalised model depicted in Figure 1(b). As noted, Brown et al. (2017) demonstrate that the generalised model can collapse to a non-generalised variant under certain parameter restrictions. For instance, restricting $\boldsymbol{\beta}_w = \boldsymbol{\beta}_b = \boldsymbol{\beta}$ and $\rho_w = \rho_b = \rho$ in the *GMIOPC* collapses it to the *MIOPC*. Additionally setting $\rho = 0$ imposes an independent error structure to the non-generalised model, and collapses the *GMIOPC* to the *MIOP*. Likelihood ratio tests with degrees of freedom given by the number of extra parameters can be performed to test between these nested model variants; the results of these tests are used to inform model selection. A proof of the nested nature of these model variants is provided in Appendix C.[14]

3 Modelling financial expectations

We use data from the BHPS, a longitudinal study which took place over the period 1991 to 2008, and was conducted by the Institute for Social and Economic Research. The BHPS is a nationally representative survey of 5,500 households covering over 10,000 individuals per year, collecting wide-ranging socio-economic and demographic information on household members. Our analysis is performed on a balanced panel composed of 24,089 observations (NT) covering 1,417 individuals (N) over an eighteen year period (T) who are of working age (18-65 years).[15]

The first part of our empirical analysis models the individual's response to the following question which elicits information on financial expectations: 'Looking ahead, how do you think you will be financially a year from now?' Respondents indicate whether they think they will be *worse off*, *about the same*, or *better off*. As stated above, these responses are respectively coded -1, 0 and $+1$ to create a financial expectations index ($\widetilde{y}$), where approximately 11% of those surveyed responded *worse off*, 61% reported *about the same* and

[14] For the more general case of $j = 1, 2, ..., J$ outcomes see Brown et al. (2017).

[15] We explain below why the focus is on a balanced panel.

28% responded *better off*. Hence, it would appear that there is inflation in the reporting of financial expectations in that the dominant category corresponds to the *about the same* response and this is prevalent over time (see Figure A.1 in Appendix A). In the first part of our analysis, $\widetilde{y}$ constitutes the dependent variable.

Following the existing literature (see for example Souleles 2004), financial expectations are conditioned on the following individual and household covariates: the age of the individual, as captured by binary indicators corresponding to whether the respondent is aged 18-30, 31-40 and 41-50, where 51 years of age and above comprises the reference category; gender; highest educational attainment, namely whether a degree (undergraduate or higher degree), a teaching or nursing qualification (or another degree level equivalent qualification), A-levels, O-levels (GCSE), and any other qualification achieved, with 'no education' being the omitted category. We additionally control for information on respondents' personality traits made available in 2005, namely the 'Big Five'—agreeableness, conscientiousness, extraversion, neuroticism, and openness to experience. Controls are also included for the number of children in a household; whether the individual is married or cohabiting; ethnicity, delineated in terms of whether an individual is white, black or Asian, where 'other ethnic groups' form the reference category; and labour market status, which distinguishes between whether the respondent is an employee, self-employed, or unemployed, with 'not in the labour market' as the omitted group. In terms of monetary variables (which are all deflated to 1991 prices), we control for the natural logarithm of: labour income in the previous month; non-labour income in the previous month (e.g., benefit income); savings made during the last month in a post office or equivalent instant access account; and wealth based upon the individual's estimate of their house value. Housing tenure is included as a control, and captures whether the home is owned outright; owned via a mortgage; or rented. Other control variables used in our strategy for modelling financial expectations comprise: the caseness subjective well-being score from the general health questionnaire (GHQ-12);[16] an index capturing how the individual perceives their job security, where 0 corresponds to not in paid employment, and values one through seven, respectively correspond to levels of satisfaction for those in employment, ranging from 'not satisfied' at all to 'completely satisfied'. Regional unemployment (defined at the government office region) is also included as a covariate to account for regional macroeconomic shocks, in addition a time trend is incorporated.

[16] This covers various dimensions, including: depression; anxiety; somatic symptoms; feelings of incompetence; difficulty in coping; and sleep disturbance. The GHQ-12 score is on the scale 0 (the least distressed) through to 12 (the most distressed).

As well as asking individuals about their financial expectations for the future, in each wave respondents are also asked about their current financial situation relative to the previous year. Specifically, individuals are asked: 'Would you say that you yourself are financially worse off, about the same, or better off than you were a year ago?' These responses are used to define a three-point financial realisations index (R): '*worse off*' responses are coded '-1', '*neither worse off nor better off*' responses are coded '0', whilst '*better off*' responses are coded '1'. Exploiting the responses to this question at time t and the responses to the financial expectations question at t–1, we then define whether an individual's financial expectation made in the previous year was realised, by creating the following variable,

$$Error_{it} = \widetilde{y}_{it-1} - R_{it}. \tag{8}$$

This variable is based upon individuals' responses to financial realisations. Specifically, individuals are asked to assess their current financial situation relative to the previous year.[17] $Error_{it}$ can take the value $-2, -1, 0, +1, +2$, where negative values indicate that the respondent was too pessimistic with respect to their financial expectations, and positive values indicate being over optimistic (Souleles 2004). A value of zero indicates that expectations have been realised.

Individuals are also asked at time t to specify why their financial situation changed between time t–1 and t. This additional information is exploited to define four binary variables corresponding to whether income and/or expenditure changes, both of which may be positive or negative, occur.[18] A positive income change occurs if the individual experiences an income increase during the past twelve months stemming from earnings (i.e., labour income), benefits, investment income, and/or a windfall. Conversely, a negative income change occurs when an individual's income from any one of the aforementioned sources falls. Turning to expenditure changes, expenditure is defined to have increased if the individual experiences greater expenses during the past twelve months or experiences a one-off expenditure increase. Expenditure is defined to have fallen if the individual reports lower expenses in response to why their financial situation changed.

These terms are then interacted with $Error_{it}$ to create 'shock' terms. These are labelled as

[17] It is also possible to define how an individual's current financial situation has changed relative to the previous year by analysing how their income changed over time. We have also conducted our analysis using this approach, and our findings remained unchanged.

[18] In related work, Coco et al. (2019) also distinguish between the main reasons that led to the change in household finances: an increase/decrease in income or higher/lower expenditure. They examine both expected and realised changes in individual finances examining expectation formation and expectation errors, controlling for individual fixed effects.

'Income shock up' ($Error_{it}\times$ financial situation changed as income went up); 'Income shock down' ($Error_{it}$ $\times$ financial situation changed as income went down); 'Expenditure shock up' ($Error_{it}$ $\times$ financial situation changed as expenditure went up); 'Expenditure shock down' ($Error_{it}$ $\times$ financial situation changed as expenditure went down). Explicitly capturing income or expenditure 'shocks' as a non-zero value of $Error_{it}$ means that the expectation at t–1 regarding the financial situation at t was incorrect: hence the individual at t–1 did not anticipate the income or expenditure change as measured at t.

In terms of modelling inflation, we condition on a subset of the above variables (namely: age; gender; highest educational attainment and the Big Five personality traits). For example, individuals' attitudes – captured by personality traits – may influence inflation and/or the better-educated are likely to be more informed about their financial situation and future finances. Additional covariates include: the number of times that the individual has been correctly optimistic in the panel (i.e. over 18 years); the number of times that the individual has correctly forecast no change in financial situation in the panel; and the number of times that the individual has been correctly pessimistic in the panel. This is why the data set is balanced; specifically, the literature on panel conditioning suggests that responses to survey questions may be influenced by the number of times respondents are observed (e.g. Williams and Mallows 1970; Das et al. 2011). This may be particularly important in measuring forecast accuracy. Other controls include proxies for interview conditions which may influence responses, namely: the number of problems affecting the interview, e.g. language, reading, interpretation etc.; and whether other individuals were present during the interview.[19] Following the existing literature we also include proxies for the level of trust that individuals may have in the questionnaire (which can influence survey responses). The measures we use are the amount of time the interview took in minutes and whether there has been a change in the interviewer between waves (e.g. Corbin and Morse 2003; Niccoletti and Peracchi 2005; and Vassallo et al. 2015).[20] A higher level of trust in the questionnaire and/or interviewer may engender a more accurate/realistic response from the interviewee rather than replying that the financial situation will not change, i.e. a neutral response. Summary statistics are provided in Table A.1 of Appendix A.

[19] If others were present during the interview then the respondent may opt to give a neutral response in order to save-face (recall the discussion in Section 1).

[20] The literature has shown that the longer a respondent spends time with the interviewer the more trusting they are of both him/her and the survey in general. Similarily, interviewer continuation is associated with respondent trust, interviewer reputation and rapport with the respondent, and hence continued survey participation over time.

Table 1: Modelling Financial Expectations – Model Diagnostics

Model	AIC	BIC	LogL
1. Panel *OP*	39,864.25	40,276.82	−19,881.13
2. *MIOP*	38,474.45	39,064.99	−19,164.23
3. Panel *MIOP*	37,527.55	**38,142.35**	−18,687.77
4. *MIOPC*	38,433.57	39,032.19	−19,142.79
5. Panel *MIOPC*	37,521.02	38,143.91	−18,683.51
6. *GMIOP*	38,200.24	38,968.74	−19,005.12
7. Panel *GMIOP*	37,477.62	38,294.66	−18,637.81
8. *GMIOPC*	38,124.59	38,909.27	−18,965.29
9. Panel *GMIOPC*	**37,433.89**	38,267.11	**−18,613.94**

Note: Smaller AIC and BIC values indicate an improved model fit. The smallest value for each respective summary statistic is highlighted in bold.

3.1 Estimation results

To ascertain the desirability of using a generalised *MIOP* estimation strategy, we estimate a number of competing specifications. These comprise a panel *OP* model, and pooled and panel variants of the *MIOP*, *MIOPC*, *GMIOP*, and *GMIOPC* models.[21] As shown in Table 1, which reports the corresponding log-likelihoods and the Akaike and Bayesian Information Criteria (AIC and BIC, respectively) for these models, the panel *OP* model performs least well, which lends support to an estimation approach that explicitly accounts for middle-inflation. Here, we observe that the panel inflated models perform better than those where the data are pooled. However, whilst the AIC measure points to the panel *GMIOPC* as being the preferred model, the BIC suggests that the panel *MIOP* performs best.

To resolve the ambiguity regarding model selection we appeal to the specification tests described in Section 2, under which the imposition of linear parameter restrictions enables the testing of nested versus non-nested variants of the *MIOP* models.[22] Restricting our focus to the panel variants, Table 2 presents the LR test results. The *MIOP*, *MIOPC,* and *GMIOP* are all overwhelmingly rejected in favour of the *GMIOPC*. Using a *GMIOPC* framework thus appears to be a more appropriate modelling strategy. This result aligns with the evidence for the AIC reported in Table 1.

To help shape intuition about the implications of using a generalised model over a non-generalised variant, Table 3 presents the output equation parameters for the *GMIOPC* and

[21] In the panel specifications to account for unobserved heterogeneity we include random effects, see Appendix B. In addition the mean of time varying covariates are incorporated as controls, see Mundlak (1978). By doing this in a random effects framework the parameter estimates then approximate those of a fixed effects estimator, see Wooldridge (2010).

[22] Note, the *OP* model is non-nested; that is, it is not possible to collapse any *MIOP* variant to an ordered probit model by the imposition of linear parameter restrictions. Further, it is not possible to undertake an LR test for *GMIOP* versus *MIOPC*, as neither model nests the other.

Table 2: Specification test results: competing *MIOP* models

Model (*nesting* vs. *nested*)	Test statistic	*df*	*p*-value
GMIOPC vs. *GMIOP*	47.74	2	$p < 0.001$
GMIOPC vs. *MIOPC*	139.14	24	$p < 0.001$
GMIOPC vs. *MIOP*	147.66	25	$p < 0.001$
GMIOP vs. *MIOP*	99.92	23	$p < 0.001$
MIOPC vs. *MIOP*	8.52	1	$p < 0.01$

Notes: *df* denotes degree of freedom. Reported *p*-values of $p < 0.01$ and $p < 0.001$ indicate rejections of the null hypothesis of no difference between the nesting and nested models below the 0.01 and 0.001 levels of significance, respectively.

