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The Existence and Persistence of Household Financial Hardship: A Bayesian Multivariate Dynamic Logit Framework

Abstract: We investigate the existence and persistence of financial hardship at the household level using data from the British Household Panel Survey. Our modelling strategy makes three important contributions to the existing literature on household finances. Firstly, we model nine different types of household financial problems within a joint framework, allowing for correlation in the random effects across the nine equations. Secondly, we develop a dynamic framework in order to model the persistence of financial problems over time by extending our multi-equation framework to allow the presence or otherwise of different types of financial problems in the previous time period to influence the probability that the household currently experiences such problems. Our third contribution relates to the possibility that experiencing financial problems may be correlated with sample attrition. Hence, we explicitly model missing observations in the panel in order to allow for such attrition. Our modelling framework allows us to identify any persistence in financial problems over time as well as any interdependence that may exist between different types of financial problems. The results reveal interesting variations in the determinants of experiencing different types of financial problems including demographic and regional differences. Our findings also highlight persistence in experiencing financial problems over time as well as the role that saving on a regular basis can play in mitigating financial problems.

Key Words: Financial Problems; Multivariate Dynamic Logit Model; Sample Attrition.
JEL Classification: C33; C35; R20.

1. Introduction and Background

The recent financial crisis has revealed the financial vulnerability and stress that many households face in a number of countries including the UK and the US, with households holding limited savings to fall back on in times of financial adversity. As Garon (2012), p. 1, comments, in the US, 'it has become painfully clear that millions lack the savings to protect themselves against foreclosures, unemployment, medical emergencies, and impoverished retirements.' Such comments arguably apply to a range of countries, where households with limited savings are particularly vulnerable to financial shocks related to unemployment, falls in real income or changes in their personal circumstances such as adverse health shocks, divorce or changes in household expenditure due to, for example, having children. Households facing such changes may experience financial problems and hardship.

Although there is a growing empirical literature exploring households' financial portfolios (see, for example, Guiso et al., 2002), one area, which has attracted limited attention, concerns the analysis of financial hardship at the household level and, in particular, the dynamics and persistence of financial problems. To be specific, the existing literature on household finances has generally focused on financial decision-making in the context of the nature and characteristics of the financial portfolios held including decisions regarding stock market participation and the diversification of financial assets (see Campbell, 2006). The existence of financial problems at the household level indicates that some households may have made mistakes in such decision-making or may have suffered from unforeseen adverse events. Our analysis of financial problems thus sheds light on an area of household finances, which has attracted surprisingly little attention in the existing literature.

Our modelling strategy, which is applied to UK household level panel data, makes three important contributions to the existing literature. Our first contribution relates to the fact that, in contrast to the existing literature, our modelling approach explicitly allows us to model different types of financial problems within a joint framework and to explore the interdependence that potentially exists between different types of financial problems. Hence, our modelling strategy is based on the premise that financial hardship is a multi-dimensional concept and allows us to define financial problems more broadly than in the existing literature which has tended to focus on housing payment problems, with a particular focus on rent and mortgage arrears.[1] We adopt a wider approach than the existing literature and explore a range of financial problems, including housing payment problems. Furthermore, our joint modelling approach, based on nine types of financial problems, is highly flexible allowing the explanatory variables to exert different influences on the different types of financial problems yet allowing for the potential interdependence between the different financial problems. We model the nine financial problems via a random effects specification, allowing for correlation in the nine random effects.[2]

As our second contribution, we develop a dynamic framework in order to model the persistence of financial problems over time by extending our multi-equation framework to allow the presence or otherwise of different types of financial problems in the previous time period to influence the probability that the household currently experiences such problems. Thus, the random effects specification allows for unobserved heterogeneity (unobserved household specific attributes that are time invariant) and the dynamic specification (i.e. the

[1] For example, Böheim and Taylor (2000) use the British Household Panel Survey (BHPS), 1991-1997, to explore the incidence of housing payment difficulties, evictions and repossessions. Their findings indicate that structural, financial and personal factors all influence the probability that households experience mortgage or rent arrears. More recently, Duygan-Bump and Grant (2009), using the European Community Household Panel 1994 to 2001, explore the incidence of arrears associated with scheduled loan repayments, utility bills or mortgage repayments. Their findings accord with the existing literature in that arrears are found to be associated with adverse shocks such as becoming unemployed or poor health.

[2] Our approach, therefore, is not based on the construction of an overall index of financial vulnerability or capability, which has been adopted by some studies in the existing literature. For example, Taylor (2011) and Taylor et al. (2011) construct a measure of financial capability using data drawn from the BHPS 1991 to 2006 on the individual's current financial situation covering their management of finances and their ability to make ends meet. Using factor analysis and also adjusting for income and business cycle effects, they construct a summary measure of seven dimensions of financial capability. Although this approach provides a useful way of reducing the dimensionality of financial problems, it does not allow one to model each dimension separately and to ascertain the potential interdependence between different types of financial problems.

inclusion of the lagged dependent variables) allows for state dependence. There are a small number of studies in the existing literature which have alluded to the potential persistence in housing payment problems but these studies have generally not explicitly modelled such dynamics or, as indicated above, have focused on only one source of financial problem. For example, the descriptive statistics of Böheim and Taylor (2000) indicate a degree of persistence in housing payment problems, with 30% of households experiencing such difficulties for at least four years. The dynamic aspect to housing payment problems is highlighted by the findings of May and Tudela (2005), who, using the BHPS 1994 to 2002, model the probability of having mortgage debt repayment problems via a dynamic probit framework, where past repayment problems are found to be positively associated with current mortgage payment problems. The findings from such studies thus indicate persistence in housing payment problems. Allowing for the dynamics of financial problems within our joint modelling framework enables us to explore such persistence whilst allowing for the potential interdependence across the nine different types of household financial difficulty.

Our third contribution relates to the possibility that experiencing financial problems may be correlated with sample attrition. For example, Böheim and Taylor (2000) argue that attrition is potentially particularly important in the context of modelling housing payment problems, which ultimately may lead to eviction, with homeless people not generally being included in surveys. Again, such issues have been discussed in the existing literature but have not been explicitly allowed for in the modelling approaches adopted potentially leading to biased inference. Hence, we model missing observations in the panel in order to allow for such attrition.

