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

We explore the finding that households often expect their financial position to remain unchanged compared to other alternatives. A generalized middle inflated ordered probit (*GMIOP*) model is used to account for the tendency of individuals to choose "neutral" responses when faced with opinion-based questions. Our analysis supports the use of a *GMIOP* model to account for this response pattern. Expectation indices based on competing discrete choice models are also explored. While financial optimism is significantly associated with increased consumption at both the intensive and extensive margin, indices which fail to take into account middle-inflation overestimate the impact of financial expectations.

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A COMMON FEATURE OF SURVEY data is the tendency for individuals to choose "neutral" responses. This is particularly so for the case of attitudinal

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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 toward the available alternative options.

In this contribution, we show how this phenomenon is characteristic of responses to questions relating to financial expectations in the annual *British Household Panel Survey* (BHPS), and moreover, find that it has significant implications for consumption behavior and life-cycle demand patterns both at the household and macro-economic levels. Although our work is not unique in exploring the role of expectations on economic activity, it is notable in that it constitutes a departure from contributions that focus on evaluating the "rationality" of households' financial expectations (Souleles 2004, Brown and Taylor 2006, Mitchell and Weale 2007), and more generally, other contributions whose focus is on whether or not survey expectations are rational.[1] Instead, the starting point for our analysis is the *distribution* of categorical responses regarding financial expectations, and specifically, a recurring feature of BHPS respondents' predictions that their financial position will remain "about the same" the following year rather than worsening or improving, despite this expectation seldom being realized in practice. This response pattern characterizes all waves of the BHPS survey, which runs from 1991 to 2008, thereby covering different points of the business cycle.[2] Across our entire sample, 11% of those surveyed responded *worse off*, 61% reported *about the same*, and 28% responded *better off*. Interest in the tendency for such responses to be concentrated in a single choice category has been generally overlooked in the literature.[3]

To empirically account for BHPS respondents' tendency to select "about the same," we draw on a body of discrete choice literature that models so-called "middle-inflation" (Bagozzi and Mukherjee 2012), and in particular the recently developed *generalized middle-inflated ordered probit* (*GMIOP*) model of Brown, Harris, and Spencer (2020). "Middle-inflation" refers to the case of a discrete choice category located in the center of a choice set—in our case the "about the same" category—having an abundance of observations relative to all others. Our work is the first to demonstrate how failing to account for the presence of such middle-inflation when modeling financial expectations leads to economic activity being overestimated.

1. Noteworthy contributions include the following: work on expectations about future prices (Mankiw, Reis, and Wolfers 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, Dominitz, and van Soest 1999). Other relevant work includes Pesaran and Weale (2006), Manski (2004), and Pesaran (1987).

2. This is reflected in Figure A.1 of Online Appendix A, which shows the responses associated with each successive wave of our data set. Other large-scale surveys also report similar findings, such as the University of Michigan *Survey of Consumers*.

3. Although a number of the papers comment on the tendency for expectations to be concentrated in a single category, the reasons for such a build-up are not explored—see, for instance, Mitchell and Weale (2007), Pesaran and Weale (2006), Nerlove (1983) using firm level data; Mankiw, Reis, and Wolfers (2004) using inflation expectations data. An early discussion of the psychological drivers of expectations is provided by Wärneryd (1995).

To anchor intuition about how the *GMIOP* model accounts for middle-inflation, it is instructive to make comparisons with a standard ordered probit (*OP*) model. Unlike the latter model, the *GMIOP* requires jointly estimating a standard *OP* model with so-called "splitting equations." These latter equations—which assume the form of binary probits—provide a mechanism by which individuals can be steered away from selecting "better off" and "worse off" responses toward the financial expectation of "about the same," which appears "inflated." The variables included in these equations are assumed to capture cognitive and psychological factors that contribute to generating an "excess" of observations in the middle category rather than driving financial expectations *per se* . In practice, our findings may suggest that "satisficing" behavior (Krosnick 1991), in which the minimum cognitive effort is used to produce a response perceived by the household to be acceptable to the interviewer, plays a role in driving such behavior.[4] Significantly, all *GMIOP* parameters are freely estimated, an approach that does not force any reallocation to the middle-inflated category by the relevant splitting equations unless supported by the data. Our findings, which can be viewed as constituting a first step in our analysis of the role played by financial expectations in driving consumption behavior, confirm the superiority of our middle-inflated models over the standard ordered probit model.[5]

From this analysis, we are able to obtain a linear prediction of financial expectations; this index explicitly controls for the effects of category inflation and is integral to the second step of our analysis, which investigates the effect of financial expectations on durable goods consumption and the amount of expenditure undertaken. The linear prediction associated with controlling for middle-inflation permits us to more appropriately model the impact of financial expectations on consumption. This issue is of interest given that much of the existing literature predicts respondents' financial expectations to be overly optimistic (see: Bovi 2009, Malmendier and Taylor 2015, Weber et al. 2022). In practice, we find that our predictions are supportive of this literature.

Here, our contribution builds on Browning, Crossley, and Luhrmann (2016), who use the BHPS to investigate the life-cycle demand patterns for services from household durable goods. However, unlike their contribution, we investigate the role played by financial expectations in driving consumption behavior. In this sense, our contribution more closely relates to Brown and Taylor (2006), who investigate the relationship between financial expectations and consumption behavior. Like Browning, Crossley, and Luhrmann (2016), these authors also focus on durable goods, decomposing overall expenditure into white goods and electronic purchases. More broadly, our investigation builds on other notable contributions in which the relationship between expectations and sentiment indicators and consumption is

4. As discussed in Section 1.2, we consider that in addition to satisficing behavior, other potential cognitive and psychological mechanisms may account for respondents being steered toward the (inflated) middle category.

5. Failing to account for category inflation can lead to model misspecification, parameter bias, and incorrect inference (Harris and Zhao 2007, Brown, Harris, and Spencer 2020).

explored. 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 U.S. consumer expenditure, particularly on consumer durables. Focusing on Dutch households' subjective expectations and realizations of future income, Giamboni, Millemaci, and Waldmann (2013) find that predictable income changes can explain changes in consumption. De Nardi, French, and Benson (2011) focus on the behavior of consumption during the Great Recession, exploiting the University of Michigan's *Survey of Consumers* with a view to accounting for the behavior of nominal expected income growth and inflationary expectations. Lower consumer income expectations are found to play a considerable role in driving the observed fall in aggregate U.S. consumption during this period. In Burke and Ozdagli (2013), microdata from the RAND *American Life Panel Survey*, which contain detailed information about expenditure on a wide range of both durable and nondurable goods, are 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.[6] Other notable studies include Carroll, Fuhrer, and Wilcox (1994), Ludvigson (2004), Bachmann, Berg, and Sims (2015), and Gillitzer and Prasad (2018).

Our results reveal that specifications which do not use a financial expectations index that explicitly controls for middle-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 modeling financial expectations appropriately when the distribution of subject responses is characterized by category inflation. This is particularly so given the key role that expectations play in our understanding of business cycles and the design of policy interventions.[7] An important implication of our findings is that if policymakers are able to better understand the susceptibility of expectations to middle-inflation, they will be better placed to influence expectations associated with fiscal and monetary policy, whose effects will ultimately be realized through affecting economic activity.