MIOPC models. For comparative purposes, we also present results for the panel *OP* model, which includes identical variables to those in the output equations. There are clear differences in the structural parameters across these specifications. Whilst the *MIOPC* and *GMIOPC* results are qualitatively very similar, both in sign and significance,[23] some differences do arise. For example, whereas some parameters associated with being in a particular age cohort are large and significant in the *GMIOPC*, this is not the case for the *MIOPC*, where all age group variables are statistically insignificant. Compared to the panel *OP* equation, we observe that outcome equation variables which also appear in the *MIOPC* and *GMIOPC* splitting equations have opposite signs. In addition to this difference, the impact of the 'shock'-based variables appear to be far more pronounced in the panel *OP* model.

The parameter estimates for the single splitting equation of the *MIOPC*, and the two splitting equations of the *GMIOPC* specification, are presented in Table 4. For the *GMIOPC* we observe asymmetries in the form of different parameter estimates across the *worse off* (w_i^*) and *better off* (b_i^*) equations. This reflects our rejection of the restriction that $\boldsymbol{\beta}_w = \boldsymbol{\beta}_b = \boldsymbol{\beta}$ in Table 2, which is imposed as part of the specification test of *GMIOPC* versus *MIOPC*.[24] As shown in Tables 3 and 4, all estimated models are also characterised by a considerable degree of unobserved heterogeneity and statistically significant correlated errors. An exception to this general finding relates to the inflation equation for a *worse off* expectation (w^*), where the random effects parameter (σ_w^2) is insignificant.

However, as the coefficients in an *OP* model, and by extension all varieties of the *MIOP* and *GMIOP* have no direct interpretation, our discussion focuses on the partial effects of our preferred *GMIOPC* specification.[25] These effects measure precisely how changes in the

[23] Where variables are statistically significant in both regressions, the size of the standard errors of many of these parameters suggests that the estimated model coefficients may not be statistically different to each other, based on the construction of confidence intervals at conventional levels of statistical significance.

[24] The restriction that $\boldsymbol{\beta}_w = \boldsymbol{\beta}_b = \boldsymbol{\beta}$ is imposed jointly with the additional restriction that $\rho_w = \rho_b = \rho$.

[25] Full estimation results for all model variants are available from the authors on request.

regressors affect our dependent variable, $\widetilde{y}$, and are evaluated at the means of our regressors. Due to the joint nature of the *GMIOPC* model, care needs to be taken when assessing the impact of a change in a variable on $\widetilde{y}$. Appendix D derives the analytical expressions for the overall partial effects evaluated here, the estimates of which are reported for our preferred specification in Table 5. Table 5 also reports the partial effects for the two splitting equations for the *GMIOPC* model, evaluated at sample means.

For the splitting equation parameters reported in Table 4, a positively signed coefficient is indicative of a variable being associated with a movement away from an *about the same* response towards *worse off* (as captured by the w^* inflation equation) or *better off* (as captured by the b^* inflation equation). Here although the marginal effects for a number of variables are strongly significant and appear sizable in the w^* and b^* equations in Table 5, the direction of these effects may be dampened—and even reversed—once the overall marginal effects are considered. This does not mean that the impact of the splitting equations is limited. To see why, we note that decomposing the overall partial effect of an *about the same* response into its constituent parts is given by

$$\partial \Pr\left(\widetilde{y}=0\right)/\partial \mathbf{x}^* = \left\{ \begin{array}{c} \overbrace{\frac{\partial\left[\Phi\left(\mu_1-\mathbf{z}_i'\boldsymbol{\gamma}\right)-\Phi\left(\mu_0-\mathbf{z}_i'\boldsymbol{\gamma}\right)\right]}{\partial \mathbf{x}^*}}^{\text{A: } y_i^* \text{ equation } (\textit{about the same})} \\ +\underbrace{\frac{\partial\Phi_2\left(\mu_0-\mathbf{z}_i'\boldsymbol{\gamma},-\mathbf{x}_i'\boldsymbol{\beta}_w;\rho_{yw}\right)}{\partial \mathbf{x}^*}}_{\substack{\text{B: Steering to } \textit{about the same} \\ \text{from } w_i^* \text{ eqn.}}} + \underbrace{\frac{\partial\Phi_2\left(\mathbf{z}_i'\boldsymbol{\gamma}-\mu_1,-\mathbf{x}_i'\boldsymbol{\beta}_b;-\rho_{yb}\right)}{\partial \mathbf{x}^*}}_{\substack{\text{C: Steering to } \textit{about the same} \\ \text{from } b_i^* \text{ eqn.}}} \end{array} \right. \tag{9}$$

where the matrix $\mathbf{x}^*$ encompasses $\mathbf{x}_i$ and $\mathbf{z}_i$. Evaluating the total partial effects of the *GMIOPC* model requires taking the latent equations into account. More saliently, even if the partial effect of being steered towards *about the same* from a propensity to choose *worse off* in the *OP* equation is positive and large—as captured by term A in expression (9)—this effect may be offset by negative values of terms B and C. Smaller or dampened overall partial effects do not therefore imply that the impacts of the respective splitting equations play no role in shaping respondents' answers.

Turning to the individual splitting equation variables in Table 5 first, whereas the impact of being in a younger age cohort is to push individuals towards choosing *worse off* in w_i^*, with the magnitude of this effect decreasing with age, an opposing effect is revealed in the splitting equation for *better off* (b_i^*). Individuals younger than 51 years of age (the omitted category) with a propensity to select *better off* in the latent *OP* equation are relatively more likely to be pushed towards an *about the same* response. This effect differs from that implied by the *MIOPC* splitting equation in Table 4, which indicates that younger individuals are less prone to being pushed towards the inflated middle category. In this sense, the single *MIOPC* splitting equation 'masks' the range of distinct impacts associated with being pushed away from different non-inflated outcomes in the generalised framework. The overall marginal effects indicate that being in younger age cohorts increases (decreases) the likelihood of choosing *better off* (*worse off*), a statistically significant effect which disappears for individuals aged 41 years or over.

In the *MIOPC* splitting equation in Table 4, the impact of educational attainment is *prima facie* suggestive of respondents engaging in 'satisficing' behaviour (Krosnick 1991), where minimum cognitive effort is used to produce a response perceived by the household to be acceptable to the interviewer (in this case, '*about the same*'). This theory argues that individuals with less education are more likely to satisfice (i.e., in our application, being pushed towards the middle outcome), when faced with a challenging question. Specifically, the positive (and significant) parameters for individuals with the highest levels of education in the *MIOPC* splitting equation seem to confirm this effect, with university graduates being least prone to satisficing, relative to individuals with no-education. However, whilst similar effects are observed in the *better off* splitting equation for the *GMIOPC* model, satisficing behaviour does not characterise the behaviour of individuals with a propensity to choose *worse off* in the latent *OP* equation. On the contrary, relative to having no education, individuals with low levels of educational attainment are likely to be pushed away from an *about the same* response.[26] This is captured by the marginal effects in Table 5.[27] Overall, the impact of educational attainment is limited to A-level, Degree, and Teaching/Nursing. All of these statistically significant impacts are associated with increasing the probability of selecting *better off*, largely at the expense of selecting *about the same*.

While the role of the 'Big Five' personality traits is limited and restricted to 'Openness to experience', two out of the three variables which capture the precision of individuals' expectation forecasts across the entire sample period are statistically significant: namely 'correct pessimistic'; and 'correct same'. The estimated splitting equation partial effects in b_i^* and w_i^* suggest that individuals with a greater ability to make correct forecasts associated with choosing *worse off* and *about the same*, respectively, are likely to be steered towards

[26]Overall, this would refute the presence of satisficing behaviour. If present, the effect should manifest itself irrespective of whether individuals have a propensity to choose *worse off* or *better off* in the latent *OP* equation.

[27]This example shows that where high statistical significance levels for a variable are observed in a *MIOPC* splitting equation, such effects will not necessarily be observed across all of the splitting equations of the *GMIOPC* model.

these respective outcomes. This finding is reinforced when observing the overall partial effects of the model. Finally, variables related to interview characteristics are generally insignificant when considering the overall partial effects, despite being significant in the splitting equations. An exception is the impact of a change in interviewer, which is associated with increasing the probability of choosing *better off*.

Turning to selected variables unique to the latent OP equation, we observe some interesting effects. The partial effects associated with $Error_{it}$ imply that individuals whose financial realisations were not met in the previous period will report financial expectations in line with the nature of these errors: being overly optimistic (pessimistic) in the previous period will lead to an individual having a *better off* (*worse off*) expectation. In the case of income, a 1% increase in labour income leads to the overall probability of selecting *worse off* (*better off*) increasing by approximately 0.028 (0.059) percentage points. Here, the inclusion of the means of time varying covariates—which includes those for income over the sample period—implies that individuals with atypically high income in a particular year often expect an income fall. An expected change in transitory income is thus negatively related to the level of transitory income.[28] Higher savings are also associated with a higher (lower) likelihood of choosing *worse off* (*better off*). An interpretation of this finding is that if the saving is precautionary in nature, it reflects an expectation that the individual will be *worse off* in the future, which is reflected in the survey response.

Interestingly, ethnicity has no impact, whereas the effect of employment status is mixed. Regarding the GHQ-12 variable, the most distressed individuals have a greater tendency to choose *worse off*. Lastly, the signs on the income up / down and expenditure up / down variables suggest that an income increase is associated with a tendency to be more financially optimistic. An expenditure increase (decrease) is associated with a lower (higher) probability of being *better off* (*worse off*) by 11 (11.2) percentage points. Turning to the statistically significant interaction effects ($Error_{it}\times$Income up, $Error_{it}\times$Expenditure down), the estimated parameters suggest that if income decreases—or expenditure increases—the probability of having a financial expectation consistent with the direction of the $Error_{it}$ index increases, i.e. the magnitude of the forecast error is amplified.

Finally, it is informative to quantify the extent to which respondents' financial expectations are attributable to the inflation equations. Table 6 presents a series of estimated model probabilities averaged over all individuals, where the extent to which inflation effects contribute to each categorical outcome is quantified. Such effects are obtained by estimat-

[28] For a similar finding in the context of the Dutch Socio-Economic Panel (SEP), see Das and van Soest (1999).

Table 3: Modelling Financial Expectations − Ordered Probit Equations for Panel Models

	OP		*MIOPC*		*GMIOPC*	
Aged 18-30	0.353	(0.036)***	0.075	(0.073)	−0.193	(0.125)
Aged 31-40	0.178	(0.027)***	0.040	(0.056)	−0.396	(0.109)***
Aged 41-50	0.083	(0.022)***	0.048	(0.041)	−0.238	(0.093)***
Male	0.041	(0.018)**	−0.018	(0.044)	−0.087	(0.067)
Degree	0.079	(0.027)**	−0.030	(0.079)	−0.087	(0.135)
Teaching/Nursing	0.046	(0.034)	0.116	(0.068)*	−0.085	(0.127)
A-level	0.065	(0.033)*	0.032	(0.075)	−0.118	(0.138)
O-level	0.056	(0.028)**	0.112	(0.069)	−0.141	(0.131)
Other education	0.003	(0.033)	0.116	(0.087)	−0.328	(0.150)**
Agreeableness	0.001	(0.008)	0.024	(0.020)	−0.033	(0.032)
Openness to experience	0.054	(0.008)***	0.036	(0.021)	0.128	(0.033)***
Neuroticism	−0.019	(0.008)**	−0.030	(0.021)	−0.020	(0.033)
Conscientiousness	−0.014	(0.009)	−0.017	(0.019)	0.007	(0.032)
Extraversion	0.014	(0.009)*	0.014	(0.020)	−0.023	(0.033)
Number of children	0.033	(0.010)***	0.075	(0.015)***	0.058	(0.013)***
Married	−0.072	(0.022)***	−0.127	(0.034)***	−0.093	(0.031)***
White	−0.100	(0.107)	−0.271	(0.232)	−0.190	(0.204)
Black	0.335	(0.156)**	0.188	(0.455)	0.188	(0.325)
Asian	−0.104	(0.125)	−0.237	(0.293)	−0.200	(0.256)
Employed	−0.195	(0.039)***	−0.214	(0.054)***	−0.192	(0.048)***
Self employed	−0.026	(0.045)	0.040	(0.067)	0.188	(0.061)
Unemployed	0.391	(0.069)***	0.459	(0.075)***	0.435	(0.069)***
Owned outright	−0.218	(0.045)***	−0.179	(0.066)***	−0.199	(0.058)***
Mortgage	−0.064	(0.041)	−0.012	(0.057)	−0.030	(0.050)
Rent	−0.110	(0.043)***	−0.103	(0.065)	−0.088	(0.057)
Log labour income	−0.149	(0.060)**	−0.199	(0.084)**	−0.194	(0.071)***
Log non-labour income	−0.073	(0.056)	−0.163	(0.075)**	−0.146	(0.065)**
Log savings	−0.227	(0.042)***	−0.322	(0.052)***	−0.276	(0.047)***
Log wealth	−0.078	(0.125)	−0.274	(0.159)*	−0.227	(0.146)
GHQ-12	−0.126	(0.029)***	−0.254	(0.037)***	−0.197	(0.034)***
Job satisfaction	0.051	(0.005)***	0.065	(0.007)***	0.056	(0.007)***
Regional UE	−0.001	(0.056)	0.004	(0.091)	0.017	(0.081)
Time trend	0.728	(0.099)***	1.245	(0.142)***	0.984	(0.140)***
$Error_{it}$	0.248	(0.018)***	0.145	(0.021)***	0.147	(0.020)***
Income up	0.632	(0.029)***	0.464	(0.040)***	0.439	(0.038)***
Income down	−0.151	(0.054)***	0.069	(0.058)	0.078	(0.055)
Expenditure up	−0.603	(0.049)***	−0.391	(0.048)***	−0.362	(0.046)***
Expenditure down	0.510	(0.061)***	0.368	(0.069)***	0.370	(0.063)***
$Error_{it}\times$Income up	0.180	(0.036)***	0.059	(0.044)	0.058	(0.040)
$Error_{it}\times$Income down	0.218	(0.048)***	0.175	(0.051)***	0.161	(0.048)***
$Error_{it}\times$Expenditure up	0.221	(0.044)***	0.124	(0.041)***	0.124	(0.038)***
$Error_{it}\times$Expenditure down	0.001	(0.068)	−0.099	(0.081)	−0.067	(0.072)
μ_0	−1.210	(0.188)***	−1.636	(0.374)***	−1.090	(0.368)**
μ_1	0.776	(0.185)***	−0.541	(0.377)	−0.484	(0.259)*
Correlation coefficients						
ρ			−0.468	(0.073)***		
ρ_{yw}					0.540	(0.106)***
ρ_{yb}					−0.564	(0.102)***
Random effects						
σ_y^2	0.228	(0.013)***	0.237	(0.021)***	0.156	(0.032)***