2. Methodology

2.1 The Multivariate Dynamic Logit Model

This section presents the empirical framework developed in this paper to model distinct, yet potentially correlated, financial problems at the household level. Specifically, we construct a correlated multivariate dynamic logit model. The econometric framework is described below in four steps. The first step relates to the specification of the incidence of the k$^{\text{th}}$ financial problem of the i$^{\text{th}}$ household at time t within a joint modelling framework. The second step concerns modelling the interdependence of the incidence of the different financial problems and how these interact with each other since the overall financial hardship of a household is a combination of each of these effects. We do this in two ways: firstly, by allowing for the dynamic aspect of the incidence of each financial problem; and, secondly, by explicitly modelling unobserved household heterogeneity, allowing for correlation between the different financial problems. The third step involves modelling missing observations using a logit model. The final step entails the construction of the joint likelihood of the financial problems of all households in the sample bringing together all three extensions outlined above.

Let $y_{kit} \in \{0,1\}$ be the incidence of the $k(= 1,2, \dots, K)^{\text{th}}$ financial problem of the $i(= 1,2, \dots, N)^{\text{th}}$ household at time $t(= 1,2, \dots, T)$. We model y_{kit} as having a binary distribution with the probability of incidence denoted by p_{kit} and, in turn, we model p_{kit} using a logit link function. Thus, we assume that the joint dynamics of household i's financial hardship is governed by the following stochastic process:

$$y_{kit} \sim \text{Bernoulli}(p_{kit}) \tag{1}$$

$$\text{logit}(p_{kit}) = \boldsymbol{X}_{kit}^{T}\beta_k + \alpha_{kk} y_{ki,t-1} + \sum_{l \neq k=1}^{K} \alpha_{lk}\, y_{li,t-1} + b_{ki} \tag{2}$$

where the second and third terms in equation (2) represent the dynamic effects and the final term in equation (2) captures household heterogeneity. The vector of explanatory variables,

$\boldsymbol{X}_{kit}^{T}$, includes controls for the impacts of a wide range of predictors covering demographic characteristics, household and financial characteristics, and regional and business cycle influences, where β_k captures the effects of these variables on the probability of experiencing financial problems. The set of control variables is discussed in detail in the following section.

The logit models are characterised by two kinds of dynamic effects: $y_{ki,t-1}$ is the indicator variable of whether the household has experienced the same type of financial problem in a previous time period; and $y_{li,t-1}$ captures the effect of the lth type of financial problem experienced in a previous time period. The corresponding parameters, α_{kk} and α_{lk}, measure the effects of this dynamic correlation. Household level heterogeneity is captured by the random effects term, b_{ki}. It is apparent that unobserved household heterogeneity affecting one response may be correlated with unobserved household heterogeneity affecting other responses. Thus, the household heterogeneity terms are assumed to be correlated, i.e., $\boldsymbol{b}_i = (b_{1i}b_{2i}, \dots, b_{Ki})^T \sim N(0, \sum)$.

The model described by equations (1) and (2) exploits the panel structure of the data in order to distinguish between three important sources of intertemporal dependence in the observations. One source is due to the 'own' lags, $y_{ki,t-1}$, which captures the notion of 'state dependence', where the probability of response k may depend on past occurrences, due to, for example, altered preferences over time. Thus, the estimated coefficients on the 'own' lagged dependent variables, α_{kk}, capture the genuine state dependence of financial problem k. A second source in our flexible statistical framework relates to the inclusion of the lagged responses for the other types of financial problems. The estimated coefficients on the lagged dependent variables relating to the other financial problems, α_{lk}, where $l \neq k$, capture the dynamic interaction between the kth financial problem and the lth $(l = 1,2, \dots, k-1, k+1, \dots, K)$ financial problem. Finally, observations $(y_{1it}, \dots, y_{Kit})$ may also be correlated due to household unobserved heterogeneity, which is captured by the household effects, $\boldsymbol{b}_i$.

Allowing for such differences across households is essential in order to guard against the emergence of spurious state dependence (Heckman, 1981a). In order to fully specify the model, the initial condition needs to be specified. An initial conditions issue arises in our model since b_{ki} is random. In order to deal with this issue, we use the estimator suggested by Heckman (1981b), which involves the specification of an approximation of the reduced form of the equations for the initial condition and which allows for the cross-correlation between the dynamic equation and the initial condition:

$$y_{ki0} \sim \text{Bernoulli}(p_{kio}) \tag{3}$$

$$\text{logit}(p_{ki0}) = \boldsymbol{X}_{ki0}^{T}\gamma_{1k} + \boldsymbol{Z}_{ki}^{T}\gamma_{2k} + \theta_k v_{ik} \tag{4}$$

where $\boldsymbol{X}_{ki0}^{T}$ are pre-sample (i.e. 1996) values of covariates, and $\boldsymbol{Z}_{ki}^{T}$ is a vector of other variables, discussed in Section 3 below, used to specify the initial condition but which do not influence the dynamic process of interest, i.e. financial problems (equation 2).

2.2 Modelling Missing Observations

Due to missing data, some information for some households is unavailable. If the missing information is unrelated to the investigation, then these missing observations can be considered as missing at random and, hence, can be ignored. However, this is unlikely to be the case for all of the missing observations. Furthermore, the probability of a missing observation may be related to the household experiencing financial problems. It has been shown (Little, 1985, 1995) that, if a missing observation is informative, then ignoring such cases may lead to biased inference.

For each y_{it} we define a missing indicator variable R_{it}, such that $R_{it} = 1$ if y_{it} was missing, and 0 otherwise. The missing data mechanism is assumed to depend on the history of measurement up to and including the t^th observation, i.e.,

$$P(R_{it} = r|H_{it}) = P_t(H_{it}, y_{it}; \varphi) \tag{5}$$

where, H_{it} represents the part of the observed y preceding a missing value (i.e. the history), and φ is a vector of unknown parameters. Thus, $\boldsymbol{R}_i = (R_{i1}, \dots, R_{iT})^T$ is a vector of missing response indicators for household i.