6. 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 behavior. 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, Gomes, and Lopes (2019), using the BHPS, find that after controlling for individual fixed effects, more optimistic individuals save less.

7. Previous research for Europe and the United States has shown that consumer sentiment is a procyclical indicator, which can predict the probability of a recession, that is, 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, Eriksen, and Moller 2014). The role of expectations in forecasting economic activity is an effect over and above other potential leading indicators.

1. MODELING FINANCIAL EXPECTATIONS

We now proceed with the first stage of our analysis, which involves exploring the extent to which our financial expectations data are characterized by middle-inflation, and creating an index that explicitly controls for the presence of middle-inflation. This is achieved through modeling individuals' responses using both the *GMIOP* model of Brown, Harris, and Spencer (2020) and the *middle-inflated ordered probit* (*MIOP*) model of Bagozzi and Mukherjee (2012). Here, the *MIOP* can be thought of as a special case of the *GMIOP* under certain parameter restrictions. In practice, we find that although both models suggest the presence of middle-inflation, the more flexible *GMIOP* model is identified as being superior based on the relevant information criteria and likelihood ratio tests.

1.1 The GMIOP Model

To fix ideas about the *GMIOP* model, it is first instructive to describe our financial expectations variable. Specifically, the interviewer asks each individual i the question "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 $\widetilde{y}_i = \{-1, 0, 1\}$. When the distribution of responses across all individuals is observed, the middle category of $\widetilde{y}_i = 0$ appears "inflated." 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.

As depicted in Figure 1(a), these processes correspond to a single ordered probit (*OP*) equation denoted by a latent variable y_i^* and two "splitting equations," denoted by the latent variables w_i^* and b_i^* and that take the form of binary probits.[8] 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. One approach to modeling this decision would be to employ a standard *OP* model. However, such a modeling 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 w_i^* and b_i^*, which allow respondents to be, respectively, steered away from choosing *worse off* or *better off* toward selecting *about the same*.[9] In this way, the observed *about the same* category $\widetilde{y}_i = 0$ is inflated.

8. Part (b) of Figure 1 depicts the *MIOP* framework of Bagozzi and Mukherjee (2012), which we describe later.

9. In this sense, the "splitting equations" can also be termed "inflation equations," due to their role in inflating the middle category.

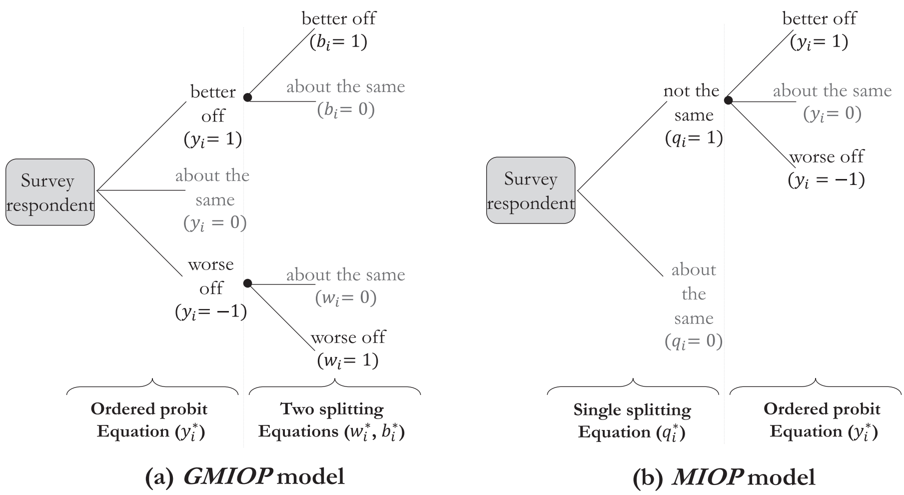

Fig 1. The Generalized Middle-Inflated Ordered Probit Model (*GMIOP*) and its Nested Variant (*MIOP*).

Formally, y_i^* is specified as a linear in parameters function of a vector of observed characteristics $\mathbf{z}_i$, with unknown weights γ and a random normal disturbance term ε_{yi}:

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

This latent equation is defined by

$$y_i = \begin{cases} -1 & \text{if} \quad y_i^* \le \mu_0 \\ 0 & \text{if} \quad \mu_0 \le y_i^* \le \mu_1, \\ 1 & \text{if} \quad \mu_1 \le y_i^* \end{cases}$$

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 therefore determined by

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

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

The latent equations w_i^* and b_i^* are specified as

$$w_i^* = \mathbf{x}_i'\beta_w + \varepsilon_{iw};\ b_i^* = \mathbf{x}_i'\beta_b + \varepsilon_{ib},$$

where $\mathbf{x}_i$ is a vector of observed characteristics, β_w and β_b are parameter vectors, and ε_{iw} and ε_{ib} are random normal disturbances. These equations are defined by

$$w_i = \begin{cases} 0 & \text{if} \quad w_i^* \le 0 \\ 1 & \text{if} \quad w_i^* > 0 \end{cases};\ b_i = \begin{cases} 0 & \text{if} \quad b_i^* \le 0 \\ 1 & \text{if} \quad b_i^* > 0 \end{cases}.$$

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 toward the *about the same* outcome are given, respectively, by

$$\Pr(w_i = 0) = \Phi\left(-\mathbf{x}_i'\beta_w\right);\ \Pr(b_i = 0) = \Phi\left(-\mathbf{x}_i'\beta_b\right).$$

Our assumption is that the same block of variables $\mathbf{x}_i$ drives each of these splitting equations.[10]

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.[11] The overall probabilities of individual *i* having financial expectations that are *worse off*, *about the same* and *better off* are given by

$$\Pr(\widetilde{y}_i) = \begin{cases} \Pr(\widetilde{y}_i = -1|\mathbf{z}_i, \mathbf{x}_i) & = & \Phi_2\left(\mu_0 - \mathbf{z}_i'\gamma, \mathbf{x}_i'\beta_w; -\rho_{yw}\right) \\ \Pr(\widetilde{y}_i = 0|\mathbf{z}_i, \mathbf{x}_i) & = & \begin{cases} \underbrace{\Phi_2\left(\mu_0 - \mathbf{z}_i'\gamma, -\mathbf{x}_i'\beta_w; \rho_{yw}\right)}_{\substack{A\text{: Probability of ``about no change''} \\ \text{due to steering away from ``worse off''}}} \\ +\underbrace{\left[\Phi\left(\mu_1 - \mathbf{z}_i'\gamma\right) - \Phi\left(\mu_0 - \mathbf{z}_i'\gamma\right)\right]}_{\substack{B\text{: Probability of ``about no change''} \\ \text{due to the } OP \text{ equation}}} \\ +\underbrace{\Phi_2\left(\mathbf{z}_i'\gamma - \mu_1, -\mathbf{x}_i'\beta_b; -\rho_{yb}\right)}_{\substack{C\text{: Probability of ``about no change''} \\ \text{due to steering away from ``better off''}}} \end{cases} \\ \Pr(\widetilde{y}_i = 1|\mathbf{z}_i, \mathbf{x}_i) & = & \Phi_2\left(\mathbf{z}_i'\gamma - \mu_1, \mathbf{x}_i'\beta_b; \rho_{yb}\right), \end{cases} \tag{1}$$

10. The variables entering $\mathbf{x}_i$ and $\mathbf{z}_i$ are discussed in Section 1.2. It would be possible to allow different variables in $\mathbf{x}_i$ to influence steering away from the *better off* and *worse off* propensities in y_i^*, but this seems difficult to justify on *a priori* grounds.