Notes: Number of observations is 24,089 for all models. Coefficients are reported with standard errors in parenthesis; * significant at 10% level; ** significant at 5% level; *** significant at 1% level; following Mundlak (1978) we include throughout the means of individual time-varying variables (not reported here) to account for fixed effects.

Table 4: Modelling Financial Expectations – Inflation Equations for Panel Models

	MIOPC		*GMIOPC*			
	q_i^*		b_i^*		w_i^*	
Aged 18-30	0.634	$(0.074)^{***}$	1.041	$(0.212)^{***}$	-0.137	(0.180)
Aged 31-40	0.239	$(0.048)^{***}$	0.845	$(0.144)^{***}$	-0.490	$(0.151)^{***}$
Aged 41-50	0.059	(0.038)	0.363	$(0.104)^{***}$	-0.331	$(0.122)^{***}$
Male	0.171	$(0.049)^{***}$	0.001	(0.099)	0.212	$(0.090)^{**}$
Degree	0.341	$(0.089)^{***}$	0.459	$(0.161)^{***}$	0.057	(0.177)
Teaching/Nursing	0.146	$(0.071)^{**}$	0.404	$(0.140)^{***}$	-0.206	(0.163)
A-level	0.162	$(0.085)^{*}$	0.379	$(0.173)^{**}$	-0.129	(0.181)
O-level	0.058	(0.078)	0.357	$(0.156)^{**}$	-0.303	$(0.169)^{*}$
Other education	-0.107	(0.093)	0.488	$(0.214)^{*}$	-0.525	$(0.191)^{***}$
Agreeableness	-0.020	(0.024)	0.055	(0.045)	-0.076	$(0.044)^{*}$
Openness to experience	0.090	$(0.024)^{***}$	-0.038	(0.048)	0.145	$(0.045)^{***}$
Neuroticism	0.014	(0.023)	0.005	(0.050)	0.014	(0.041)
Conscientiousness	-0.007	(0.023)	-0.042	(0.049)	0.032	(0.044)
Extraversion	0.037	(0.025)	0.097	$(0.049)^{**}$	-0.026	(0.043)
Correct optimistic	-0.070	(0.117)	0.023	(0.178)	-0.288	(0.180)
Correct same	-1.197	$(0.096)^{***}$	-1.288	$(0.166)^{***}$	-0.703	$(0.129)^{***}$
Correct pessimistic	0.427	$(0.209)^{**}$	0.024	(0.307)	0.502	$(0.247)^{***}$
Change in interviewer	0.085	$(0.029)^{***}$	0.098	$(0.041)^{**}$	0.041	(0.039)
Total number of problems	-0.103	(0.138)	0.136	(0.208)	-0.531	$(0.217)^{**}$
Other present in interview	-0.015	(0.031)	-0.002	(0.042)	-0.047	(0.041)
Length of interview	0.064	(0.065)	0.080	(0.088)	0.096	(0.099)
Constant term	0.095	(0.101)	0.529	$(0.193)^{***}$	0.177	(0.234)
Random effects						
σ_q^2	0.324	$(0.038)^{***}$				
σ_w^2				0.117	$(1.513e+04)$	
σ_b^2				0.111	$(0.044)^{**}$	

Note: Coefficients are reported with standard errors in parenthesis; * significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Table 5: Modelling Financial Expectations – *GMIOPC* Model Marginal Effects

	Overall marginal effects						*Marginal effects of inflation equations only*			
	worse off		*about the same*		*better off*		*worse off* (w_i^*)		*better off* (b_i^*)	
Aged 18-30	0.012	(0.012)	−0.162	(0.023)***	0.150	(0.025)***	0.054	(0.072)	−0.140	(0.019)***
Aged 31-40	0.008	(0.009)	−0.049	(0.016)***	0.049	(0.017)***	0.195	(0.060)***	−0.038	(0.015)**
Aged 41-50	−0.004	(0.007)	0.004	(0.014)	0.001	(0.015)	0.132	(0.048)***	0.008	(0.010)
Male	0.010	(0.007)	−0.041	(0.013)***	0.030	(0.013)***	−0.084	(0.035)***	−0.042	(0.009)***
Degree	0.019	(0.013)	−0.084	(0.025)***	0.065	(0.025)***	−0.023	(0.070)	−0.085	(0.018)***
Teaching/Nursing	−0.012	(0.010)	−0.043	(0.021)**	0.055	(0.022)***	0.082	(0.064)	−0.024	(0.015)
A-level	0.002	(0.012)	−0.042	(0.024)*	0.040	(0.024)*	0.051	(0.072)	−0.035	(0.016)**
O-level	−0.015	(0.011)	−0.013	(0.023)	0.028	(0.023)	0.120	(0.067)*	0.003	(0.016)
Other education	−0.014	(0.013)	0.016	(0.028)	−0.002	(0.027)	0.209	(0.075)***	0.026	(0.021)
Agreeableness	−0.004	(0.005)	0.003	(0.009)	0.001	(0.011)	0.030	(0.018)*	0.006	(0.005)
Openness to experience	−0.001	(0.004)	−0.029	(0.010)***	0.031	(0.010)***	−0.058	(0.017)***	−0.022	(0.005)***
Neuroticism	0.005	(0.005)	0.001	(0.011)	−0.005	(0.008)	−0.005	(0.016)	−0.004	(0.004)
Conscientiousness	0.003	(0.004)	0.004	(0.010)	−0.006	(0.010)	−0.012	(0.018)	0.001	(0.004)
Extraversion	0.001	(0.004)	−0.013	(0.011)	0.013	(0.011)	0.001	(0.017)	−0.001	(0.004)***
Number of children	−0.008	(0.002)***	−0.009	(0.002)***	0.018	(0.004)***				
Married	0.013	(0.005)***	0.015	(0.005)***	−0.028	(0.009)***				
White	0.028	(0.030)	0.030	(0.033)	−0.058	(0.062)				
Black	−0.028	(0.048)	−0.030	(0.053)	0.057	(0.098)				
Asian	0.029	(0.037)	0.032	(0.042)	−0.061	(0.078)				
Employed	0.028	(0.007)***	0.030	(0.008)***	−0.058	(0.015)***				
Self employed	−0.003	(0.009)	−0.003	(0.009)	0.006	(0.019)				
Unemployed	−0.063	(0.010)***	−0.069	(0.014)***	0.132	(0.021)***				
Owned outright	0.029	(0.009)***	0.032	(0.009)***	−0.061	(0.017)***				
Mortgage	0.004	(0.007)	0.004	(0.008)	−0.009	(0.015)				
Rent	0.013	(0.008)	0.014	(0.009)	−0.027	(0.017)				
Log labour income	0.028	(0.010)***	0.031	(0.012)***	−0.059	(0.022)***				
Log non-labour income	0.021	(0.009)***	0.023	(0.010)**	−0.044	(0.020)**				
Log savings	0.040	(0.007)***	0.044	(0.008)***	−0.084	(0.014)***				
Log wealth	0.033	(0.021)	0.036	(0.023)	−0.069	(0.044)				
GHQ-12	0.029	(0.005)***	0.031	(0.006)***	−0.060	(0.010)***				
Job satisfaction	−0.008	(0.001)***	−0.009	(0.001)***	0.017	(0.002)***				
Regional UE	−0.002	(0.011)	−0.003	(0.013)	0.005	(0.024)				
Time trend	−0.143	(0.020)***	−0.156	(0.025)***	0.299	(0.040)***				
$Error_{it}$	−0.021	(0.003)***	−0.023	(0.004)***	0.045	(0.006)***				
Income up	−0.064	(0.006)***	−0.070	(0.008)***	0.133	(0.011)***				
Income down	−0.011	(0.008)	−0.012	(0.009)	0.023	(0.017)				
Expenditure up	0.053	(0.007)***	0.057	(0.008)***	−0.110	(0.014)***				
Expenditure down	−0.054	(0.009)***	−0.059	(0.011)***	0.112	(0.019)***				
$Error_{it}$×Income up	−0.008	(0.006)	−0.009	(0.006)	0.018	(0.012)				
$Error_{it}$×Income down	−0.023	(0.007)***	−0.026	(0.008)***	0.049	(0.014)***				
$Error_{it}$×Expenditure up	−0.018	(0.006)***	−0.020	(0.006)***	0.038	(0.011)***				
$Error_{it}$×Expenditure down	0.009	(0.011)	0.011	(0.012)	−0.020	(0.022)				
Correct optimistic	−0.034	(0.021)	0.029	(0.035)	0.005	(0.036)	0.115	(0.072)	0.054	(0.024)**
Correct same	−0.083	(0.013)***	0.340	(0.025)***	−0.258	(0.025)***	0.280	(0.051)***	0.346	(0.025)***
Correct pessimistic	0.059	(0.028)**	−0.064	(0.059)	0.005	(0.061)	−0.200	(0.098)**	−0.104	(0.041)**
Change in interviewer	0.005	(0.005)	−0.024	(0.008)***	0.020	(0.008)***	−0.016	(0.016)	−0.024	(0.006)***
Total number of problems	−0.062	(0.024)	0.035	(0.041)	0.027	(0.042)	0.211	(0.086)***	0.084	(0.028)***
Other present in interview	−0.006	(0.005)	0.006	(0.009)	0.001	(0.008)	0.018	(0.016)	0.009	(0.006)
Length of interview	0.011	(0.012)	−0.027	(0.019)	0.016	(0.018)	−0.038	(0.039)	−0.031	(0.014)**

Note: Marginal effects are reported with standard errors in parenthesis; * significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Table 6: Summary Probabilities for the Panel *GMIOPC* Model

Category	Sample proportion	Overall	Purged
worse off	0.1066	0.094	0.324
		(0.004)***	(0.047)***
about the same	0.6098	0.635	0.216
		(0.006)***	(0.045)***
better off	0.2836	0.271	0.459
		(0.006)***	(0.031)***
Amount(Middle-inflation)		0.419	
		(0.047)***	

Note: Standard errors in parenthesis; *** significant at 1% level.

ing the probabilities solely associated with the underlying *OP* component of the *GMIOPC* model. These probabilities effectively 'purge' or 'net-out' any inflation effects. We estimate the amount of middle-inflation in the model—denoted *Amount* (Middle-inflation)—as the difference between the overall predicted probability of choosing *about the same* and the corresponding purged amount. This quantity is then used to calculate the proportion of overall *about the same* responses that is attributable to the effects of model inflation. Expressed as a percentage, the *GMIOPC* model suggests that approximately 42% of the *about the same* observations can be attributed to the impact of the inflation equations and, furthermore, this is statistically significant. This finding points to a large proportion of middle responses being attributable to the impact of model inflation.