Then a simple model can be constructed to describe the non-ignorable missing response:

$$R_{it} \sim \text{Bernoulli}(\eta_{it}) \quad \text{where} \quad \eta_{it} = p\left(R_{it} = 1 \middle| y_{it}, \boldsymbol{y}_{i(t-1)}\right) \tag{6}$$

$$\text{logit}(\eta_{it}) = \lambda + \sum_{k=1}^{K} \theta_k \, y_{kit} + \sum_{k=1}^{K} \delta_k \, y_{ki,t-1} + \boldsymbol{G}_{kit}^T \boldsymbol{\pi}_k. \tag{7}$$

The non-ignorable 'missingness' is modelled via the dependence of each of the unobserved financial problems at the time of the missing observation on the outcomes prior to the missing observation, i.e. AR(1), and in addition a set of covariates, given in the vector $\boldsymbol{G}_k^T$ (these are discussed explicitly in Section 3 below), which affect attrition but not the dynamic process of interest, i.e. financial problems. The parameters θ, δ and $\boldsymbol{\pi}$ relate the drop outs to the response process. Note that, when $\theta_k \neq 0$, $\delta_k \neq 0$ or $\boldsymbol{\pi}_k \neq 0$, the missing observation is informative. The missing data mechanism is modelled as a binomial regression with two states, where it is assumed that $R_{i0} = 0$.

2.3 The Likelihood Function

The econometric model described above consists of two components. Thus, the complete data likelihood has contributions from both the dynamic logit model and the model for non-ignorable missing data. Conditional on the random effects, $\boldsymbol{b}_i$, and the initial values, $\boldsymbol{y}_{i0} = (y_{1i0}, \dots, y_{Ki0})^T$ and under the assumption of non-ignorable drop-out, the joint likelihood for the i[th] household can be written as:

$$L_i(\boldsymbol{y}_i, \boldsymbol{R}_i | \boldsymbol{b}_i, \boldsymbol{y}_{i0}; \Omega) \propto$$

$$L_i\left(\boldsymbol{y}_{obs,i} | \boldsymbol{y}_{i0}, \boldsymbol{b}_i; \Omega_1\right) \times L_i(\boldsymbol{R}_i | \boldsymbol{y}_i, \boldsymbol{b}_i; \Omega_2) \times L_i(\boldsymbol{b}_i) \tag{8}$$

where,[3] $L_i\left(\boldsymbol{y}_{obs,i}|\boldsymbol{y}_{i0},\boldsymbol{b}_i;\Omega_1\right)$ is the conditional likelihood for the observed multivariate logit model and is given by:

$$L_i\left(\boldsymbol{y}_{obs,i}|\boldsymbol{y}_{i0},\boldsymbol{b}_i;\Omega_1\right)=\prod_{k=1}^{K}\prod_{t=1}^{T}p_{kit}^{y_{kit}}(1-p_{kit})^{1-y_{kit}} \quad (9)$$

where Ω_1 is the set of parameters from model (1). Similarly, $L_i(\boldsymbol{R}_i|\boldsymbol{y}_i,\boldsymbol{b}_i;\Omega_2)$ is the model for the missing data and is given by:

$$L_i(\boldsymbol{R}_i|\boldsymbol{y}_i,\boldsymbol{b}_i;\Omega_2)=\prod_{t=1}^{n_i}\{p(r_{it}=1)\}^{r_{it}}\{1-p(r_{it}=1)\}^{1-r_{it}} \quad (10)$$

where n_i is the last observation prior to the missing data. Finally, $L_i(\boldsymbol{b}_i)$ is the likelihood of the multivariate normal random effects with 0 mean, i.e. $L_i(\boldsymbol{b}_i)\propto \exp\frac{1}{|\Sigma|}\exp\left(\boldsymbol{b}_i^T\Sigma^{-\boldsymbol{1}}\boldsymbol{b}_i\ \right)$.

We then obtain the unconditional likelihood function for household i as follows:

$$L_i(\boldsymbol{y}_i,\boldsymbol{R}_i|\boldsymbol{y}_{i0};\Omega)=\int L_i(\boldsymbol{y}_i,\boldsymbol{R}_i|\boldsymbol{b}_i,\boldsymbol{y}_{i0};\Omega)\,L_i(\boldsymbol{b}_i)d\boldsymbol{b}_i \quad (11)$$

The final step of the model is to construct the likelihood function for all households observed in the sample. Assuming independence across households, the overall log likelihood function for the sample is:

$$logL=\sum_i \log\left(L_i(\boldsymbol{y}_i,\boldsymbol{R}_i|\boldsymbol{y}_{i0};\Omega)\right) \quad (12)$$

We use a Bayesian Markov Chain Monte Carlo (MCMC) method for parameter estimations for the following main reasons.[4] Firstly, our Bayesian estimation procedure, with the incorporation of the recent development of the MCMC method (Gelfand and Smith, 1990; Korteweg, 2012; Robert and Casella, 1999), is powerful and flexible in dealing with such a complex joint model, where the classical maximum likelihood approach encounters severe computational difficulties (Lopes and Carvalho, 2007). Finally, our approach allows us to

[3] Expression (8) is a joint conditional likelihood of **y**, **R** and **b**. Since **b** is shared with **y** and **R**, the composite likelihood is independent conditional on **b**. Thus, conditional on **b**, the joint likelihood is independent and a product of the two individual likelihoods.

[4] To implement the model, we used the WinBUGS 1.4 software, with the necessary simulations efficiently performed with the R2WinBUGS package in R. The software, which is based on Bayesian inference using Gibbs sampling, enables analysis of complex models using MCMC methods (see Lunn et al., 2009). The samples from the posteriors obtained from MCMC allowed us to achieve summary measures of the parameter estimates and to obtain credible intervals of the parameters of interest.

perform Bayesian model selection and cross-validation procedures, with considerable gains in computational efficiency over those used in conventional classical estimation approaches.