11. 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.

where $\Phi_2(a, b; \rho)$ represents the standardized bivariate normal CDF. We refer to the model in expression (1) 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, which are denoted A, B, and C. The inflation components of the "*about the same*" category are captured by terms A and C, which, respectively, denote the probabilities associated with respondents being steered away from the $y_i = -1$ (*worse off*) and $y_i = 1$ (*better off*) outcomes in y_i^*; the remaining term, B, denotes the probability of an *about the same* expectation arising in the *OP* equation. The log-likelihood function for the *GMIOP* model is shown in Online Appendix B.

As a counterpoint to the *GMIOP*, the *MIOP* framework of Bagozzi and Mukherjee (2012) is illustrated in Figure 1(b). An *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

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

where $\mathbf{x}_i$ is the same vector of observed characteristics in expressions w_i^* and b_i^*, β is a parameter vector, and ε_{iq} is a random normal disturbance.[13] Expression q_i^* is estimated simultaneously with an *OP* equation identical to that used in the *GMIOP* framework. 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.

Brown, Harris, and Spencer (2020) demonstrate that the generalized model collapses to the nongeneralized variant in Figure 1(b) under certain parameter restrictions. Restricting $\beta_w = \beta_b = \beta$ 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 nongeneralized model, and collapses the *GMIOPC* to the *MIOP*. Likelihood ratio tests with degrees of freedom given by the number of extra parameters can be

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 characterized 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 while 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. The latent variable q_i^* is defined by $q_i = \begin{cases} 0 & if \quad q_i^* \leq 0 \\ 1 & if \quad q_i^* > 0 \end{cases}$, where $\Pr(q_i = 0) = \Phi(-\mathbf{x}_i' \beta_q)$.

performed to test between these nested model variants; in Section 1.2 we use the results of these tests to inform model selection.[14]

In setting out the above statistical framework, we are now better placed to detail how accounting for middle-inflation is central to our analysis of consumption. Here, previous empirical work has modeled the impact of financial expectations on consumption through assuming that

$$E = f(\widetilde{y}_i, \mathbf{s}),$$

where E denotes consumption expenditure, financial expectations are indexed by $\widetilde{y}_i = \{-1, 0, 1\}$, and $\mathbf{s}$ captures all other potential influences (see, e.g., Brown and Taylor 2006). This general relationship is the starting point of our econometric analysis in Section 2—see equation (2)—in which both durable goods consumption and the amount of expenditure are modeled using $\widetilde{y}_i$ as one of the controls. We aim to build on this approach by obtaining a linear prediction of financial expectations that explicitly controls for the presence of middle-inflation, with a view to using this measure in place of $\widetilde{y}_i$. We now discuss how we obtain such a linear prediction.

1.2 Data and Estimation

The BHPS data set, which forms the basis of our empirical analysis is a longitudinal study spanning the period 1991 to 2008. Conducted by the *Institute for Social and Economic Research*, it is a nationally representative survey of 5,500 households covering over 10,000 individuals per year, collecting wide-ranging socioeconomic 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 18-year period (*T*) who are of working age (18–65 years).[15]

Following the existing literature (Souleles 2004, Brown and Taylor 2006) financial expectations, $\widetilde{y}_i$, are conditioned on a number of individual and household covariates, summary statistics for which are provided in Online Appendix A, Table A.1. For the *OP* equation, the matrix $\mathbf{z}$ predominantly includes a suite of standard controls relating to: the age of the respondent; gender; highest educational attainment; the number of children in a household; marital and cohabitation status; ethnicity; home ownership; labor market status; and household income, savings, and wealth. Other controls include the caseness subjective well-being score from the general health questionnaire (GHQ-12) and a job satisfaction index. Regional unemployment is included as a covariate to account for regional macro-economic shocks, as well as time fixed effects. We also construct a number of variables inspired by Coco, Gomes, and Lopes (2019),

14. A proof of the nested nature of these model variants is provided in Online Appendix C. For the more general case of $j = 1, 2, \ldots, J$ outcomes, see Brown, Harris, and Spencer (2020).

15. The literature on panel conditioning suggests that responses to survey questions may be influenced by the number of times respondents are observed (Williams and Mallows 1970, Das, Toepoel, and van Soest 2011). In using a sample comprising only of respondents with the same amount of survey experience, we explicitly control for this potential effect.

which capture realized changes in household income and expenditure between time $t-1$ and t.

For the splitting equations, the choice of variables in $\mathbf{x}$ is guided by their potential role in steering respondents away from choosing *worse off* or *better off* in y_i^*, rather than being determinants of financial expectations *per se*. This overarching consideration guides the nature of our exclusion restrictions, thereby informing the choice of covariates in $\mathbf{z}$ and $\mathbf{x}$. In relation to our splitting equations, it is well established that survey participants may be subject to psychological and cognitive influences (Tourangeau, Rips, and Rasinski 2000). Accordingly, equations w^* and b^* are conditioned on a subset of the above variables—age, gender, and highest educational attainment—whose inclusion may proxy for psychological and cognitive factors, which steer individuals toward the middle category, as well as information corresponding to respondents' personality traits made available in 2005, namely, the "Big Five" (agreeableness, conscientiousness, extraversion, neuroticism, and openness to experience). In the case of education, lower levels of attainment may be associated with some respondents engaging in "satisficing" behavior (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*"), especially given that a middle alternative may be perceived as representing what is "normal" (Price et al. 2017), or the safest choice, minimizing the potential for error. Perceived question complexity (Boxall, Adamowicz, and Moon 2009)—which may also be a function of educational attainment—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. Here, the better educated may be better informed about their financial situation and future finances. These effects may also be associated with age, in that older respondents may be more financially and economically literate based on the culmination of their life experiences. In the case of gender, there is evidence to suggest that in some settings, women are more prone to choosing a middle outcome than men.[16]

We also control for the total number of times over the course of the entire panel (i.e., 18 years) that the individual's year-ahead financial expectations are realized; this assumes the form of a count variable whose value ranges from 0 to 17. This captures a potential link between poorer forecasting ability and the type of satisficing behavior described above. The remaining controls proxy for interview conditions.[17] The first of these remaining controls captures the number of problems affecting the interview due to language, reading, and interpretation. A second variable captures the number of

16. Greene et al. (2016) find that when reporting self-assessed health, female respondents are more likely to be steered away from reporting excellent health toward the middle category; Fumagalli and Fumagalli (2022) find that the presence of a male comparison group increases the probability of women disproportionally choosing the middle "neutral" outcome in self-assessed measures of health satisfaction.