Figure A.2 in Appendix A plots the financial expectations index (the shaded columns) with values as defined above in Section 2 (bounded -1 to +1). We also provide density plots of the linear predictions from the panel *OP* model (the red line) and the panel *GMIOPC* model (the blue line), where the latter has been purged of the effects of inflation. It should be noted that both linear predictions are not bounded to the -1 to +1 space. It is noticeable that the linear prediction from the panel *OP* model has considerable inflation at zero, as in the underlying financial expectations index. Conversely, once inflation has been purged from the linear prediction there is clear evidence of a shift in the distribution away from zero as is apparent from the plot for the panel *GMIOPC*. For the linear prediction from the panel *GMIOPC* model, responses have been steered away from the *about the same* category to either being pessimistic or optimistic — although given the shift in the *GMIOPC* distribution to the left hand side, compared to the alternative expectations indices, after purging inflation respondents are typically more pessimistic. This is not surprising given that 42% of the 61% responding in the underlying financial expectations index *about the same* was found to be due to inflation.

Overall, our findings point to the panel *GMIOPC* being an appropriate statistical framework to model the financial expectations of UK households, which as discussed below, has important implications for accouting for patterns of household consumption expenditure given that without accounting for inflation respondents are typically over-optimistic, a finding consistent with the existing literature (Bovi 2009, Malmendier and Taylor 2015).

4 Modelling consumption expenditure

In this section, we explore the implications of applying the *GMIOPC* modelling approach to financial expectations for analysing the effect of expectations on household expenditure decisions. We focus on a sub-sample of individuals who are the head of household and are asked questions regarding household expenditure. The prediction that consumer sentiment or individual expectations affect spending on consumer goods has been documented in a well established literature, see the overview by Ludvigson (2004).

For instance, Mishkin et al. (1978) found the *Index of Consumer Sentiment* compiled by the University of Michigan's Survey Research Center to be effective in accounting for US consumer expenditure, particularly on consumer durables. Focusing on Dutch households' subjective expectations and realisations of future income, Giamboni et al. (2013) find that predictable income changes can explain changes in consumption. DeNardi et al. (2011) focus on the behaviour of consumption during the Great Recession. The University of Michigan's *Survey of Consumers* is exploited with a view to accounting for the behaviour of nominal expected income growth and inflationary expectations. A notable finding is that lower consumer income expectations play a considerable role in driving the observed fall in aggregate US consumption during this period. In Burke and Ozdagli (2013), micro-data from the RAND *American Life Panel Survey*, which contains detailed information about expenditure on a wide range of both durable and non-durable goods is used to explore the relationship between household inflation expectations and consumer spending. Very little support is found for the hypothesis that current consumer spending is caused by higher expectations of inflation.[29]

Following Brown and Taylor (2006), we investigate the relationship between financial expectations and consumption behaviour. In line with Browning et al. (2016), our focus lies

[29] Puri and Robinson (2007) use the *Survey of Consumer Finances* to explore the relationship between expectations, in particular optimism, and a number of economic outcomes including financial behaviour. For example, they find that more optimistic people save more, although their analysis is based on repeated cross sections and hence they are unable to account for panel effects. In contrast, Coco et al. (2019) using the BHPS find that after controlling for individual fixed effects more optimistic individuals save less.

on demand for household durable goods. Specifically, we explore the determinants of the probability of purchasing different goods as well as the level of expenditure undertaken. We also split the analysis by investigating these effects on expenditure relating to both household appliances and consumer electronic goods.[30] In contrast to Browning et al. (2016), financial expectations are included in the set of explanatory variables. The aim of the analysis is to ascertain the effect of financial expectations on each expenditure outcome, in terms of the likelihood of purchase and the amount spent on durable goods. We compare the effects of the original expectations index, with its linear prediction from a panel *OP* model and its prediction from the panel *GMIOPC* modelling approach (where in the latter the linear prediction is purged of the effects of any inflation). In the following, we firstly introduce the expenditure/consumption data and the empirical methodology, followed by the results from modelling expenditure.

4.1 Data and econometric strategy

In each year of the BHPS, information is available on household expenditure on durable goods in the previous year, where from 1991 those individuals who are the head of the household are asked whether any of the following items were purchased: (1) *colour television*; (2) *VCR*; (3) *freezer*; (4) *washing machine*; (5) *tumble dryer*; (6) *dish washer*; (7) *microwave*; (8) *home computer*; and (9) *CD player*. From 1997 onwards, the categories were expanded to include the following items: (10) *satellite dish*; (11) *cable TV*; (12) *telephone*; and (13) *mobile phone*. For each type of good purchased, the head of household was asked, 'How much in total have you paid for this, excluding interest paid on loans?' Clearly, the data does not include all types of consumption expenditure but it does serve as a proxy for consumption. Following Browning et al. (2016), we consider expenditure on white good household appliances (freezers, microwaves, dishwashers, washing machines and tumble dryers) and expenditure on consumer electronics (personal computers, CD players, TVs, VCRs, phones, cable TV and satellite dishes).

We estimate models of the following form, as a dynamic specification, as outlined below, but also, for comparison purposes, as a static model with $\gamma = 0$ and $\alpha_i = \alpha_0$:

$$E_{it}^{g} = \gamma E_{it-1}^{g} + \mathbf{s}_{it}'\boldsymbol{\lambda} + \phi\widetilde{y}_{it} + \alpha_i + \nu_{it} \tag{10}$$

[30] Browning et al. (2016) find that purchases of consumer electronics typically rise with age, whilst, in contrast, the demand for household appliances is relatively flat.

$$\alpha_i = \alpha_0 + \alpha_1 E_{i0}^g + \bar{\mathbf{s}}_i' \boldsymbol{\pi} + \omega_{it} \tag{11}$$

The dependent variable, E_{it}^g , is either binary (modelled as a correlated random effects probit model) or the natural logarithm of the amount of expenditure (modelled as a correlated random effects tobit model) for group g. The groups we consider are: g = all goods, electronics, white good appliances; or g = 1,2,...,13, i.e. denoting each specific type of durable good. In the dynamic specifications, the correlation between the fixed effect, α_i, and the lagged dependent variable, E_{it-1}^g, yields an endogeneity problem, which will result in inconsistent estimates. We follow Wooldridge (2005) and specify the fixed effect in equation (10) conditional on the initial state, E_{i0}^g, i.e. whether the household purchases good g (or the amount spent) when first observed in the panel, and the group means of time varying covariates, $\bar{\mathbf{s}}_i$, i.e. Mundlak (1978) fixed effects, as shown in equation (11). Substitution of equation (11) into (10) yields an augmented random effects model. State dependence is explored in terms of the statistical significance of E_{it-1}^g and the magnitude of γ.

The set of control variables in $\mathbf{s}_{it}$ draws on the existing literature, e.g. Browning et al. (2016), and includes both household and head of household charateristics. Our particular interest lies in the head of household's financial expectations index $\widetilde{y}_{it}$, which as described in Section 2, corresponds to the choice set $\widetilde{y}_i = \{-1, 0, 1\}$. In alternative specifications, it is replaced by its linear prediction from a panel *OP* model and its linear prediction from the panel *GMIOPC* modelling approach. In order to make the magnitude of financial expectations comparable across the different estimators we standardise each measure to have a zero mean and standard deviation of unity. Our main focus is on the estimate of ϕ in terms of its sign, magnitude and statistical significance, and whether the effects differ once inflation has been purged from the measure of expectations. Other head of household charateristics comprise: a quartic in age; a quadratic in year of birth cohort; the number of health problems reported; labour market status (i.e. whether an employee, self-employed or unemployed, where out of the labour market is the omitted category). Household characteristics include the number of children aged 0-2, 3-4, 5-11, 12-15, and 16-18; the number of adults in the household; and the natural logarithm of household income.

Summary statistics for the variables used in the expenditure models are reported in Table A.2 in Appendix A. Over the period, approximately 40% of respondents purchased electronic goods and 24% purchased household appliances, whilst the respective amounts spent were £350.85 and £189.59. The most common types of expenditure are on televisions, VCRs and computers, with each at around 12%. Whilst the BHPS has information on whether household and electronic goods were purchased from 1991 onwards, information on the amount spent on each type of good is only recorded from 1997 onwards (the amount spent is deflated to 1991 prices). Hence, when modelling expenditure, the sample sizes for the static and dynamic models are 9,107 and 7,810, respectively. However, we do have information on the total amount of expenditure on all durable goods for the full period. On average, households purchase one durable good per year, 47% do not undertake expenditure on durables, whilst 4% purchase four or more products. For the two broad categories of electronic goods and household appliances, when considering the likelihood of purchase, the sample sizes for the static and dynamic models are 12,629 and 11,270, respectively.

4.2 Estimation results

The results are presented in Tables 7 to 9. Table 7 focuses on the log of total expenditure on all durable goods, and the log amount spent on electronics and household appliances in the static and dynamic frameworks, whilst Table 8 focuses on the probability of incurring expenditure on any durable good, which is then decomposed into electronics and household appliances for both the static and dynamic models. In Table 9, static models are estimated for each of the 13 types of expenditure. In each of the tables, Panel A presents the full results when financial expectations, $\widetilde{y}_{it}$, are treated as exogenous. In Panels B and C of each table, financial expectations, $\widetilde{y}_{it}$, are replaced by the linear prediction from: a panel *OP* model and the panel *GMIOPC* model (where in the latter the linear prediction is net of inflation). Due to the inclusion of a generated variable, we follow Krinsky and Robb (1986) in calculating the standard errors.[31] Each alternative measure of financial expectations has been standardised enabling us to compare the magnitude across each specification (i.e. Panels A to C).

With respect to the amount of expenditure (see Table 7, Panel A), focusing on all durable goods (the first two columns), there is clear evidence of life cycle effects in the static model, this is driven by the effect of age upon household appliances (see Table 7, final two columns) whilst there is no evidence of life cycle effects on the level expenditure undertaken upon electronic goods.[32] In contrast, there is no association between age and the likelihood of purchasing household appliances, see Table 8, yet life cycle effects are apparent for the probability of purchasing electronic goods (albeit only in the static framework). This reflects

[31] The results based on the Krinsky and Robb (1986) standard errors are very similar to those derived via the delta method.

[32] Whilst Browning et al. (2016) find evidence of life cycle effects in modelling the amount of expenditure on electrical goods, their sample size is much larger as it is based upon an unbalanced panel. Moreover, their estimation framework differs substantially to ours and also they do not account for dynamics. Furthermore, we also consider consumption at the intensive and extensive margins.

the different effects covariates can have at the intensive and extensive margins.

We also control for household size and family composition as the literature suggests that these factors affect the demand for durables, see, e.g., Fernandez-Villaverde and Krueger (2005), and Fernandez-Villaverde and Krueger (2007). Household size only influences the likelihood of expenditure on durable goods in the static models (see Table 8). Interestingly, focusing on the dynamic models, the number of children in the household has no effect on the likelihood of purchasing or the amount spent on household appliances. Conversely, for electronic goods, the key child ages are five and above, with the effects increasing monotonically for both the likelihood and the amount spent on electronic goods (see Tables 7 and 8).

In the dynamic models, typically there is no effect of employment status on durable good expenditure or the probability of purchase, although there is some evidence that individuals who are self-employed are more likely to purchase household appliances and also spend more (albeit only reaching statistical significance at the 10 per cent level). In general, the number of health problems is positively associated with both the likelihood and the amount of expenditure for both electronics and household appliances, which is consistent with Browning et al. (2016) for the amount spent on electronics.

With respect to the dynamic models, a 1% increase in household income increases the probability of spending on electronics (household appliances) by approximately 2 (3) percentage points (see Table 8). However, in the case of both types of goods, the amount spent is inelastic (see Table 7), a finding consistent with the results of Bachmann et al. (2015) for the US. Specifically, a 1% increase in household income is associated with an increase in expenditure on electronics (household appliances) by 0.18% (0.15%), see Table 7. The demand for household appliances is found to be more income inelastic than electronic goods, which is consistent with such products being necessities, for example, a washing machine or a freezer versus a home computer or a satellite TV. From the dynamic models, there is clear evidence of state dependence in both the likelihood of making a purchase and the amount spent for all durable goods, as well as by the type of good purchased. For example, it is apparent from Table 7 that the effect of the amount of expenditure in the previous year is inelastic and is approximately 24% (86%) of the income effect for electronic purchases (household appliances). The probability of having purchased electronic goods (household appliances) in the previous period increases the probability of buying electronic goods (household appliances) by 5.0 (5.5) percentage points, see Table 8.