2.4 Model Performance

To ascertain model performance, we construct a test of parameter significance obtained by calculating the Bayes factor (see Kass and Raftery, 1995, and Greene, 2012). This is constructed by formulating the null hypothesis H_0 that all of the slope parameters of the model are simultaneously equal to zero against the alternative hypothesis H_1 that the former is not true. The Bayes factor has been used in existing finance literature to compare the quality of fit between competing models (see, for example, Eraker et al., 2003, and Duffie et al., 2009). Prior probabilities can be assigned to the two hypotheses denoted as $p(H_0)$ and $p(H_1)$, respectively. The prior odds ratio is given as $p(H_0)/p(H_1)$ and the posterior is generally given by $B_{01} \times (p(H_0)/p(H_1))$, where B_{01} is the Bayes factor for comparing the two hypotheses. Based upon the observed data, the Bayes factor is given as:

$$B_{01} = \frac{f(\boldsymbol{y}|\boldsymbol{X}, H_0)}{f(\boldsymbol{y}|\boldsymbol{X}, H_1)} = \frac{\int p(\boldsymbol{y}|\boldsymbol{X}, \beta_0)\pi_0(\beta_0)d\beta_0}{\int p(\boldsymbol{y}|\boldsymbol{X}, \beta_1)\pi_1(\beta_1)d\beta_1} \tag{13}$$

where β_0 and β_1 are the parameters of the probability densities for the data that hold under the two respective hypotheses, and $\pi_0(\beta_0)$ and $\pi_1(\beta_1)$ are the prior probability densities. Hence, the Bayes factor is a ratio between the posterior odds and the prior odds. Generally, there will be very strong evidence against the null hypothesis if the log Bayes factor is above 20 in magnitude, see Kass and Raftery (1995). The Bayes factor is not affected by the complexity of the model as its computation is based on the marginal nature of the likelihood.

3. Data

We use the British Household Panel Survey (BHPS), a survey conducted by the Institute for Social and Economic Research comprising approximately 10,000 annual individual interviews. For wave one, interviews were conducted during the autumn of 1991. The same individuals are re-interviewed in successive waves – the last available being 2008.[5] The focus of our analysis is the household reference person who we follow over time. We focus on household reference persons as they are responsible for meeting primary household expenditures, such as housing payments, and play the primary role in household financial decision making (we refer to them as household heads for brevity).[6] The BHPS contains a range of detailed questions relating to household finances. Firstly, information is available in all waves relating to whether households over the last 12 months have had any difficulties paying for their accommodation (denoted fprob1). Secondly, information was gathered on the extent to which households experienced financial problems relating to loans (denoted fprob2). Thirdly, in the BHPS from 1996 onwards, information on financial hardship at the household level can be discerned from the responses of the head of household regarding the ability of the household to: afford to keep their home adequately warm (denoted fprob3); be able to pay for a week's annual holiday (denoted fprob4); replace worn-out furniture (denoted fprob5); be able to buy new, rather than second-hand, clothes (denoted fprob6); be able to eat meat, chicken, fish every second day (denoted fprob7); and be able to have friends or family for a drink or meal at least once a month (denoted fprob8). Finally, information is available indicating whether the household is unable to save anything on a monthly basis (denoted by nosave). Thus, over the period 1996 to 2008, we use the BHPS to jointly model these nine types of financial problems, which are potentially experienced at the household level.

Our estimation sample covers 1997 to 2008 given the inclusion of lagged dependent variables in the modelling framework to allow for the potential dynamic aspect to such problems and also to specify the initial condition in equation (4). The exclusion restrictions

[5] The BHPS was replaced by Understanding Society in 2009.

[6] It is possible that households may change over time due to, for example, marriage or divorce. In the BHPS, when a household splits up the household of the 'reference person' continues with the same household identifier and a new household is created with a new reference person. Hence, we control for characteristics which we might expect would be associated with household splits, such as marital status and household composition (see below).

are based upon 1996 values of covariates and the inclusion of a vector of controls in $\boldsymbol{Z_k^T}$, specifically whether the father and/or the mother of the head of household were working when the respondent was aged 14. Our line of reasoning for using these controls follows the economics of education literature where typically family background variables such as parental education or parental employment status observed during the respondent's childhood are argued to have no direct effect on the respondent's outcome of interest as an adult, typically income or in the current context financial problems beyond the initial condition, for a detailed review and test of the validity of such instruments see Hoogerheide et al. (2012).[7]

The total number of observations in the panel is 123,432 observations. The households can be split into two categories: those households observed in the panel for each of the 12 years, which comprises 1,669 households and those households which dropout of the sample, where they could be missing, for example, for just one year but then may re-enter the sample in later years, or they may never re-enter the sample, this group comprises 8,617 households where the average number of times households are observed in the panel, $\bar{\mathbf{T}}$, is 7 years.[8] Hence, out of the total number of observations, 16% (20,028 observations) represent the households which are always in the panel, 84% (103,404 observations) represent the households with missing observations. In terms of modelling attrition, as well as specifying the missing data problem as an AR(1) process in financial problems, we also condition 'missingness' upon a vector of covariates $\boldsymbol{G_k^T}$. In particular, we follow Cappellari and Jenkins (2008) by conditioning upon whether there was a change in interviewer over time.[9] The idea

[7] Note that identification requires that the variables in $\boldsymbol{Z}_k^T$ affect the initial condition in equation (4) but not the dynamic process of interest, i.e. financial problems, in equation (2). This condition is satisfied in the model.
[8] The minimum (maximum) value of T is 3 (11) years.
[9] Identification requires that $\boldsymbol{G}_k^T$ influences attrition but has no effect upon financial problems.

behind the use of this control is that interviewer continuation is associated with respondent trust and hence continued survey participation over time (see Schräpler, 2004).[10]

We analyse a nine equation system, where we jointly model fprob1, fprob2, fprob3, fprob4, fprob5, fprob6, fprob7, fprob8 and nosave. As a proportion of the total number of observations observed in the panel for the households who are in the panel for the entire 12 year period, the percentages indicating that they experience financial problems for fprob1, fprob2, fprob3, fprob4, fprob5, fprob6, fprob7, fprob8 and nosave are 3%, 8%, 1%, 9%, 7%, 2%, 1%, 3% and 59%, respectively. Out of the total sample, the corresponding percentages are: 5%, 11%, 1%, 14%, 9%, 3%, 2%, 5% and 66%, respectively. Hence, with the exception of fprob3, the incidence of financial problems experienced is lower for the sample of households who are present in the survey across all 12 waves, which ties in with the argument that experiencing financial problems may be correlated with sample attrition. Figure 1A shows the evolution of the incidence of financial problems over time. Clearly, in comparison to the earliest period in the sample, which is closest to the economic recession of the early 1990s, each type of financial problem has become less prevalent in the raw data. However, there is some evidence that financial hardship was starting to increase in 2008, which coincides with the start of the recent global financial crisis. In Figure 1B, the percentage of households not saving on a monthly basis is shown over time. Clearly, this is much more volatile than the other measures of financial hardship and also of a much greater magnitude in terms of the proportion of households concerned. Figure 1C shows the percentage of households reporting financial problems including not saving on a monthly basis, where 49%, 11% and 6% of households report between 1 and 3 problems, respectively.