17. There is no evidence in the literature to suggest that the splitting equation controls relating to interview conditions should influence financial expectations or consumption behavior.

individuals who were present during the interview.[18] Two further variables proxy for the level of trust that individuals may have in the interviewer or questionnaire. These variables, respectively, capture 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).[19] A higher level of trust in the questionnaire or interviewer may engender a more accurate or realistic response from the interviewee rather than replying that the financial situation will not change (e.g., a neutral response).

Finally, to account for unobserved heterogeneity in the panel specifications, we adopted a *correlated random effects* (CRE) framework as in Mundlak (1978), in which the means of time-varying covariates, $\bar{\mathbf{z}}_i$ are included as additional controls when estimating random effects. In a nonlinear framework such as ours, the CRE approach relaxes the assumption of independence between the unobserved random effect and covariates while avoiding the incidental parameters problem (see Wooldridge 2010). Significant evidence of unobserved heterogeneity characterizes our findings.[20]

We estimated a number of competing specifications. These comprised a panel *OP* model, and pooled and panel variants of the *MIOP*, *MIOPC*, *GMIOP*, and *GMIOPC* models.[21] Statistically significant correlated errors characterized all estimated middle-inflated models. The log-likelihoods and the Akaike information criterion and Bayesian information criterion (AIC and BIC, respectively) indicated that the panel *OP* model performed least well, lending support to a middle-inflation estimation approach. Significantly, the panel inflated models performed better than those where the data were pooled, and both the AIC and BIC measures identified the panel *GMIOPC* model as performing best.[22] This finding is reinforced by the results of specification tests described in Section 1, under which the *MIOP*, *MIOPC*, and *GMIOP* were all overwhelmingly rejected in favor of the *GMIOPC*.[23] For this

18. If others are present during the interview then the respondent may opt to give a neutral response. As suggested above, a middle category may be perceived as being the safest choice, or representing what is "normal."

19. 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. Similarly, interviewer continuation is associated with respondent trust, interviewer reputation, and rapport with the respondent, and hence continued survey participation over time.

20. A CRE approach to accounting for unobserved heterogeneity is also used in our exploration of the determinants of consumption behavior in Section 3. In the case of the *GMIOPC* model, specification tests indicate that unobserved heterogeneity is characterized by CRE. See Online Appendix B for details.

21. Full estimation results for all model variants are available from the authors on request.

22. These results are reported in Online Appendix D, Table D.1.

23. The results of the associated LR tests—which focus on the panel variants—are presented in Table D.2 of Online Appendix D, along with a detailed comparison of the results associated with the *GMIOPC* and all other competing models. Note, the *OP* model is nonnested; 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 1

Summary Probabilities for the Panel *GMIOPC* Model

Category	Sample proportion	Purged (y^* only)	*GMIOPC* (full model)	Decomposition of *about the same*	
worse off	0.1066	0.298 (0.034)***	0.122 (0.006)***		
				from *worse off*	0.176 (0.036)***
about the same	0.6098	0.249 (0.033)***	0.517 (0.011)***	from y_i^*	0.249 (0.033)***
				from *better off*	0.092 (0.028)***
better off	0.2836	0.453 (0.018)***	0.361 (0.009)***		
Amount (Middle-inflation)		0.268*** (0.037)			

Note: Standard errors in parentheses; ***Significant at 1% level.

reason, our discussion of the first stage of our analysis focuses on the results of our preferred model.

Table 1 presents a series of estimated model probabilities averaged over all individuals, which capture the extent to which category inflation characterizes respondents' financial expectations in the *GMIOPC*. We first report the predicted probabilities corresponding to choosing *worse off*, *about the same*, and *better off*, associated with the latent *OP* equation of the *GMIOPC* model. These probabilities are presented in the "Purged (y^* only)" column, and "net out" or "purge" the impact of inflation. The adjoining column, ("*GMIOPC* (full model)"), presents the predicted probabilities for the full *GMIOPC* model, which incorporates the impact of the splitting equations. Using this information permits us to estimate the amount of middle-inflation in the model—denoted *Amount* (Middle-inflation)—as the difference between the predicted probability of choosing *about the same* for the full *GMIOPC* model and the corresponding "purged" amount as implied by the y^* equation. This quantity is used to calculate the overall proportion of responses in the model attributable to the effects of category inflation. Expressed as a percentage, the *GMIOPC* model suggests that approximately 26.8% of responses can be attributed to the impact of middle-inflation, a statistic that is statistically significant. Significantly, we also obtain the probabilities that correspond to the five possible outcomes depicted on the right-hand side of the *GMIOP* diagram in part (a) of Figure 1. The probabilities of choosing *worse off* or *better off* without being steered towards the middle outcome are respectively given by 0.122 and 0.361. Here, the final column of the table ("Decomposition of *about the same*") decomposes the predicted probability for the inflated middle category into its constituent parts. We observe that the probability associated with being steered away from *worse off* (0.176) is greater than for *better off* (0.092).[24]

24. These probabilities correspond to terms *A* and *C*, respectively, in expression (1).

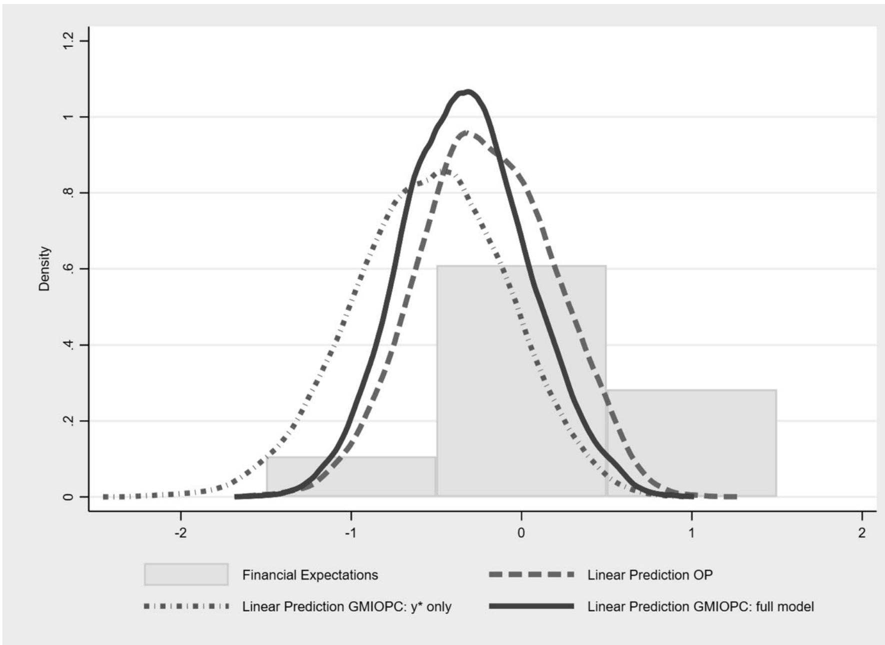

Fig 2. Alternative Measures of Financial Expectations—Distribution of the Exogenous Expectations ($\widetilde{y}_{it}$) Index and Density Plots of Linear Predictions from the Panel *OP* Model and the Panel *GMIOPC* Model.