We now turn to the effect of financial expectations on the amount spent (Table 7) and on the likelihood of undertaking expenditure (Table 8), on electronics and household appliances. Interestingly, there is no association between financial expectations and the amount spent on household white goods in either the static or dynamic frameworks, see Table 7. However, focusing on the amount spent on all durable goods and electronic goods, Table 7 Panel A shows that the exogenous expectations index is positively associated with the level of expenditure, and that, under the dynamic framework, the magnitude of the effect is moderated compared to the static model. In the dynamic model a one standard deviation increase in financial expectations is associated with around a 0.17% increase in the amount spent on electronic goods. The finding that optimistic expectations regarding future income are generally positively associated with consumption expenditure is consistent with Bachmann et al. (2015) and Gillitzer and Prasad (2018).[33,34] From the corresponding analysis for the likelihood of purchasing goods, see Table 8 Panel A, it is apparent that the exogenous index of financial expectations is only associated with expenditure on electronic goods. Specifically, in the dynamic model a one standard deviation increase in financial expectations is associated with a 3.63 percentage point higher probability of purchasing an electronic product.

The majority of the literature to date, which has explored the relationship between expectations and household financial behaviour (such as saving, debt and consumption expenditure), has largely treated expectations as exogenous. However, it is difficult to argue that consumption decisions are made independently from expectations regarding future income. Consequently, in Panels B and C of Tables 7 and 8, we use the linear prediction from the alternative models of expectations (a panel *OP* model and a panel *GMIOPC* model where expectations are purged of inflation). Each measure is standardised and so the effect of financial expectations can be compared across panels. Again, as found in Panel A of Tables 7 and 8, the results show throughout each panel that the linear prediction of financial expectations is positively associated with the amount spent on durable goods and the likelihood of purchase. Moreover, for both the amount spent (Table 7) and the likelihood of purchase (Table 8), the magnitude is smaller for the measure of expectations based upon the linear prediction derived from the panel *GMIOPC* model (Panel C) compared to the measure based on the linear prediction of expectations from the panel *OP* model (Panel B). For example, focusing

[33] Bachmann et al. (2015) explore the relationship between inflation expectations and households' readiness to purchase consumption goods, using the Michigan *Survey of Consumers*. Gillitzer and Prasad (2018) consider the effect of consumer sentiment (which includes expectations regarding future income) on consumption in Australia.

[34] In related work, Souleles (2004) shows using US data from the Michigan *Index of Consumer Sentiment* that sentiment helps to forecast consumption growth, whilst Giamboni et al. (2013) using Dutch micro data from the De Nederlandsche Bank (DNB) Household Survey find that agents who are overly optimistic have lower consumption growth.

on expenditure on all goods a one standard deviation increase in financial expectations is associated with an increase in the amount spent by approximately 0.12% and 0.09% (see Table 7 Panels B and C). Similarly, considering the likelihood of purchasing durable goods a one standard deviation increase in financial expectations is associated with a 2.4 and 1.8 percentage point higher probability of purchasing a durable good (see Table 8 Panels B and C). Hence, once inflation effects have been purged from predicted financial expectations the impact on both the intensive and extensive margins of consumption is smaller, this is because inflation serves to shift the distribution of financial expectations to the right (as is evident from Figure A.2 in Appendix A).

In Table 9, the probability of purchasing each type of good is estimated in a static framework.[35] The sample covers 12,629 observations for goods ($g =$) 1 to 9, whilst for the sub-sample which covers the remaining goods, there are 9,107 observations. The table is constructed in the same way as Tables 7 and 8, but we only report the key parameter of interest, i.e. the effect associated with the standardised measure of financial expectations, ϕ. Whilst the association between expectations and the likelihood of expenditure is generally positive, it is only significant for 6 of the 13 goods (see Panel A) and this is solely for electronic goods, i.e.: VCR; home computer; CD player; satellite dish; cable TV and mobile phone. Panels B and C relate to the standardised linear prediction of financial expectations, where, for the aforementioned goods, the positive relationship generally remains. Moreover, the effect of the standardised linear prediction from the panel *OP* model on the probability of undertaking expenditure on specific durable goods (see Panel B), where statistically significant, is typically larger than that stemming from the exogenous expectations index (see Panel A). But as found above, the effect of financial expectations upon the probability of purchasing different types of durable goods is larger in terms of economic magnitude from the panel *OP* compared to the panel *GMIOPC* specification, where in the latter inflation has been purged from the linear prediction.

In general, we have found that financial expectations are significantly associated with consumption: specifically, more optimistic individuals are more likely to purchase durable goods and to incur greater expenditure. The results tie in with the existing literature, which has found a role for expectations and sentiment indicators in predicting consumption, e.g. Carroll et al. (1994), Brown and Taylor (2006), Ludvigson (2004), Bachmann et al. (2015) and Gillitzer and Prasad (2018). The relationship between consumption and financial

[35] It is unlikely that households purchase the same type of durable good, e.g. a washing machine, a TV or a home computer, year on year. Hence, a dynamic framework does not seem appropriate when modelling the probability of purchasing specific durable goods.

Table 7: Log Amount of Expenditure

	Type of Expenditure											
	All Goods				Electronics				Household Appliances			
Panel A	*Static*		*Dynamic*		*Static*		*Dynamic*		*Static*		*Dynamic*	
Lag dependent variable	–		0.0478	(0.009)***	–		0.0327	(0.018)*	–		0.1363	(0.038)***
Age	1.3127	(0.639)**	0.8749	(0.782)	1.0286	(0.830)	1.6495	(1.302)	1.6705	(0.604)***	1.2583	(0.624)**
Age^2	−0.0513	(0.023)**	−0.0354	(0.028)	−0.0778	(0.064)	−0.0991	(0.079)	−0.2509	(0.126)**	−0.3458	(0.157)**
Age^3	0.0009	(0.000)**	0.0006	(0.004)	0.0012	(0.001)	0.0015	(0.001)	0.0039	(0.002)**	0.0054	(0.002)**
Age^4	−0.0000	(0.000)**	−0.0000	(0.000)	−0.0000	(0.000)	−0.0000	(0.000)	−0.0000	(0.000)**	−0.0000	(0.000)**
Year of birth	0.0815	(0.082)	0.1304	(0.091)	0.0978	(0.160)	0.3083	(0.212)	0.0617	(0.290)	0.3842	(0.383)
Year of birth^2	−0.0003	(0.001)	−0.0011	(0.001)	−0.0009	(0.002)	−0.0038	(0.002)	−0.0003	(0.004)	−0.0044	(0.005)
Household size	0.0677	(0.050)	0.0863	(0.053)	0.0892	(0.098)	0.1190	(0.106)	0.1532	(0.196)	0.3089	(0.211)
Children 0-2	−0.1114	(0.111)	−0.1385	(0.121)	−0.4382	(0.228)*	−0.5733	(0.255)**	−0.0362	(0.441)	−0.0851	(0.488)
Children 3-4	−0.1170	(0.102)	-0.0641	(0.109)	−0.1312	(0.205)	−0.0759	(0.228)	0.4945	(0.397)	0.5440	(0.438)
Children 5-11	0.2026	(0.061)***	0.1938	(0.065)***	0.2847	(0.124)**	0.2430	(0.136)*	0.2470	(0.245)	0.1803	(0.268)
Children 12-15	0.2624	(0.068)***	0.2811	(0.072)***	0.4297	(0.131)***	0.3771	(0.142)***	0.3014	(0.261)	0.2737	(0.282)
Children 16-18	0.3508	(0.118)***	0.3001	(0.120)***	0.4836	(0.207)**	0.5151	(0.221)***	0.6071	(0.414)	0.4710	(0.443)
Number of problems	0.0979	(0.038)***	0.1031	(0.040)***	0.1087	(0.047)**	0.1603	(0.076)**	0.2817	(0.140)**	0.4219	(0.152)***
Employee	0.1545	(0.130)	−0.0200	(0.139)	−0.1056	(0.247)	−0.1852	(0.269)	0.2351	(0.491)	0.4368	(0.539)
Self employed	0.2174	(0.173)	0.0467	(0.184)	−0.2532	(0.332)	−0.2768	(0.360)	1.1930	(0.668)*	1.3722	(0.715)*
Unemployed	−0.2150	(0.211)	−0.3629	(0.228)	−0.4600	(0.425)	−0.4310	(0.460)	−0.7159	(0.861)	−0.4951	(0.941)
Log real household income	0.2203	(0.066)***	0.1984	(0.070)***	0.4170	(0.052)***	0.1826	(0.074)**	0.5364	(0.056)***	0.1504	(0.063)**
Expectations index 1 ($\widetilde{y}_{it}$)	0.0976	(0.054)**	0.0973	(0.049)*	0.1955	(0.084)**	0.1739	(0.091)**	0.0651	(0.096)	0.0605	(0.104)
Panel B												
Expectations index 2	0.1183	(0.035)***	0.1182	(0.034)***	0.2414	(0.067)***	0.2344	(0.069)***	0.1651	(0.126)	0.0940	(0.129)
Panel C												
Expectations index 3	0.0771	(0.031)**	0.0866	(0.031)***	0.1491	(0.059)**	0.1311	(0.063)**	0.0473	(0.110)	0.0329	(0.116)
No. of observations	12,629		11,270		9,107		7,810		9,107		7,810	

Notes: Marginal effects are reported with standard errors in parenthesis; * significant at 10% level; ** significant at 5% level; *** significant at 1% level; Expectations index 1 is based on exogenous financial expectations; Expectations index 2 is the linear prediction from the panel *OP* model; and Expectations index 3 uses the linear prediction from the panel *GMIOPC* model. Each index has been standardised to have zero mean and standard deviation of unity.

Table 8: Probability of Expenditure

	Type of Expenditure											
	All Goods				Electronics				Household Appliances			
Panel A	*Static*		*Dynamic*		*Static*		*Dynamic*		*Static*		*Dynamic*	
Lag dependent variable	–		0.0590	(0.010)***	–		0.0500	(0.010)***	–		0.0550	(0.018)***
Age	0.1955	(0.104)*	0.2043	(0.141)	0.1666	(0.081)**	0.2039	(0.140)	0.1009	(0.089)	0.1386	(0.122)
Age^2	−0.0079	(0.004)**	−0.0081	(0.005)	−0.0065	(0.003)**	−0.0075	(0.005)	−0.0046	(0.003)	−0.0056	(0.004)
Age^3	0.0001	(0.000)**	0.0001	(0.000)*	0.0001	(0.000)**	0.0001	(0.000)	0.0000	(0.000)*	0.0000	(0.000)
Age^4	−0.0000	(0.000)***	−0.0000	(0.000)	−0.0000	(0.000)**	−0.0000	(0.000)	−0.0000	(0.000)	−0.0000	(0.000)
Year of birth	0.0105	(0.006)*	0.0176	(0.016)	0.0077	(0.006)	0.0158	(0.016)	0.0090	(0.005)*	0.0099	(0.013)
Year of birth^2	−0.0001	(0.000)	−0.0001	(0.000)	−0.0000	(0.001)	−0.0000	(0.000)	−0.0001	(0.000)	−0.0000	(0.000)
Household size	0.0250	(0.007)**	−0.0089	(0.010)	0.0220	(0.006)***	0.0083	(0.009)	0.0152	(0.005)***	−0.0025	(0.008)
Children 0-2	−0.0223	(0.019)	−0.0124	(0.022)	−0.0563	(0.018)***	−0.0572	(0.022)***	0.0044	(0.015)	0.0253	(0.018)
Children 3-4	−0.0272	(0.017)	−0.0015	(0.020)	−0.0413	(0.017)**	−0.0218	(0.019)	0.0115	(0.014)	0.0276	(0.019)
Children 5-11	0.0242	(0.009)***	0.0403	(0.012)***	0.0164	(0.009)*	0.0303	(0.011)***	0.0079	(0.008)	0.0165	(0.010)
Children 12-15	0.0328	(0.012)***	0.0545	(0.013)***	0.0291	(0.011)***	0.0465	(0.013)***	0.0103	(0.009)	0.0153	(0.011)
Children 16-18	0.0220	(0.021)	0.0343	(0.022)	0.0279	(0.020)	0.0481	(0.021)***	0.0033	(0.017)	0.0109	(0.019)
Number of problems	0.0184	(0.004)***	0.0149	(0.007)**	0.0144	(0.005)***	0.0113	(0.007)	0.0123	(0.004)***	0.0171	(0.006)***
Employee	0.0515	(0.018)***	0.0149	(0.024)	0.0300	(0.017)*	−0.0014	(0.025)	0.0250	(0.015)*	0.0046	(0.022)
Self employed	0.0751	(0.023)***	0.0335	(0.033)	0.0462	(0.022)**	0.0206	(0.033)	0.0479	(0.019)**	0.0414	(0.029)
Unemployed	−0.0250	(0.034)	−0.0651	(0.041)	0.0001	(0.034)	−0.0230	(0.040)	−0.0128	(0.030)	−0.0558	(0.037)
Log real household income	0.0440	(0.009)***	0.0275	(0.012)**	0.0368	(0.009)***	0.0215	(0.010)**	0.0252	(0.007)***	0.0302	(0.012)***
Expectations index 1 ($\widetilde{y}_{it}$)	0.0246	(0.005)***	0.0213	(0.005)***	0.0396	(0.005)***	0.0363	(0.007)***	0.0003	(0.004)	0.0003	(0.004)
Panel B												
Expectations index 2	0.0281	(0.006)***	0.0240	(0.006)***	0.0463	(0.006)***	0.0429	(0.006)***	0.0057	(0.006)	0.0051	(0.005)
Panel C												
Expectations index 3	0.0213	(0.006)***	0.0184	(0.005)***	0.0310	(0.005)***	0.0258	(0.005)***	0.0021	(0.004)	0.0018	(0.004)
No. of observations	12,629		11,270		12,629		11,270		12,629		11,270	