State dependence is potentially important in modelling financial problems and the empirical model we adopt, as detailed in Section 2.1, allows an examination of the dynamics

[10] Note that interviewers in the BHPS are randomly allocated to respondents and are hence independent of respondent characteristics.

of financial problems. For example, whether the household currently experiences problems relating to loan repayments (fprob2) may be associated with whether such problems have been experienced in the past. Furthermore, there is potential interdependence between the different types of financial hardship experienced by the household. For example, experiencing a particular type of financial problem in the past may lead to the household experiencing a different type of financial problem in the current period. Table 1A in the Appendix provides a correlation matrix between the dependent variables. Clearly, all the indicators of financial hardship are positively related at the 5 per cent level of statistical significance.

We define the control variables included in our empirical analysis below. As discussed in Section 1 above, there is a lack of existing research in this area, hence there are only a small number of studies to draw on with respect to the selection of control variables. We largely follow Böheim and Taylor (2000), Duygan-Bump and Grant (2009), Giarda (2013) and May and Tudela (2005) and include controls for a relatively standard set of socio-economic characteristics. With respect to demographic characteristics, we control for the following head of household characteristics: being male; being white; marital status distinguishing between married, separated or divorced, and widowed (where never married is the omitted category); age distinguishing between being aged 18 to 24, 25 to 34, 35 to 44, 45 to 54, 55 to 64, 65 to 74, 75 to 84 and 85 and over (the omitted category); highest educational qualification distinguishing between degree, teaching or nursing qualification, Advanced (A) level, General Certificate of Secondary Education (GCSE), other (CSE grades 2-5, apprenticeship, commercial qualification and other qualifications) and no educational attainment (the omitted category); labour market status, i.e. employed, self-employed, unemployed, retired and out of the labour market (the omitted category); whether the head of household has a working spouse; and, finally, self-assessed health (SAH) distinguishing between very poor (the omitted category), poor, good, very good and excellent. With respect to health status, there has been some interest in the relationship between health and financial problems in the existing literature, which generally supports a positive association between being in poor health and financial problems, although the direction of causality remains an unresolved issue (see, for example, Bridges and Disney, 2010, and Jenkins et al. 2008). Thus, in order to allow for the potential endogeneity of the self-assessed health measure, we follow the approach suggested by Terza et al. (2008), namely two stage residual inclusion, where the first stage residuals from modelling self-assessed health are included as additional regressors in the second stage along with the observed value of self-assessed health, the potentially endogenous regressor.[11]

With respect to household characteristics, we control for: household composition by including the number of other adults in the household and the number of children in the household; whether the house is owned outright or via a mortgage; the natural logarithm of household labour income; and, finally, the natural logarithm of household non labour income. Our final set of control variables includes region of residence, namely, inner and outer London (the omitted category), the South East, the South West, East Anglia, the East Midlands, the West Midlands conurbation, the rest of the West Midlands, Greater Manchester, Merseyside, the North West, South Yorkshire, West Yorkshire, the rest of Yorkshire and Humberside, Tyne and Wear, the rest of the North, Wales and Scotland. We also control for the month of interview to capture seasonal effects and year to capture any changes in the financial and economic climate over the time period. Summary statistics

[11] In the first stage, SAH is conditioned on its lagged value and variables that are assumed to determine SAH and reporting of SAH, which may vary over time, explicitly specific health problems and the following socio-economic characteristics: age; educational attainment and income. The more objective measures of health, i.e. specific health problems, are used to instrument the endogenous and potentially error ridden subjective health measure. The binary health problems we condition SAH on are reported problems with: arms, legs, hands; sight; hearing; skin condition/allergy; chest/breathing; heart/blood pressure; stomach or digestion; diabetes; anxiety, depression; alcohol or drugs; epilepsy; migraine; and other. These variables pass the exclusion restrictions criteria as they are jointly insignificant in the dynamic financial problems equation.

relating to the explanatory variables incorporated in our econometric analysis are presented in Table 1B in the Appendix.

4.1 Results

Overall Model Performance

The results from estimating the model detailed in Section 2 above are presented in Tables 2, 3 and 4 in the Appendix, which present the Bayesian posterior mean estimates. In terms of overall model performance, the calculated log Bayes factor is 34.02, giving very strong support for rejecting the null hypothesis that the slope parameters are jointly equal to zero, see Kass and Raftery (1995). In terms of the correlations in the unobservable effects across the equations, i.e. the estimated variance – co-variance matrix, these are all statistically significant (see Table 2). In particular, positive correlations are found to exist between all of the financial problems and being unable to save on a monthly basis. These findings indicate interdependence across the different parts of the estimated model and, hence, endorse our joint modelling approach since a univariate approach would overlook such interdependence. Moreover, not taking interdependence into account would result in less efficient parameter estimates from an econometric perspective.

Table 3 in the Appendix presents the results from estimating the missing data selection model, which is estimated jointly with the multi-equation dynamic logit framework. Past and current values of the dependent variables that have statistically significant influences on the probability of dropout are experiencing problems with loan repayments, not being able to keep the home adequately warm and not saving on a monthly basis. Attrition is clearly highly autoregressive and the binary indicator of whether there was a change in interviewer between interviews at periods t and t-1 has a significant effect on dropout, decreasing the likelihood of panel retention, which is consistent with the findings of Cappellari and Jenkins (2008).[12]

Persistence and Interdependence across Financial Problems

In Table 4 Panels A to C in the Appendix, we present the results from estimating the system of nine logit equations of financial hardship. Table 4 Panel A presents the estimates associated with the dynamic process of the dependent variables. Persistence in financial problems, as indicated by a statistically significant positive estimated effect on the relevant lagged dependent variable, is found for experiencing problems paying for accommodation, problems with loan repayments, affordability issues with annual holidays, new furniture and entertaining family and friends as well as being unable to save on a monthly basis. With the exception of entertaining friends and family, it is apparent that the financial problems characterised by the most persistence are those associated with the types of expenditure that are often financed by credit such as loans, mortgages and credit cards. In contrast, the categories of financial problems characterised by the least persistence are those associated with expenditure on food, clothes and heating, which are generally paid for with cash/debit cards rather than via the use of credit. Experiencing problems paying for things bought on credit potentially means falling into arrears, which then means more to pay off in the next period, which can lead to more arrears in the next period and so on, leading to a debt spiral and, hence, persistence in experiencing financial problems.