To complement Table 1, Figure 2 plots the distribution of the discrete financial expectations index $\widetilde{y}_{it} = \{-1, 0, 1\}$ in shaded columns. We also provide density plots of the linear predictions from the panel *OP* model (the dashed line), the *OP* component of the panel *GMIOPC* model (the dot-dashed line), and the full panel *GMIOPC* model (the solid line), where it is noted that all linear predictions are not bounded to the -1 to $+1$ space. The linear prediction from the panel *OP* model more closely "mimics" the observed responses of the $\widetilde{y}_{it}$ index. However, explicitly accounting for middle-inflation is associated with a leftward shift in the *GMIOPC*-based distributions. Here, the fact that the distributions shift is arguably unsurprising: the motivation behind using middle-inflated models such as the *GMIOPC* is to separate out the various underlying processes. Doing so thus reveals the "true" distribution of linear predictions associated with the financial expectations equation y^* *once the presence of steering effects are explicitly controlled for via the splitting equations*. This is the most leftward distribution. Once the impact of steering is accounted for, the prediction associated with the full *GMIOPC* model, which is located closer to the "true" distribution for y^*, shifts rightwards. Intuitively, this is to be expected, due to the impact of the splitting equations adding mass to the *about no change* outcome. An interpretation of these shifts is that without accounting for middle-inflation—through, for instance using an inappropriate modeling approach such as a standard *OP* model—respondents are typically predicted to be over-optimistic, a result, which as noted in the introduction, aligns with the existing literature (see Bovi 2009; Malmendier and Taylor 2015; Weber et al. 2022).

Finally, we briefly comment on the partial effects of the *GMIOPC* model. Given our focus on the role that the splitting equations play in driving middle-inflation, attention is restricted to the variables, which appear in these equations. Table 2 reports the model's *overall* partial effects and those specific to the splitting equations w_i^* and b_i^*.[25] In the splitting equations, a negative partial effect is associated with being steered toward *about the same*, conditional on choosing *worse off* or *better off* in the *OP* equation.

The partial effects for the splitting equations suggest that the variables in $\mathbf{x}$ are more prone to steering individuals from *better off* to *about the same*, than *worse off* to *about the same*. This is reflected in the number of negative statistically significant parameters in each equation. Most variables in b^* (11 out of 17) are statistically significant, and all but one of the estimated coefficients are negatively signed. Considerably fewer variables in w^* (5 out of 17) are statistically significant, and only one—the impact of being aged between 18 and 30 years—steers respondents toward the middle outcome. However, the magnitude of this effect is considerable.[26] The omitted reference category is respondents aged between 51 and 65 years. An estimate of 0.224 suggests that the impact of being in this cohort, which accounts for around 18% of our entire sample, is to increase the probability of being steered away from worse off to about the same by approximately 22%. The *GMIOPC* specification thus reveals asymmetries in the propensities to be steered toward *about the same* from the respective *worse off* and *better off* categories. Table 2 also shows that statistically significant marginal effects in the splitting equations need not imply statistically significant *overall* marginal effects. As described in Online Appendix D, the mechanism behind this finding is attributable to *OP* equation variables counteracting the steering effects of the splitting equations, thereby offsetting their impact.[27] This appears to be

25. For instance, the overall partial effect associated with *about no change* is the sum of the individual partial effects corresponding to the probabilities A, B, and C in expression (1). Analytical expressions for the overall partial effects are derived in Online Appendix E. A comprehensive discussion of our empirical findings is provided in Online Appendix D, which are suggestive of respondents engaging in "satisficing" behavior (Krosnick 1991).

26. As suggested above, this may indicate that financial and economical literacy based on the culmination of an individual's life experience plays a role in steering a response to the *about the same* outcome. However, given the asymmetric nature of the effect (i.e., the effect of age in the b^* splitting equation is statistically insignificant), an alternative explanation may be that younger individuals are more likely to be affected by "unrealistic optimism" (Weinstein 1980, Jeffersona, Bortolottia, and Kuzmanovicb 2017), where respondents may expect their financial position to worsen in the future, but still report "about the same." As Online Appendix D describes, this is in contrast to "defensive pessimism" (Ben-Mansour, Jouini, and Napp 2006), where future uncertainties may cause households to anticipate the worst. It is important to note here that a standard *MIOP* model would not be able to capture these kinds of asymmetric effects.

27. Online Appendix D describes how this effect is consistent with the impact of a number of variables which appear jointly in $\mathbf{x}$ and $\mathbf{z}$. For instance, consider a variable v that appears in both y^* and b^*. Even if v is associated with steering toward *about the same* in b^*, if it is associated with a large enough positive and significant effect in y^*, the steering effect may be offset.

TABLE 2

MODELING FINANCIAL EXPECTATIONS – *GMIOPC* MODEL MARGINAL EFFECTS FOR SPLITTING EQUATION VARIABLES

	Overall marginal effects[a]						Marginal effects of splitting equations			
	worse off		*about the same*		*better off*		*worse off* (w_i^*)		*better off* (b_i^*)	
Aged 18–30[b]	0.009	(0.016)	−0.182	(0.025)***	0.173	(0.026)***	−0.224	(0.051)***	−0.095	(0.061)
Aged 31–40[b]	0.001	(0.011)	−0.071	(0.019)***	0.071	(0.021)***	−0.048	(0.037)	−0.115	(0.049)***
Aged 41–50[b]	−0.004	(0.008)	−0.021	(0.015)	0.025	(0.016)	0.006	(0.028)	−0.060	(0.035)*
Male[b]	0.011	(0.009)	−0.057	(0.017)***	0.046	(0.018)***	−0.044	(0.032)	−0.097	(0.045)*
Degree[b]	0.012	(0.014)	−0.101	(0.031)***	0.089	(0.032)***	−0.029	(0.051)	−0.262	(0.071)***
A-level[b]	0.009	(0.016)	−0.060	(0.043)	0.051	(0.042)	0.120	(0.059)**	−0.442	(0.096)***
O-level[b]	−0.017	(0.014)	−0.005	(0.031)	0.021	(0.032)	0.095	(0.054)*	−0.187	(0.067)***
Agreeableness	−0.007	(0.008)	0.006	(0.008)	0.003	(0.007)	0.015	(0.009)*	−0.001	(0.018)
Openness to experience	0.002	(0.006)	−0.031	(0.011)***	0.029	(0.008)***	−0.004	(0.009)	−0.088	(0.022)***
Neuroticism	0.004	(0.005)	0.001	(0.008)	−0.005	(0.007)	−0.009	(0.009)	0.017	(0.018)
Conscientiousness	0.004	(0.006)	0.003	(0.008)	−0.007	(0.008)	−0.008	(0.010)	0.020	(0.017)
Extraversion	−0.003	(0.007)	−0.010	(0.008)	0.012	(0.009)	0.006	(0.009)	−0.037	(0.019)**
Number of times correct prediction	0.001	(0.001)	0.020	(0.004)***	−0.021	(0.004)***	−0.002	(0.003)	0.062	(0.009)***
Change in interviewer	0.001	(0.006)	−0.014	(0.008)*	0.014	(0.007)**	−0.006	(0.013)	−0.043	(0.020)**
Total number of problems	−0.081	(0.037)**	0.070	(0.042)	0.012	(0.039)	0.174	(0.080)**	−0.036	(0.114)
Other present in interview	−0.009	(0.006)	0.004	(0.008)	0.005	(0.006)	0.019	(0.013)	−0.015	(0.019)
Length of interview	0.023	(0.015)	−0.025	(0.019)	0.002	(0.014)	−0.049	(0.032)	−0.007	(0.041)***