Notes: Marginal effects are reported with standard errors in parenthesis; * significant at 10% level; ** significant at 5% level; *** significant at 1% level; Expectations index 1 is based on exogenous financial expectations; Expectations index 2 is the linear prediction from the panel *OP* model; and Expectations index 3 uses the linear prediction from the panel *GMIOPC* model. Each index has been standardised to have zero mean and standard deviation of unity.

Table 9: Probability of Expenditure Models Random Effects Probit – Detailed Expenditure Iterms

	TV	VCR	Freezer	Washing machine	Tumble dryer	Dish washer	Microwave	PC	CD player	Satellite dish	Cable TV	Telephone	Mobile phone
Panel A													
Expectations index 1 ($\widetilde{y}_{it}$)	0.0029	0.0194	0.0023	0.0023	0.0017	−0.0022	−0.0001	0.0190	0.0176	0.0091	0.0041	0.0023	0.0026
	(0.003)	(0.003)***	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)***	(0.002)***	(0.002)**	(0.001)**	(0.002)	(0.001)**
Panel B													
Expectations index 2	0.0036	0.0270	0.0008	0.0063*	0.0023	0.0001	−0.0009	0.0245	0.0227	0.0121	0.0043	0.0186	0.0045
	(0.004)	(0.004)***	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.004)***	(0.003)***	(0.002)***	(0.001)***	(0.003)***	(0.002)**
Panel C													
Expectations index 3	0.0025	0.0126	-0.0003	0.0015	0.0016	-0.0004	−0.0032	0.0121	0.0104	0.0088	0.0039	0.0167	0.0026
	(0.007)	(0.003)***	(0.003)	(0.003)	(0.002)	(0.004)	(0.002)	(0.003)***	(0.003)***	(0.002)***	(0.001)***	(0.002)***	(0.001)**
No. of observations					12,629						9,107		

Notes: Marginal effects are reported with standard errors in parenthesis; * significant at 10% level; ** significant at 5% level; *** significant at 1% level; Expectations index 1 is based on exogenous financial expectations; Expectations index 2 is the linear prediction from the panel *OP* model; and Expectations index 3 uses the linear prediction from the panel *GMIOPC* model. Each index has been standardised to have zero mean and standard deviation of unity.

expectations is still evident when we relax the assumption that expectations are exogenous.

The analysis reveals that financial expectations have a positive impact on both the amount of expenditure undertaken and the decision to purchase a product, although this is typically limited to electronic goods. The linear prediction from a panel *OP* model overestimates the effect of financial expectations on consumption both at the intensive and extensive margin. This is due to the fact that once expectations have been purged of the effects of inflation (as in the panel *GMIOPC* modelling approach) they are found to have a smaller impact on the amount spent and the decision to undertake expenditure on durable goods. This is as expected *a priori*, given that the linear prediction from the panel *GMIOPC* model has been purged of the effects of inflation, the impact of which is to steer responses towards the *about the same* category, and away from being *worse off* or *better off*.

5 Conclusion

The BHPS reveals that households often report that they expect their financial position to remain unchanged compared to other alternatives. Given that the distribution of this response variable is characterised by middle-inflation, our statistical approach has been to model individuals' financial expectations using a panel *GMIOPC* model. In doing so, we account for the common tendency of individuals to choose a 'neutral' response when confronted with this type of survey question. Our empirical analysis strongly supports the use of a panel *GMIOPC* model to account for this response pattern and indices generated using both exogenous and endogenous financial expectations are found to play a non-neligible role in driving household consumption behaviour. In contrast to previous contributions that have explored the relationship between expectations and household financial behaviour, we deviate from the commonly used approach in which financial expectations are treated as being exogenous. Central to our approach is the argument that if financial expectations are endogenous, it is essential that they are modelled appropriately. Appropriately taking into account the endogenous nature of financial expectations clearly matters, in that although financial optimism is significantly associated with greater consumption, indices which neglect the role of middle-inflation overstate the impact of financial expectations on household consumption. Considering the amount of expenditure (probability of purchase) on durable goods, the overestimate from the panel *OP* model compared to the panel *GMIOPC* is approximately 36%

(30%).[36]

Given the importance in the academic literature placed on using expectations and sentiment indicators to predict household consumption and other forms of household financial behaviour, our findings have potentially important implications for future research in this area. Moreover, there are also potential policy implications given that govenment media presence and changes in fiscal policy through tax cuts have been found to impact upon economic activity and consumer expectations (He 2017, Konstantinou and Tagkalakis 2011, Goidel et al. 2010). Therefore, it is important when considering any intended manipulation of consumer sentiment through policy intervention that expectations are accurately measured and *purged* of inflation effects (which are substantial in the case of the UK), otherwise the predicted effects on economic activity are likely to be erroneous.

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[36] Based upon comparing the estimates from the dynamic specification reported in Panels B and C of Table 7 for the amount spent (Table 8 for the likelihood of expenditure), respectively.

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Appendix

A Summary statistics and figures

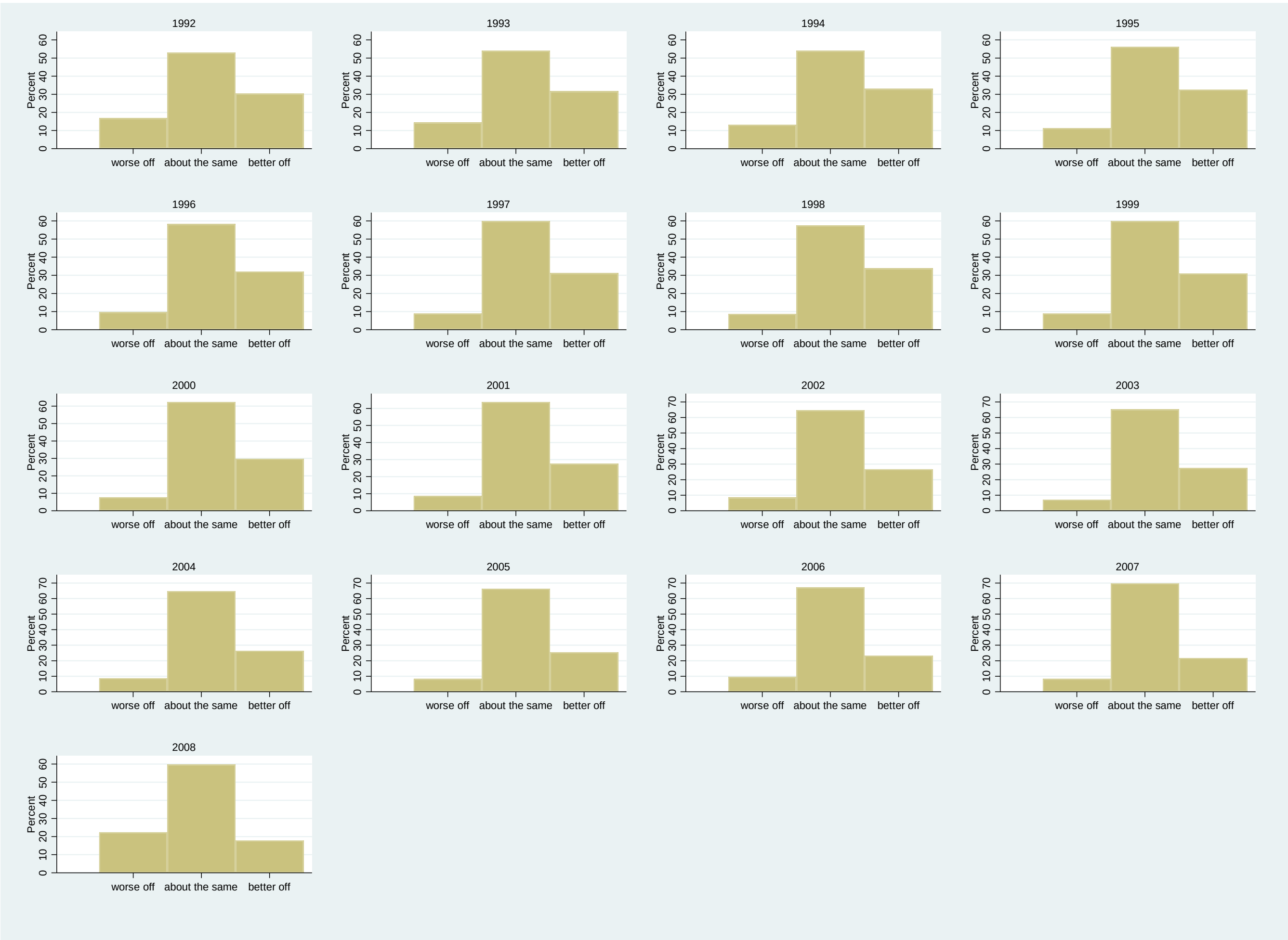

Figure A.1: Distribution of financial expectations – BHPS 1992 to 2008

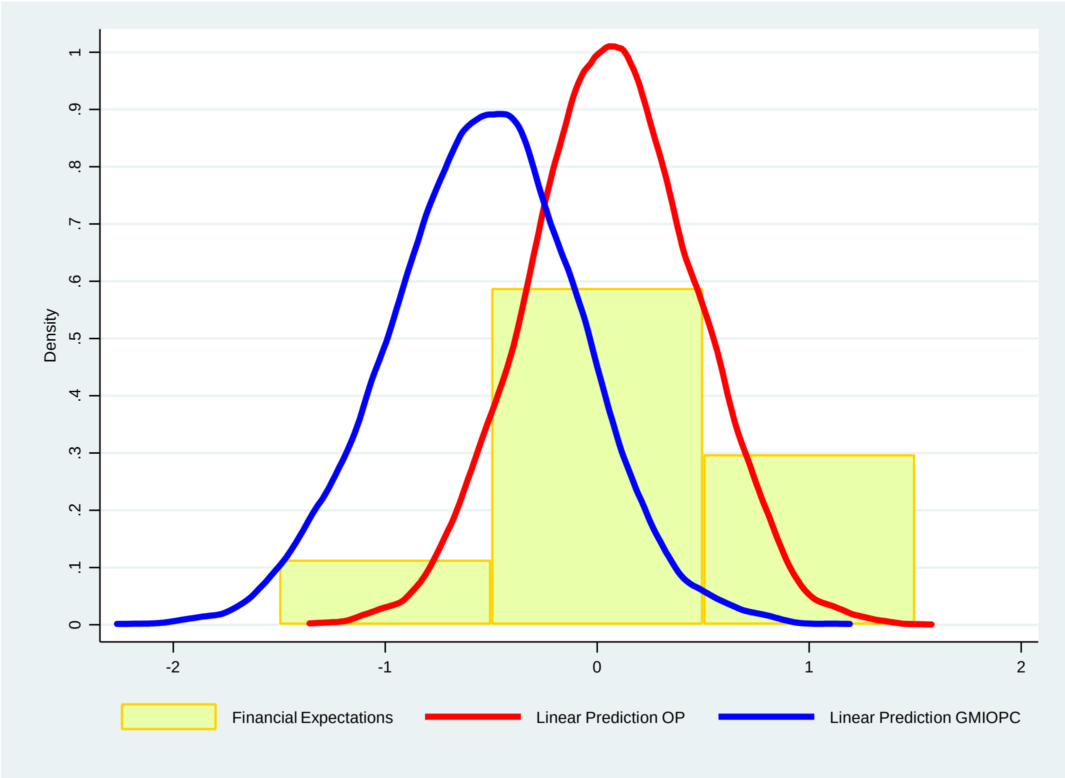

Figure A.2: Alternative measures of financial expectations – distribution of the exogenous expectations ($\widetilde{y}_{it}$) index and density plots of linear predictions from the panel *OP* model and the panel *GMIOPC* model