The results from our flexible modelling framework reveal that there is considerable heterogeneity in terms of state dependence as evidenced by the shaded lead diagonal in Table 4 Panel A. The largest effect is found for problems with loan repayments, where, if the same problem was experienced in the previous year, the likelihood of it occurring in the current period increases considerably. The 'Odds Ratio' (OR) is given by $\exp(\hat{\alpha}_{kk}) = \exp(0.578)$

[12] This is the variable that is used to define the exclusion conditions for identification of the missing-data mechanism.

and is equal to 1.78. Hence, the relative probability of currently reporting problems with loan repayments, conditional on whether they were experienced in the previous year, is 78%. This finding is consistent with other studies for the UK, which have found evidence of state dependence in mortgage arrears (Burrows 1997), general financial housing problems (Böheim and Taylor 2000) and mortgage repayment problems (May and Tudela 2005). The persistence in the occurrence of financial problems over time is also consistent with Giarda (2013), who analyses the Bank of Italy Survey on Household Income and Wealth, where financial distress is based upon the distribution of household net wealth.

With respect to interdependence across the different types of financial problem, it is apparent that experiencing problems with loan repayments in the previous period is positively associated with current difficulties in paying for accommodation, which may lead to issues with respect to access to credit in the future. In addition, it is noticeable that being unable to save on a monthly basis in the previous period is positively associated with the probability of experiencing the eight types of financial problem in the current period, where the largest effect is between being unable to save on a monthly basis in the previous time period and not currently being able to afford new clothes. Such findings may reflect a lack of regular saving leading to households having insufficient funds to draw on in times of financial adversity. For example, in the descriptive analysis of Kempson et al. (2004), a lack of savings was identified as one of the key factors that increase the probability of being in arrears for households with children. Thus, the results from our flexible statistical framework serve to highlight where interdependence exists between the different types of financial problems as well as the absence of interdependence between other types of financial problems thereby providing support to the premise that financial hardship is a complex multi-dimensional concept.

In sum, our modelling contributions presented in Section 2 have unveiled some interesting findings related to the persistence of financial problems as well as the interdependence between financial problems at the household level. It is apparent that our flexible statistical framework has provided further insights into the process behind experiencing financial problems at the household level than afforded by approaches adopted in the existing literature, thereby endorsing our modelling contributions. Moreover, the statistical significance of the lagged dependent variables and the variables capturing interdependence presented in Table 4 Panel A suggests that ignoring such factors would lead to a mis-specified model. Indeed, the log Bayes factor of the full multivariate model (the alternative hypothesis) compared with a model which excludes dynamics and interdependence (the null hypothesis) is 25.9 giving very strong support for rejecting the null hypothesis.

Financial Problems and Demographic Characteristics

In Table 4 Panel B in the Appendix, we present the results associated with the demographic characteristics and how they influence the probability of experiencing the various financial problems. It is apparent from the results that having a male head of household is negatively associated with the probability of experiencing difficulties paying for accommodation, as well as the probability of experiencing financial problems related to paying for heating, an annual holiday, clothes and entertaining friends or family on a monthly basis. This finding is consistent with Giarda (2013) where having a female head potentially exposes the household to higher levels of financial distress. Having a white head of household, on the other hand, is inversely related to the probability of experiencing problems with loan repayments as well as experiencing problems with affording an annual holiday or replacing worn-out furniture. The marital status of the head of household only has a limited influence on the likelihood of experiencing financial problems (the only categories to attain statistical significance for a married head of household are affordability issues with respect to paying for a holiday, purchasing furniture and entertaining friends or family).

In terms of age effects, the probability of experiencing problems paying for housing is positively associated with having a head of household in the youngest age category, aged 18 to 24, relative to being in the oldest age category. Individuals in the youngest age category are more likely to report experiencing such a problem, with OR= $\exp(\hat{\beta}_k) = \exp(0.201)$ =1.22. This is not surprising given that such age groups are likely to be relatively credit constrained, which may reflect limited labour market opportunities at this stage of the life cycle. Although we do control for being employed and labour income, the limited labour market opportunities of young individuals may lead to financial problems via, for example, longer travel to work times and commuting costs or costs associated with training.

Interestingly, having a head of household aged 35 to 44 is also positively correlated with experiencing such financial problems, which may reflect budgetary pressures at this stage of the life cycle related to, for example, children growing up or changes in accommodation requirements. The only other head of household age category to exert a statistically significant influence on the probability of experiencing problems paying for accommodation is having a head of household aged 65 to 74, which is typically the first period of retirement from the labour market. An inverse association is found here which may reflect households having paid off their mortgages as well as possibly benefiting from lump sum pension pay-outs at the point of retirement. In contrast, having a head of household aged 25 to 34, 35 to 44, 45 to 54 and 55 to 64 are all positively associated with experiencing problems repaying loans relative to being in the oldest age category. It is striking to note that such problems are experienced virtually throughout the standard working life of the head of household, although the effect is non linear, in that it increases in magnitude until the age range 35-44, after which the effect tails off in terms of magnitude, although it remains positive and statistically significant up until age 64. The evidence that younger adults are more likely to experience financial difficulties is consistent with the existing literature, see, for example, Kempson et al. (2004), Atkinson et al. (2006) and Taylor (2011).

With respect to the affordability of the various aspects of household expenditure, it is apparent that the head of household age effects vary across the types of expenditure. For example, problems affording heating are only statistically significant for having a head of household aged 65 to 74 and 75 to 84, whereas having a head of household aged 18 to 24, 25 to 34, 35 to 44, 45 to 54, 55 to 64 are all positively associated with experiencing problems affording an annual holiday, which may reflect changes in preferences over the life cycle. A similar pattern of results is evident for affordability issues regarding buying new furniture. In contrast, experiencing problems purchasing new clothes appears to be only prevalent amongst the older age categories. Affordability issues with respect to eating meat or fish every other day appear to be mostly experienced by the younger age groups, whereas there appears to be no clear pattern in head of household age effects in terms of financial problems related to entertaining friends or family. Taken across the eight types of financial problems, having a head of household aged 35 to 44 is positively correlated with all types of financial problem, with the exception of the heating category, which indicates that a range of budgetary pressures are experienced at this particular stage of the life cycle. Conversely, this is one of only two age categories, which is significantly associated with being unable to save on a monthly basis, where such heads of household are less likely to report being unable to save on a regular basis in comparison to the oldest age category, where OR$= \exp(\hat{\beta}_k) = \exp(-0.161) = 0.85$.