NOTE: Marginal effects are reported with standard errors in parentheses; *Significant at 10% level; **significant at 5% level; ***significant at 1% level; [a]Analytical expressions for the overall partial effects are derived in Online Appendix E; [b]Variables appear jointly in the *OP* and splitting equations; for the age dummy variables, the omitted reference category is respondents aged between 51 and 65 years; for the education attainment dummy variables, the omitted category corresponds to individuals with a highest level of educational attainment that is below GCSE O-level.

especially true for the b^* equation. However, what is notable is that even despite the presence of this latter mechanism, the linear predictions associated with the *GMIOPC* model are *still* clearly more pessimistic than for the panel *OP* model. Given the role that middle-inflation plays in shaping individuals' financial expectations, the second stage of our analysis now reveals that accounting for it holds significant implications in the context of explaining patterns of UK household consumption behavior.

2. MODELING CONSUMPTION EXPENDITURE

The second stage of our analysis entails analyzing the effect of expectations on household expenditure decisions. We focus on a subsample 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.[28] Following Brown and Taylor (2006), we investigate the relationship between financial expectations and consumption behavior. In line with Browning, Crossley, and Luhrmann (2016), our focus is on the 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 split the analysis by investigating these effects on expenditure relating to both household appliances and consumer electronic goods.[29] In contrast to Browning, Crossley, and Luhrmann (2016), financial expectations are included in the set of explanatory variables with a view to ascertaining 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 both a panel *OP* model and the panel *GMIOPC* model. We first introduce the expenditure/consumption data and the empirical methodology, followed by the results from modeling expenditure.

2.1 Data and Econometric Strategy

In each year of the BHPS, information is available for household expenditure on durable goods in the previous year. From 1991, the head of household was asked whether any of the following items were purchased: (1) *color 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: (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?" Although the

28. An excellent overview is provided by Ludvigson (2004).

29. Browning, Crossley, and Luhrmann (2016) find that purchases of consumer electronics typically rise with age, while, in contrast, the demand for household appliances is relatively flat.

data do not include all types of consumption expenditure, they do serve as a proxy for consumption. Following Browning, Crossley, and Luhrmann (2016), we consider expenditure on white good household appliances (freezers, microwaves, dishwashers, washing machines, and tumble dryers) and consumer electronics (personal computers, CD players, TVs, VCRs, phones, cable TV, and satellite dishes).

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

$$E_{it}^{g} = \gamma E_{it-1}^{g} + \mathbf{s}_{it}'\lambda + \phi\widetilde{y}_{it} + \alpha_i + \nu_{it}, \tag{2}$$

where

$$\alpha_i = \alpha_0 + \alpha_1 E_{i0}^{g} + \bar{\mathbf{s}}_i'\pi + \omega_{it}. \tag{3}$$

The dependent variable, E_{it}^{g} , is either binary (modeled as a CRE probit model) or the natural logarithm of the amount of expenditure (modeled as a CRE Tobit model) for group g. The groups we consider are: $g =$ all goods, electronics, white good appliances; or $g = 1,2,\ldots,13$, that is, 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 (2) conditional on the initial state, E_{i0}^{g}, that is, whether the household purchases good g (or the amount spent) when first observed in the panel, and the group means of time-varying covariates, $\bar{\mathbf{s}}_i$, that is, Mundlak (1978) fixed effects, as shown in equation (3). Substitution of equation (3) into (2) yields an augmented CRE model, where the parameter estimates approximate those of a fixed effects estimator. 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, for example, Browning, Crossley, and Luhrmann (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 1, 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* modeling approach, which explicitly controls for the impact of middle-inflation. In order to make the magnitude of financial expectations comparable across the different estimators, we standardize 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 explicitly controlled for in the measure of expectations. Other head of household characteristics comprise: a quartic in age, a quadratic in year of birth cohort, the number of health problems reported, and labor market status (i.e. whether employed, self-employed or unemployed, where out of the labor 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 real household income.

Summary statistics for the variables used in the expenditure models are reported in Table F.1 in Online Appendix F. Over the period, approximately 40% of respondents purchased electronic goods and 24% purchased household appliances, while 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%. While 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 modeling 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, while 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.

2.2 Estimation Results

The results are presented in Tables 3 and 4. As our primary interest is with the impact of financial expectations on consumption, we restrict ourselves to reporting the estimates for $\widetilde{y}_{it}$ ("Expectations 1") and two subsequent specifications, where $\widetilde{y}_{it}$ is, respectively, replaced by the linear prediction from the panel *OP* model ("Expectations 2"), and the *GMIOPC* model ("Expectations 3"). A discussion of the results associated with the remaining control set is provided in Online Appendix F. In Table 3, Panel A, focuses on the log of total expenditure on *all* durable goods, specifically the log amount spent on electronics and household appliances in the static and dynamic frameworks. Panel B 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.[30] In Table 4, static models are estimated for each of the 13 types of expenditure. 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 is standardized, enabling us to compare the magnitude across each specification.

The final part of each table reports diagnostic tests for exogeneity of the original financial expectations index and instrument validity tests for the *GMIOPC* model. The former is based on a Wu–Hausman Wald test, where clearly, for each outcome

30. Full tables of results corresponding to when financial expectations, $\widetilde{y}_{it}$, are treated as exogenous are reported in Online Appendix F, see Tables F.2 and F.3.