Table A.1: Variable Definitions – Financial Expectations Models

		Mean	Std.Dev
$\widetilde{y}_{it}$	Financial expectations {-1=pessimistic; 0=no change; 1=optimistic}	0.1770	0.599
Aged 18-30	1=aged 18-30; 0=otherwise	0.1320	0.339
Aged 31-40	1=aged 31-40; 0=otherwise	0.3156	0.465
Aged 41-50	1=aged 41-50; 0=otherwise	0.3353	0.472
Male	1=male; 0=female	0.4488	0.497
Degree	1=highest education degree; 0=otherwise	0.1659	0.372
Teaching/Nursing	1=highest education teaching or nursing; 0=otherwise	0.3252	0.469
A-level	1=highest education A-level; 0=otherwise	0.1176	0.322
O-level	1=highest education O-level (GCSE); 0=otherwise	0.1939	0.395
Other education	1=highest education other qualification; 0=otherwise	0.0800	0.271
Agreeableness	BIG5 agreeableness (standardised)	0	1
Openness to experience	BIG5 openness to experience (standardised)	0	1
Neuroticism	BIG5 neuroticism (standardised)	0	1
Conscientiousness	BIG5 conscientiousness (standardised)	0	1
Extraversion	BIG5 extraversion (standardised)	0	1
Number of children	Number of children 0-5	0.8022	1.019
Married	1=married/cohabiting; 0=otherwise	0.8159	0.388
White	1=white; 0=otherwise	0.9753	0.155
Black	1=black; 0=otherwise	0.0056	0.075
Asian	1=asian; 0=otherwise	0.0134	0.115
Employed	1=employee; 0=otherwise	0.7402	0.439
Self employed	1=self employed; 0=otherwise	0.0825	0.275
Unemployed	1=unemployed; 0=otherwise	0.0193	0.137
Owned outright	1=home owned outright; 0=otherwise	0.1747	0.379
Mortgage	1=home owned via a mortgage; 0=otherwise	0.6797	0.467
Rent	1=home rented; 0=otherwise	0.0721	0.259
Log labour income	Natural logarithm of labour income last month	0.6759	0.198
Log non-labour income	Natural logarithm of non-labour income last month	0.4022	0.203
Log savings	Natural logarithm of saving last month	0.2345	0.255
Log wealth	Natural logarithm of wealth	1.1481	0.146
GHQ-12	General Health Questionnaire – caseness	0.1772	0.292
Job satisfaction	Job security; 0=not employed, 1=not satisfied,...,7=completely satisfied	4.2991	2.478
Regional UE	Natural logarithm of regional unemployment	0.6575	0.242
Error_{it}	{-2, -1, 0, 1, 2} = subjective expectation ($\widetilde{y}_{it-1}$) – subjective realisation (R_{it})	0.1266	0.821
Income up	1=financial situation income increased; 0=otherwise	0.2012	0.401
Income down	1=financial situation income decreased; 0=otherwise	0.0795	0.271
Expenditure up	1=financial situation expenditure increased, 0=otherwise	0.1130	0.317
Expenditure down	1=financial situation expenditure decreased, 0=otherwise	0.0429	0.203
Correct optimistic	Number of times correctly optimistic	0.1227	0.171
Correct same	Number of times correctly same	0.0467	0.100
Correct pessimistic	Number of times correctly pessimistic	0.2380	0.231
Change in interviewer	1=change in interviewer between waves; 0=otherwise	0.3009	0.459
Total number of problems	Number of problems affecting interview; 0-2	0.0091	0.103
Other present in interview	1=others present during interview; 0=otherwise	0.6391	0.480
Length of interview	Interview time in minutes (divided by 100)	0.4756	0.197

Notes: Sample all individuals; NT = 24,089; N=1,417.

Table A.2: Variable Definitions – Expenditure Models

		Mean	Std.Dev
All durables	1=durable goods brought in last year; 0=otherwise	0.5278	0.499
Electronics	1=electronic goods brought in last year; 0=otherwise	0.3969	0.489
Household appliances	1=household appliances brought in last year; 0=otherwise	0.2356	0.424
Log total expenditure	Natural logarithm of amount spent on all durable goods last year	3.2994	3.137
Log electronics#	Natural logarithm of amount spent on electronic items last year	2.5344	3.133
Log household appliances#	Natural logarithm of amount spent on household appliances last year	1.4906	2.708
TV	1=colour tv brought in last year; 0=otherwise	0.1268	0.333
VCR	1=vcr brought in last year; 0=otherwise	0.1172	0.321
Freezer	1=freezer brought in last year; 0=otherwise	0.0760	0.265
Washing machine	1=washing machine brought in last year; 0=otherwise	0.0930	0.290
Tumble dryer	1=tumble dryer brought in last year; 0=otherwise	0.0416	0.200
Dish washer	1=dish washer brought in last year; 0=otherwise	0.0456	0.209
Microwave	1=microwave brought in last year; 0=otherwise	0.0653	0.247
PC	1=pc brought in last year; 0=otherwise	0.1192	0.324
CD player	1=cd player brought in last year; 0=otherwise	0.0783	0.269
Satellite dish	1=satellite dish brought in last year; 0=otherwise	0.0311	0.174
Cable TV	1=cable tv brought in last year; 0=otherwise	0.0121	0.109
Telephone	1=telephone brought in last year; 0=otherwise	0.0709	0.257
Mobile phone	1=mobile phone brought in last year; 0=otherwise	0.0243	0.154
Age	Age of individual at date of interview	42.9164	9.815
Year of birth	Year of birth of individual	1958	9.831
Household size	Number of adults in household	1.9242	0.305
Children 0-2	Number of children in household aged 0-2	0.0768	0.276
Children 3-4	Number of children in household aged 3-4	0.0882	0.295
Children 5-11	Number of children in household aged 5-11	0.3695	0.691
Children 12-15	Number of children in household aged 12-15	0.2184	0.499
Children 16-18	Number of children in household aged 16-18	0.0499	0.230
Number of problems	Number of health problems	0.8905	1.108
Employee	1=employee; 0=otherwise	0.7641	0.425
Self employed	1=self employed; 0=otherwise	0.1074	0.310
Unemployed	1=unemployed; 0=otherwise	0.0224	0.148
Log real household income	Natural logarithm of annual income last year	10.4568	0.759

Notes: Sample heads of household only; NT = 12,629; $^{\#}NT$ = 9,107.

B The likelihood function for the panel G*MIOP* model

In the analysis that follows, we analyse panel data: that is, for each individual i, we have repeated observations over time periods $t = 1, \ldots, T_i$. Given the assumed form for the probabilities and an independent and identically distributed sample of size $i = 1, \ldots, N$ from the population on $(y_i, \mathbf{z}_i, \mathbf{x}_i)$, this satisfies all of the standard regularity conditions for maximum likelihood estimation (see Greene 2012). The full parameter set $\boldsymbol{\theta} = \left(\boldsymbol{\gamma}', \boldsymbol{\beta}', \boldsymbol{\mu}', \boldsymbol{\rho}'\right)'$ of the model can be consistently and efficiently estimated using standard maximum likelihood techniques, with the likelihood function given by

$$\log L(\boldsymbol{\theta}) = \sum_{i=1}^{N} \sum_{t=1}^{T_i} \sum_{j=-1}^{J=+1} d_{itj} \log \left[\Pr\left(y_{it} = j \left| \mathbf{x}_i, \mathbf{z}_i \right.\right)\right] \tag{B.1}$$

where d_{itj} is the indicator function, $1\ [y_{itj} = j]$ and $j = -1, 0, +1$. Formulating the above model in this context allows one to account for unobserved individual heterogeneity in the underlying equations, $\boldsymbol{\alpha}$, and as is standard in the literature it is assumed that $\boldsymbol{\alpha} \sim N(0, \Sigma)$ with the individual elements of Σ denoted by $\widetilde{y}^*$, w^* and b^*, respectively. The presence of such unobserved effects complicates evaluation of the resulting likelihood function and hence we utilise the method of maximum simulated likelihood. Defining $\mathbf{v}_i$ as a vector of standard normal random variates, which enter the model generically as $\boldsymbol{\Gamma}\mathbf{v}_i$, such that for a single draw of $\mathbf{v}_i$, $\boldsymbol{\Gamma}\mathbf{v}_i = (\alpha_{i,\widetilde{y}^*}, \alpha_{i,w^*}, \alpha_{i,b^*})$, where $\boldsymbol{\Gamma}$ is the $chol\,(\Sigma)$ and $\Sigma = \boldsymbol{\Gamma}\boldsymbol{\Gamma}'$. Conditioned on $\mathbf{v}_i$, the sequence of T_i outcomes for individual i are independent, such that the contribution to the likelihood function for a group of t observations is defined as the product of the sequence of the probabilities which we denote c_i, corresponding to the observed outcome of y_i, $c_i \mid \mathbf{v}_i$,

$$c_i \mid \mathbf{v}_i = \prod_{t=1}^{T_i} \prod_{j=-1}^{J=+1} \left[\Pr\left(y_{it} = j \left| \mathbf{x}_i, \mathbf{z}_i, \mathbf{v}_i \right.\right)\right]^{d_{itj}} \tag{B.2}$$

The unconditional log-likelihood function is found by integrating out the $\mathbf{v}_i$ as

$$\log L(\boldsymbol{\theta}) = \sum_{i=1}^{N} \log \int_{v_i} \prod_{t=1}^{T_i} \prod_{j=-1}^{J=+1} \left[\Pr\left(y_{it} = j \left| \mathbf{x}_i, \mathbf{z}_i, \boldsymbol{\Gamma}\mathbf{v}_i \right.\right)\right] f(\mathbf{v}_i) d\mathbf{v}_i, \tag{B.3}$$

where all parameters of the model are contained in $\boldsymbol{\theta}$. Using the usual assumption of multivariate normality for $\mathbf{v}_i$ yields

$$\log L(\boldsymbol{\theta}) = \sum_{i=1}^{N} \log \int_{v_i} \prod_{t=1}^{T_i} \prod_{j=-1}^{J=+1} \left[\Pr\left(y_{it} = j \left| \mathbf{x}_i, \mathbf{z}_i, \boldsymbol{\Gamma}\mathbf{v}_i\right.\right)\right] \prod_{k=1}^{K} \phi(\mathbf{v}_{ik}) d\mathbf{v}_{ik}, \tag{B.4}$$

where k indexes the different unobserved effects in the model. The expected values in the integrals can be evaluated by simulation by drawing R observations on $\mathbf{v}_i$ from the multivariate standard normal population. The following is the resulting simulated log-likelihood function

$$\log_S L(\boldsymbol{\theta}) = \sum_{i=1}^{N} \log \frac{1}{R} \sum_{r=1}^{R} \prod_{t=1}^{T_i} \prod_{j=-1}^{J=+1} \left[\Pr\left(y_{it} = j \left| \mathbf{x}_i, \mathbf{z}_i, \boldsymbol{\Gamma}\mathbf{v}_i\right.\right)\right]. \tag{B.5}$$

Halton sequences of length $R = 1000$ were used, see Train (2009), and this now feasible function is maximized with respect to $\boldsymbol{\theta}$. As is common in the non-linear panel data literature, given that these unobserved heterogeneity terms are (potentially) correlated with observed heterogeneity terms, the correction proposed by Mundlak (1978) is applied. Consequently, we include averages of the continuous covariates of individual i in the set of explanatory variables, $\overline{x_i} = \frac{1}{T_i} \sum_{t=1}^{T_i} x_{it}$.