With respect to the head of household's highest level of educational attainment, there is no clear pattern evident across the levels of education and types of financial problem. One exception, however, is that the two highest levels of educational attainment are inversely associated with the probability that the household is unable to save on a regular basis. For example, a head of household with a degree is less likely to report being unable to save on a monthly basis in comparison to a comparative individual without any education, ceteris paribus, where OR= $\exp(\hat{\beta}_k) = \exp(-0.169) = 0.84$.

Turning to self-assessed health status, it is apparent that the estimated coefficients on the first stage residuals are positive and statistically significant for the majority of the types of financial problems as well as inability to save on a monthly basis, indicating that self-assessed health generally is an endogenous variable in this framework thereby endorsing our two stage residual inclusion approach. No clear pattern exists with respect to the effect of observed self-assessed health status, with arguably the exception of the poor health category, where statistically significant effects are found with the exception of problems repaying loans, affording an annual holiday and being unable to save on a monthly basis. Such positive effects relative to the very poor health category may reflect the provision of financial support via the social security system for those in very poor health which those in poor health are unable to benefit from.

Having an employed head of household is positively associated with experiencing problems paying for accommodation, which may reflect the lack of benefit support for those in employment. A similar positive association is found in the case of repaying loans, which may reflect the fact that loans are often conditional on being in employment. Employees are more likely to report problems repaying loans than heads of household currently not in the labour market, where OR= $\exp(\hat{\beta}_k) = \exp(0.218) = 1.24$. Noticeably, having an unemployed head of household is positively associated with experiencing all eight types of financial problem. This is consistent with Taylor (2011) who found that being unemployed reduces financial capability. With the exception of heads of household who are employees, labour market status has no association with the probability of reporting inability to save on a monthly basis. Employees are less likely to report being unable to save on a regular basis (in comparison to the reference group), where OR= $\exp(\hat{\beta}_k) = \exp(-0.209) = 0.81$. This is not an income effect as income sources are included as separate controls, as discussed below. Interestingly, there is no significant effect from whether the spouse of the head of household is employed on the likelihood of experiencing financial problems.

Financial Problems, Household and Financial Characteristics

In Table 4 Panel B in the Appendix, we also present the results associated with household and financial characteristics and how they influence financial problems. As expected, the probability of not being able to save on a monthly basis is inversely associated with both household labour income and household non labour income. Specifically, higher labour income is associated with a lower likelihood of being unable to save on a monthly basis, OR= $\exp(\hat{\beta}_k) = \exp(-0.028) = 0.97$ and, similarly, for non labour income, i.e. OR= $\exp(\hat{\beta}_k) = \exp(-0.084) = 0.92$. Interestingly, non labour income is positively correlated with the probability that the household has difficulties repaying loans. This potentially reflects the fact that non labour income includes transfer payments, such as benefit income, and the recipients of such may be likely to fall into repayment difficulties.

The number of adults in the household has no influence on any of the financial problems. However, the number of children does appear to matter. It is apparent that the number of children in the household is positively associated with experiencing a range of financial issues such as those related to accommodation, loan repayments, annual holidays, new furniture, new clothes and entertaining friends and family. In terms of housing tenure, home ownership is inversely associated with the same set of financial problems as well as the probability of being unable to save on a monthly basis. This potentially reflects a wealth effect associated with home ownership.

Financial Problems, Regional and Business Cycle Influences

In Table 4 Panel C in the Appendix, we present the results associated with regional and business cycle effects. The findings indicate the existence of regional differences in the extent to which households experience financial problems. In addition, there appear to be regional differences in the type of financial problems experienced by households. Such findings tie in with those of Böheim and Taylor (2000), who find that the regional unemployment rate has an important influence on the probability that households face difficulties in meeting housing costs, with high unemployment rates being positively related to the probability of households facing such problems. All of the statistically significant estimated coefficients on the regional controls are positive indicating that financial problems are likely to be experienced outside of the London region, which may reflect the concentration of job opportunities in the London area. With the exception of residing in the South West, which is positively associated with experiencing seven of the financial problems, which is perhaps indicative of the high economic inactivity rates over the period relative to London, see UK Office for National Statistics (ONS) (2009), financial problems appear to be particularly prevalent in the northern regions, although there are differences found in the type of financial problems reported. Residing in the Yorkshire and Humberside region, for example, is positively related to experiencing seven types of financial problems, with the largest coefficient estimated for problems paying for accommodation. In contrast, residing in Scotland is positively related to five of the eight financial problems, with statistically insignificant effects for problems paying for accommodation and loan repayments.

Interestingly, differences are also found for regions which are geographically close. For example, residing in West Yorkshire is positively associated with experiencing five of the eight financial problems, where statistically insignificant effects are found in the case of affordability issues with respect to annual holidays, replacing worn out furniture and the purchase of meat and fish on a regular basis. In contrast, residing in the South Yorkshire region is positively associated with reporting three types of financial problems namely affordability issues regarding heating, clothing and entertaining friends or family. The month of interview covariates which are used to control for seasonality are predominantly statistically insignificant. With respect to year, it is apparent that the estimated coefficients across all of the nine dependent variables are inversely related to the probability of experiencing financial problems relative to 1997. Although, the year 1997 is the closest year to the recessionary period of the early 1990s, it should be acknowledged that the UK economy had moved out of recession by this time.

4.2 Caveats

In order to place our findings into a broader context, in this sub-section we discuss some caveats to our proposed modelling approach as well as a comparison with alternative modelling approaches.

Random Effects versus Fixed Effects

Our analysis has shown the importance of state dependence for experiencing current financial problems and has revealed a degree of serial dependence between different types of financial problems. The estimation strategy we have adopted is innovative in that it allows for a multivariate analysis of each outcome simultaneously whilst also controlling for sample missingness, i.e. dropout. However, it is important to acknowledge that the approach relies on random effects and hence we have to make assumptions about the initial condition.