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

TABLE 3

Log Amount of Expenditure and Probability of Expenditure

Type of expenditure	All goods				Electronics				Household appliances			
Panel A: Log amount of expenditure	Static		Dynamic		Static		Dynamic		Static		Dynamic	
Expectations index 1 ($\widetilde{y}_{it}$)	0.1204	(0.032)***	0.1091	(0.033)***	0.1878	(0.060)**	0.1396	(0.063)**	0.1305	(0.122)	0.0543	(0.129)
Expectations index 2 (*OP*)	0.1340	(0.035)***	0.1218	(0.035)***	0.2299	(0.065)***	0.1921	(0.069)***	0.1537	(0.113)	0.0889	(0.120)
Expectations index 3 (*GMIOPC*)	0.0947	(0.022)***	0.0885	(0.023)***	0.1151	(0.049)**	0.1096	(0.053)**	0.0251	(0.113)	0.0305	(0.104)
Exogeneity & IV tests												
Wald exogeneity test: $\chi^2(1)$	4.32		8.20		6.53		4.91		0.32		0.14	
	$p = 0.0352$		$p = 0.0042$		$p = 0.0099$		$p = 0.0266$		$p = 0.5743$		$p = 0.7065$	
GMIOPC IV validity test: $\chi^2(17)$	13.30		13.47		15.63		19.74		31.67		28.38	
	$p = 0.7160$		$p = 0.7043$		$p = 0.5505$		$p = 0.2876$		$p = 0.0165$		$p = 0.0407$	
No. of observations	12,629		11,270		9,107		7,810		9,107		7,810	
Panel B: Probability of expenditure	Static		Dynamic		Static		Dynamic		Static		Dynamic	
Expectations index 1 ($\widetilde{y}_{it}$)	0.0253	(0.006)***	0.0214	(0.005)***	0.0335	(0.005)***	0.0300	(0.005)***	0.0021	(0.004)	0.0032	(0.004)
Expectations index 2 (*OP*)	0.0273	(0.006)***	0.0244	(0.006)***	0.0383	(0.006)***	0.0340	(0.006)***	0.0028	(0.005)	0.0039	(0.005)
Expectations index 3 (*GMIOPC*)	0.0247	(0.005)***	0.0197	(0.005)***	0.0119	(0.005)***	0.0152	(0.005)***	0.0015	(0.004)	0.0012	(0.005)
Exogeneity & IV tests												
Wald exogeneity test: $\chi^2(1)$	5.28		6.96		6.20		5.77		0.02		0.33	
	$p = 0.0216$		$p = 0.0084$		$p = 0.0128$		$p = 0.0163$		$p = 0.8780$		$p = 0.5675$	
GMIOPC IV validity test: $\chi^2(17)$	13.22		12.91		14.95		18.75		32.92		28.46	
	$p = 0.7213$		$p = 0.7425$		$p = 0.5990$		$p = 0.3430$		$p = 0.0116$		$p = 0.0399$	
No. of observations	12,629		11,270		12,629		11,270		12,629		11,270	

Note: Marginal effects are reported with standard errors in parentheses; *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 standardized to have zero mean and standard deviation of unity.

TABLE 4

PROBABILITY OF EXPENDITURE MODELS RANDOM EFFECTS PROBIT—DETAILED EXPENDITURE ITEMS

Part 1: 1991–2008	TV	VCR	Freezer	Washing Machine	Tumble Dryer	Dish Washer	Microwave	PC	CD Player
Expectations index 1 ($\widetilde{y}_{it}$)	0.0022	0.0180	0.0016	0.0045	0.0026	−0.0008	0.0020	0.0129	0.0162
	(0.003)	(0.003)***	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.004)***	(0.003)***
Expectations index 2 (*OP*)	−0.0007	0.0192	0.0020	0.0058*	0.0027	−0.0003	−0.0015	0.0090	0.0190
	(0.004)	(0.003)***	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)***	(0.003)***
Expectations index 3 (*GMIOPC*)	−0.0021	0.0121	0.0010	0.0017	0.0016	0.0015	−0.0010	0.0076	0.0142
	(0.004)	(0.004)***	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)***	(0.004)***
Exogeneity & IV tests									
Wald exogeneity test: $\chi^2(1)$	0.32	8.91	0.41	8.91	0.15	0.12	1.52	4.66	15.69
	$p = 0.5733$	$p = 0.0028$	$p = 0.0028$	$p = 0.9880$	$p = 0.6950$	$p = 0.7323$	$p = 0.2173$	$p = 0.0309$	$p = 0.0001$
GMIOPC IV validity test: $\chi^2(17)$	28.23	15.59	30.76	24.15	18.68	28.14	23.60	22.95	15.81
	$p = 0.0424$	$p = 0.5528$	$p = 0.0214$	$p = 0.1153$	$p = 0.3469$	$p = 0.0433$	$p = 0.1306$	$p = 0.1509$	$p = 0.5371$
No. of observations					12,629				

Part 2: 1997-2008	Satellite Dish	Cable TV	Telephone	Mobile Phone
Expectations index 1 ($\widetilde{y}_{it}$)	0.0064	0.0041	0.0023	0.0029
	(0.002)**	(0.001)**	(0.002)	(0.002)**
Expectations index 2 (*OP*)	0.0071	0.0035	0.0179	0.0065
	(0.002)***	(0.001)***	(0.003)***	(0.001)***
Expectations index 3 (*GMIOPC*)	0.0061	0.0032	0.0166	0.0026
	(0.002)***	(0.001)***	(0.003)***	(0.001)**
Exogeneity & IV tests				
Wald exogeneity test: $\chi^2(1)$	5.18	9.46	3.26	9.94
	$p = 0.0228$	$p = 0.0021$	$p = 0.0712$	$p = 0.0016$
GMIOPC IV validity test: $\chi^2(17)$	13.26	17.85	32.20	11.49
	$p = 0.7186$	$p = 0.3329$	$p = 0.0142$	$p = 0.7781$
No. of observations		9,107		

NOTE: Marginal effects are reported with standard errors in parentheses; *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 standardized to have zero mean and standard deviation of unity.

explored, it is generally the case that the financial expectations index is found to be endogenous at both the intensive (Panel A, Table 3) and extensive margins (Panel B, Tables 3 and 4). The exception is for household appliances, as is evident from the broad expenditure splits and the detailed decomposition of durable goods purchased provided in Table 4. We also explore whether the covariates used to identify the *GMIOPC* splitting equations are valid instruments in a statistical sense, having already argued that they are valid on *a priori* grounds above. A Wald test of the joint significance of the instruments in the expenditure equation reveals that they are valid for overall expenditure and electronics at both the intensive and extensive margins. However, once again, the exception is household appliances.

We now turn to the effect of financial expectations on the amount spent (Panel A, Table 3) and on the likelihood of undertaking expenditure (Panel B, Table 3), 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 Panel A, Table 3. However, focusing on the amount spent on all durable goods and electronic goods, Panel A of Table 3 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 0.14% 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, Berg, and Sims (2015), Gillitzer and Prasad (2018) and Duca-Radu, Kenny, and Reuter (2021).[32,33] From the corresponding analysis for the likelihood of purchasing goods, see Panel B, Table 3, 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 percentage point higher probability of purchasing an electronic product.

32. Bachmann, Berg, and Sims (2015) explore the relationship between inflation expectations and households' readiness to purchase consumption goods, using the Michigan *Survey of Consumers*. They find that a 1 percentage point increase in inflationary expectations (i.e., a more pessimistic outlook of future prices) is associated with a fall in the likelihood of households making a consumer purchase by 0.5 percentage points. Duca-Radu, Kenny, and Reuter (2021) use a cross-country survey of EU economies to explore the spending response of consumers to their beliefs about future inflation. The authors model the probability that "*now is the right time to spend*." The results reveal that, during periods when the lower bound on nominal interest rates is nonbinding, a 1 percentage point increase in the expected change (level) of subjective inflation is associated with a 0.26 (0.09) percentage point increase in the probability of being ready to spend. Interestingly, those consumers who are more optimistic about their future financial situation tend to have a larger consumption response to an expected change in inflation. Gillitzer and Prasad (2018) consider the effect of consumer sentiment (which includes expectations regarding future income) on consumption in Australia. Their results show that consumers who have more optimistic beliefs about future economic conditions report more positive spending intentions on consumable goods.