C A Specification test for the *MIOP* model

The *GMIOP* and the *MIOP* models both present themselves as viable candidates for modelling the preponderance of 'about the same' responses: each model is seemingly able to account for the observed spike in financial expectations responses. In what follows, we demonstrate that under certain parameter restrictions, the *GMIOPC* model encompasses the *MIOPC*. This permits us to ascertain if the propensities for *better off* or *worse off* responses are tempered to the same extent: formally, does $\boldsymbol{\beta}_w = \boldsymbol{\beta}_b$? In the correlated model shown in expression (6), such a linear parameter restriction is testable by enforcing the restriction that $\boldsymbol{\beta}_w = \boldsymbol{\beta}_b = \boldsymbol{\beta}$ and $\rho_w = \rho_b = \rho$. This yields

$$\Pr\left(\widetilde{y}_i\right) = \begin{cases} -1 & = & \Phi_2\left(\mu_0 - \mathbf{z}_i'\boldsymbol{\gamma}, \mathbf{x}_s'\boldsymbol{\beta}_s; -\rho\right) \\ 0 & = & \begin{array}{l} \left[\Phi\left(\mu_1 - \mathbf{z}_i'\boldsymbol{\gamma}\right) - \Phi\left(\mu_0 - \mathbf{z}_i'\boldsymbol{\gamma}\right)\right] + \\ \Phi_2\left(\mu_0 - \mathbf{z}_i'\boldsymbol{\gamma}, -\mathbf{x}_i'\boldsymbol{\beta}; \rho\right) + \Phi_2\left(\mu_1 - \mathbf{z}_i'\boldsymbol{\gamma}, -\mathbf{x}_i'\boldsymbol{\beta}; \rho\right) \end{array} \\ 1 & = & \left[\Phi_2\left(\mathbf{z}_i'\boldsymbol{\gamma} - \mu_1, \mathbf{x}_i'\boldsymbol{\beta}; \rho\right)\right]. \end{cases} \tag{C.1}$$

where we note that rearranging the $\Pr(\widetilde{y}=0)$ expression as 1 minus the sum of the $\Pr(\widetilde{y}=-1)$ and $\Pr(\widetilde{y}=1)$ terms of equation (C.1) gives

$$\Pr(\widetilde{y}_i=0) = 1-\Phi_2\left(\mu_0-\mathbf{z}_i'\boldsymbol{\gamma},\mathbf{x}_s'\boldsymbol{\beta}_s;-\rho\right)-\left[\Phi_2\left(\mathbf{z}_i'\boldsymbol{\gamma}-\mu_1,\mathbf{x}_i'\boldsymbol{\beta};\rho\right)\right] \tag{C.2}$$

Noting that the term $\Phi_2\left(\mathbf{z}_i'\boldsymbol{\gamma}-\mu_1,\mathbf{x}_i'\boldsymbol{\beta};\rho\right)$ can be re-written as $\Phi\left(\mathbf{x}_i'\boldsymbol{\beta}\right)-\Phi_2\left(\mu_1-\mathbf{z}_i'\boldsymbol{\gamma},\mathbf{x}_i'\boldsymbol{\beta};-\rho\right)$ implies that $\Pr(\widetilde{y}_i=0)$ can be re-expressed as

$$\Pr(\widetilde{y}_i=0) = \left[1-\Phi\left(\mathbf{x}_i'\boldsymbol{\beta}\right)\right]+\Phi_2\left(\mu_1-\mathbf{z}_i'\boldsymbol{\gamma},\mathbf{x}_i'\boldsymbol{\beta};-\rho\right)+\Phi_2\left(\mu_0-\mathbf{z}_i'\boldsymbol{\gamma},\mathbf{x}_s'\boldsymbol{\beta}_s;-\rho\right) \tag{C.3}$$

Using this result yields the re-written restricted probabilities as

$$\Pr(\widetilde{y}_i) = \begin{cases} -1 & = & \Phi_2\left(\mu_0-\mathbf{z}_i'\boldsymbol{\gamma},\mathbf{x}_s'\boldsymbol{\beta}_s;-\rho\right) \\ 0 & = & \left[1-\Phi\left(\mathbf{x}_i'\boldsymbol{\beta}\right)\right]+\Phi_2\left(\mu_1-\mathbf{z}_i'\boldsymbol{\gamma},-\mathbf{x}_i'\boldsymbol{\beta}_w;\rho\right)-\Phi_2\left(\mu_0-\mathbf{z}_i'\boldsymbol{\gamma},-\mathbf{x}_i'\boldsymbol{\beta}_w;\rho\right) \\ 1 & = & \left[\Phi_2\left(\mathbf{z}_i'\boldsymbol{\gamma}-\mu_1,\mathbf{x}_i'\boldsymbol{\beta};\rho\right)\right] \end{cases} \tag{C.4}$$

which is identical to the model probabilities for the *MIOPC* (see for instance: Bagozzi and Mukherjee (2012); Brooks, Harris, and Spencer (2012)). The restricted form of the *GMIOPC* model is thus equivalent to the *MIOPC*. That is, even though different inherent sequences in the choice process are used to justify both models, they are equivalent under a simple set of parameter restrictions. Further, setting $\boldsymbol{\beta}_w=\boldsymbol{\beta}_b=\boldsymbol{\beta}$ and $\rho=0$ in (6) implies that the *GMIOPC* collapses to a *MIOP* model with independent errors. In this case, the distribution of errors would no longer be assumed bivariate normal, which characterises the *MIOPC* model in expression (C.4). Testing the parameter restrictions associated with these model variants entails testing (i) the more flexible functional form of the *GMIOPC* model versus the simpler nested forms of the *MIOPC* and *MIOP* models and (ii) the *GMIOP* versus the *MIOP* model. As demonstrated in Brown et al. (2017), likelihood ratio tests with degrees of freedom given by the number of extra parameters can be performed to test between these nested model variants.

D Partial effects

The partial effects of the $J=3$ outcomes are likely to be of interest post-estimation. For a change in any given covariate, it is informative to determine how much of the change in the predicted probability for the inflated variable is attributable to the tempering equations. Below we present the associated analytical expressions for the *GMIOPC* model, where the *GMIOP* variant merely requires setting $\rho_{yw} = \rho_{yb} = 0$. Partition the covariates and coefficient vectors as

$$\mathbf{z} = \begin{pmatrix} \mathbf{c} \\ \widetilde{\mathbf{z}} \end{pmatrix}, \ \boldsymbol{\gamma} = \begin{pmatrix} \gamma_c \\ \widetilde{\gamma} \end{pmatrix}, \ \mathbf{x} = \begin{pmatrix} \mathbf{w} \\ \widetilde{\mathbf{x}} \end{pmatrix}, \ \boldsymbol{\beta}_u = \begin{pmatrix} \boldsymbol{\beta}_{cb} \\ \widetilde{\boldsymbol{\beta}}_b \end{pmatrix}, \ \boldsymbol{\beta}_d = \begin{pmatrix} \boldsymbol{\beta}_{cw} \\ \widetilde{\boldsymbol{\beta}}_w \end{pmatrix} \tag{D.1}$$

where $\mathbf{c}$ represents the common variables that appear in both $\mathbf{z}$ and $\mathbf{x}$**,** with the corresponding coefficients $\boldsymbol{\gamma}_c$, $\boldsymbol{\beta}_{cb}$ and $\boldsymbol{\beta}_{cw}$ for the ordered probit, *better off*, and *worse off* latent equations respectively. $\widetilde{\mathbf{z}}$ denotes the set of variables that appears solely in the the ordered equation with associated coefficients $\widetilde{\boldsymbol{\gamma}}$, whereas $\widetilde{\mathbf{x}}$ denotes the set of variables both common and exclusive to the splitting equations, with associated coefficients $\widetilde{\boldsymbol{\beta}}_b$ for better expectations and $\widetilde{\boldsymbol{\beta}}_w$ for worse expectations. Let $\mathbf{x}^* = (\mathbf{c}', \widetilde{\mathbf{z}}', \widetilde{\mathbf{x}}')'$, $\boldsymbol{\gamma}^* = (\boldsymbol{\gamma}_c', \widetilde{\boldsymbol{\gamma}}', \mathbf{0}')'$, $\boldsymbol{\beta}_b^* = (\boldsymbol{\beta}_{cb}', \mathbf{0}', \widetilde{\boldsymbol{\beta}}_b')'$ and $\boldsymbol{\beta}_w^* = (\boldsymbol{\beta}_{cw}', \mathbf{0}', \widetilde{\boldsymbol{\beta}}_w')'$. The partial effects with respect to $\mathbf{x}^*$ of equation (6) are thus

$$\frac{\partial \Pr(\widetilde{y}_i = -1)}{\partial \mathbf{x}^*} = \begin{cases} \Phi\left(\frac{\mu_0 - \mathbf{z}_i'\boldsymbol{\gamma} - \rho_{yw}(\mathbf{x}_i'\boldsymbol{\beta}_w)}{\sqrt{1-\rho_{yw}^2}}\right)\phi\left(\mathbf{x}_i'\boldsymbol{\beta}_w\right)\boldsymbol{\beta}_w^* \\ -\Phi\left(\frac{\mathbf{x}_i'\boldsymbol{\beta}_w - \rho_{yw}(\mu_0 - \mathbf{z}_i'\boldsymbol{\gamma})}{\sqrt{1-\rho_{yw}^2}}\right)\phi\left(\mu_0 - \mathbf{z}_i'\boldsymbol{\gamma}\right)\boldsymbol{\gamma}^* \end{cases} \tag{D.2}$$

$$
\frac{\partial \Pr(\widetilde{y}_i = 0)}{\partial \mathbf{x}^*} = \begin{cases} \phi\left(\mu_0 - \mathbf{z}_i'\boldsymbol{\gamma}\right)\boldsymbol{\gamma}^* \left[1 - \Phi\left(\frac{-\mathbf{x}_i'\boldsymbol{\beta}_w - \rho_{yw}(\mu_0 - \mathbf{z}_i'\gamma)}{\sqrt{1-\rho_{yw}^2}}\right)\right] \\ +\phi\left(\mu_1 - \mathbf{z}_i'\boldsymbol{\gamma}\right)\boldsymbol{\gamma}^* \left[\Phi\left(\frac{-\mathbf{x}_i'\boldsymbol{\beta}_b - \rho_{yb}(\mathbf{z}_i'\gamma - u_1)}{\sqrt{1-\rho_{yb}^2}}\right) - 1\right] \\ +\Phi\left(\frac{(\mu_0 - \mathbf{z}_i'\gamma) - \rho_{yw}(-\mathbf{x}_i'\boldsymbol{\beta}_w)}{\sqrt{1-\rho_{yw}^2}}\right)\phi\left(-\mathbf{x}_i'\boldsymbol{\beta}_w\right)\boldsymbol{\beta}_w^* \\ -\Phi\left(\frac{(\mathbf{z}_i'\gamma - \mu_1) - \rho_{yb}(-\mathbf{x}_i'\boldsymbol{\beta}_b)}{\sqrt{1-\rho_{yb}^2}}\right)\phi\left(-\mathbf{x}_i'\boldsymbol{\beta}_b\right)\boldsymbol{\beta}_b^* \end{cases} \tag{D.3}
$$

$$
\frac{\partial \Pr(\widetilde{y}_i = 1)}{\partial \mathbf{x}^*} = \begin{cases} \Phi\left(\frac{(\mathbf{z}_i'\boldsymbol{\gamma} - \mu_1) - \rho_{yb}(\mathbf{x}_i'\boldsymbol{\beta}_b)}{\sqrt{1-\rho_{yb}^2}}\right)\phi\left(\mathbf{x}_i'\boldsymbol{\beta}_b\right)\boldsymbol{\beta}_b^* \\ +\Phi\left(\frac{\mathbf{x}_i'\boldsymbol{\beta}_b - \rho_{yb}(\mathbf{z}_i'\boldsymbol{\gamma} - \mu_1)}{\sqrt{1-\rho_{yb}^2}}\right)\phi\left(\mathbf{z}_i'\boldsymbol{\gamma} - \mu_1\right)\boldsymbol{\gamma}^* \end{cases} \tag{D.4}
$$

where $\phi(.)$ is the probability density function (PDF) of the standard univariate normal distribution. Standard errors of the marginal effects can be obtained by the delta method (Greene 2012). Based on equation (6) several related quantities may be of interest. For example, equation (6) can be differentiated with respect to different subsets of $\mathbf{x}^*$, which would provide a decomposition of the overall partial effect with respect to these blocks. The various components of equations (D.2)–(D.4) can also be considered.