33. In related work, Souleles (2004) shows using U.S. data from the Michigan *Index of Consumer Sentiment* that sentiment helps to forecast consumption growth, while Giamboni, Millemaci, and Waldmann (2013) using Dutch microdata from the De Nederlandsche Bank (DNB) Household Survey find that agents who are overly optimistic have lower consumption growth.

The majority of the literature to date, which has explored the relationship between expectations and household financial behavior (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 Table 3, we also use the linear prediction from the panel *OP* model and the panel *GMIOPC* model of expectations. Each measure is standardized and so the effect of financial expectations can be compared across panels. Again, as found with the exogenous measure $\widetilde{y}_{it}$, 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 and the likelihood of purchase in Table 3, the magnitude is smaller for the measure of expectations based on the linear prediction derived from the panel *GMIOPC* model compared to that for the panel *OP* model. For example, focusing 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% (Panel A, Table 3, Expectations 2, and Expectations 3 measures). Similarly, considering the likelihood of purchasing durable goods, a one standard deviation increase in financial expectations is associated with a 2.4 and 1.9 percentage point higher probability of purchasing a durable good (Panel B, Table 3, Expectations 2 and Expectations 3 measures). Hence, once middle-inflation effects have been explicitly accounted for when modeling financial expectations, the impact on both the intensive and extensive margins of consumption is smaller. This is because failing to correctly account for the presence of middle-inflation serves to shift the distribution of financial expectations to the right as is evident from Figure 2.

In Table 4, the probability of purchasing each type of good is estimated in a static framework.[34] The sample covers 12,629 observations for goods ($g =$) 1 to 9, part 1 of the table, while for the subsample, which covers the remaining goods, part 2 of the table, there are 9,107 observations. The table is constructed in the same way as in Table 3, and again we only report the key parameter of interest, that is, the effect associated with the standardized measure of financial expectations, ϕ. While the association between expectations and the likelihood of expenditure is generally positive, it is only significant for 6 of the 13 goods and this is solely for electronic goods, that is, VCR, home computer, CD player, satellite dish, cable TV, and mobile phone. The variables labelled Expectations Index 2 and 3 relate to the standardized linear prediction of financial expectations, where, for the aforementioned goods, the positive relationship generally remains. Moreover, the effect of the standardized linear prediction from the panel *OP* model on the probability of undertaking expenditure on specific durable goods, where statistically significant, is typically larger than that stemming from the exogenous expectations index. But as found above, the effect of financial expectations upon the probability of purchasing different types of durable

34. It is unlikely that households purchase the same type of durable good, for example, a washing machine, a TV, or a home computer, year on year. Hence, a dynamic framework does not seem appropriate when modeling the probability of purchasing specific durable goods.

TABLE 5

Growth in Expenditure during Recessionary Periods Explained by Income and/or Financial Expectations

Proportion of variation accounted for by:	Growth in total expenditure	Growth in expenditure on electronics	Growth in expenditure on household appliances
1. Income	6.26%	11.91%	6.61%
2. Exogenous: Expectations index 1 ($\widetilde{y}_{it}$)	18.80%	7.67%	3.86%
3. Income & Expectations index 1 ($\widetilde{y}_{it}$)	28.18%	18.80%	11.14%
4. Endogenous: Expectations index 3 (*GMIOPC*)	15.54%	4.75%	1.21%
5. Income & Expectations index 3 (*GMIOPC*)	22.45%	12.87%	8.08%

Note: Each row is a separate regression of the growth in expenditure during recessionary periods on all covariates, then including income and/or expectations. Expectations index 1 is based on exogenous financial expectations and Expectations index 3 uses the linear prediction from the panel *GMIOPC* model. Each index has been standardized to have zero mean and standard deviation of unity.

goods is larger in terms of economic magnitude from the panel *OP* compared to the panel *GMIOPC* specification.

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, for example, Carroll, Fuhrer, and Wilcox (1994), Brown and Taylor (2006), Ludvigson (2004), Bachmann, Berg, and Sims (2015), and Gillitzer and Prasad (2018). The relationship between consumption and financial 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 at both the intensive and extensive margins. This is due to the fact that once the impact of middle-inflation is appropriately accounted for in the panel *GMIOPC* model, financial expectations have a smaller impact on the amount spent and the decision to undertake expenditure on durable goods. This is as expected, given that the linear prediction from the panel *GMIOPC* model captures the effect of responses being steered toward the *about the same* category from *worse off* and *better off*.

In order to place the role of expectations in a macro-economic context, the final exercise we undertake is to examine how much income and financial expectations can explain in terms of the change in expenditure during recessionary periods. To do this, we model the *growth* in expenditure on overall consumer durables, electronics, and household appliances. This analysis is conducted for recession years or when household income was most volatile: 1998–99, 2000–01, and the financial crisis of 2007–08, where in each period approximately 30% (15%) of households experienced a fall in real household income (expenditure on durable goods). The results are shown in Table 5, where each row is a separate linear random effects regression, where the dependent variable is ΔE_{it}^{g}, and the proportion of the growth in each type of expenditure is that amount of model variation explained by: real household income, financial expectations, and the two covariates combined (over and above the other control variables).[35] This allows us to place the estimates of the role of expectations into a macro-economic context and to provide a comparison with the role of household income. For example, focusing on the first column, including income into the growth in total expenditure model increases the model's explanatory power by over 6% (row 1), compared to exogenous financial expectations, which explain around 18.8% (row 2). The endogenous linear financial expectations index estimated from the *GMIOPC* explains just under 16% of the variation in expenditure growth (row 4), and combined total income and financial expectations account for between 23% and 28% of the model variation (depending on whether expectations are treated as endogenous or exogenous). Splitting the growth in total expenditure in recessionary periods into electronics and household appliances reveals that, although household income plays a similar role in terms of the proportion of variation explained in overall consumer spending on durables, the role of financial expectations is largely limited to that of electronics. This analysis reveals the importance of incorporating expectations into modeling consumption behavior (both levels and growth) in terms of the economic magnitude of the effects as well as for policy purposes, which we discuss in the conclusion below.

3. 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 characterized 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 nonnegligible role in driving household consumption behavior. In contrast to previous contributions that have explored the relationship between expectations and household financial behavior, 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 modeled 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 ignore the role of middle-inflation overstate the impact of financial expectations on

35. The variation accounted for by income and/or financial expectations is calculated from the percentage change in the model R^2 statistic stemming from the inclusion of the specific covariate in rows 1–5.

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 38% (24%).[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 behavior, our findings have salient implications for future research in this area. There exist significant policy implications given that government media presence (through, e.g., communicating policy decisions) and changes in fiscal policy through tax cuts have been found in practice to influence economic activity and consumer expectations (Goidel et al. 2010, Konstantinou and Tagkalakis 2011, He 2017). If the objective of government policy is to influence consumer sentiment through policy interventions, then is it essential that expectations—financial or otherwise—are accurately measured and appropriately modeled. This is especially so given the substantial middle-inflation, which characterizes financial expectations in the United Kingdom. Failure to do so suggests that the predicted effects on economic activity are likely to be flawed.

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36. Based on comparing the estimates from the dynamic specification reported in Online Appendix F, Panels B and C of Table F.2 for the amount spent (Table F.3 for the likelihood of expenditure), respectively.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

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