Whilst alternative estimators exist to model dynamic binary outcomes, as far as we are aware, these are all for univariate models. For example, as an alternative strategy we could estimate each outcome one by one, i.e. in a univariate setting, via a conditional maximum likelihood (CML) approach, see Bartoulucci and Nigro (2010) who develop the estimator and Giardi (2013) for an application. This approach does not encounter the initial condition problem and is a fixed effects (FE) estimator. The CML dynamic logit model is asymptotically normally distributed and has good finite properties in terms of bias and efficiency. The CML approach also has some advantages compared to other fixed effects estimators, for example Honoré and Kyriazidou (2000), in that it is more efficient in small panels and performs better as the number of observational units (N) and the degree of state dependence, i.e. α_{kk}, increases and as the panel length (T) decreases, see Bartoulucci and Nigro (2012). In the context of our analysis the panel element T is relatively long (max T=12) and hence this is arguably a disadvantage. There are other disadvantages with this approach in the context of our specific application. In particular, given that the CML is a FE estimator, only time varying covariates can be included in the model and, perhaps a more restrictive feature is that the panel needs to be balanced – that is the same heads of household need to be observed in each year. In our approach, individuals can drop-out of the sample and re-enter the panel. Arguably, this is particularly pertinent given that financial problems are shown to increase the probability of sample dropout.

Random Time Invariant Unobserved Heterogeneity

A typical empirical feature of panel data models is time invariant unobserved heterogeneity which is either assumed to be a fixed effect or a random effect, as is the case in our application. However, this may be unrealistic where time varying unobserved heterogeneity could arise as a result of unobserved time varying omitted variables or macro level shocks which influence each observational unit (N) in a different way. As a consequence, parameter estimates may be biased when the individual effects are assumed to be time invariant when in fact they are really time varying, see Bartolucci et al. (2013). This is also likely to be more problematic in long panels. In the context of our analysis, the panel element (T) is relatively long and hence the above caveat should be noted. Conceptually, it is possible to allow for time varying random effects in our framework. However, it will increase the number of parameters substantially and, consequently, the complexity of the estimation procedure. In addition, the covariance matrix becomes quite sparse when the number of parameters is large. Developing a method for handling estimation of large covariance matrices would be interesting, yet due to the very high-dimensional nature in the context of our particular application, we leave this as an avenue for future research.

5. Conclusion

We have investigated the existence and persistence of financial hardship at the household level using data from the British Household Panel Survey. In particular, we have developed a modelling strategy that makes three important contributions to the existing literature. Firstly, we have modelled nine different types of financial problem within a joint framework, allowing for correlation in the random effects across the nine equations. Such an approach allows for the fact that household financial hardship is influenced by a variety of financial problems, as well as the interdependence which may exist between such problems. In addition, we have developed a dynamic framework in order to model the persistence of financial problems over time by extending our multi-equation framework to allow the presence or otherwise of different types of financial problems in the previous time period to influence the probability that the household currently experiences such problems. Our third contribution relates to the possibility that experiencing financial problems may be correlated with sample attrition. Indeed, the raw data indicates a higher incidence of financial problems for those households who are not in the panel for the entire period under investigation. We have thus modelled missing observations in the panel in order to allow for such attrition. The results from our flexible statistical framework arguably unveil more detailed information on the pattern of financial hardship at the household level than can be discerned from the approaches adopted in the existing literature.

A range of observable characteristics are found to be associated with household financial problems. Hence, policy intervention or help/advice could be targeted at the most vulnerable groups identified, such as the unemployed, who were found to have a higher probability of experiencing financial difficulties across a range of problems relative to those not in the labour market. At a more aggregated level, the results also revealed significant differences between regions in terms of the probability of experiencing financial difficulties, which may be related to local labour market conditions, and so appropriate regional policies might help to reduce such disparities.

Evidence suggesting persistence in financial problems is found for a wide range of problems including problems paying for accommodation, problems with loan repayments, affordability issues with annual holidays, new furniture and entertaining family and friends as well as being unable to save on a monthly basis. Furthermore, interdependence across financial problems is also found to exist between experiencing problems with loan repayments in the previous period and current difficulties in paying for accommodation. Such a finding is potentially problematic since many loans in the UK are secured on the basis of housing. Hence, loan repayment problems may ultimately jeopardise a family's accommodation. Finally, inability to save on a regular basis in the previous time period is positively associated with the likelihood of experiencing eight types of financial problems in the current period. Such findings highlight the important role that savings can play in mitigating a household's future financial problems and lend support to the relatively widespread concern amongst policymakers in a number of countries regarding the relatively low levels of household saving.

References

Albert, P. S. and D. A. Follmann (2003) 'A Random Effects Transition Model for Longitudinal Binary Data with Informative Missingness.' Statistica Neerlandica, 57, 100-11.

Atkinson, A., McKay, S., Kempson, E. and S. Collard (2006) ‘Levels of Financial Capability in the UK: Results of a Baseline Survey.’ FSA Consumer Research Paper 47. FSA: London.

Bartolucci, F. and V. Nigro (2010) ‘A Dynamic Model for Binary Panel Data with Unobserved Heterogeneity Admitting a root-n Consistent Conditional Estimator.’ Econometrica, 78, 719-33.

Bartolucci, F. and V. Nigro (2012) ‘Pseudo Conditional Maximum Likelihood Estimation of the Dynamic Logit Model for Binary Panel Data.’ Journal of Econometrics, 170, 102-16.

Bartolucci, F., Belotti, F. and F. Peracchi (2013) ‘Testing for Time-Invariant Unobserved Heterogeneity in Generalised Linear Models for Panel Data.’ EIEF Working Paper 12/13.

Böheim, R. and M. P. Taylor (2000) ‘My Home was my Castle: Evictions and Repossessions in Britain.’ Journal of Housing Economics, 9, 287-319.

Bridges, S. and R. Disney (2010) ‘Debt and Depression.’ Journal of Health Economics, 29, 388-403.

Burrows, R. (1997) ‘Who Needs a Safety-Net? The Social Distribution of Mortgage Arrears in England.’ Housing Finance, 34, 17-24.

Cappellari, L. and S. Jenkins (2008) ‘Estimating Low Pay Transition Probabilities Accounting for Endogenous Selection Mechanisms.’ Journal of the Royal Statistical Society, Series C, 57, 165-86.

Duffie, D., Eckner, A, Horel, G. and L. Saita (2009) ‘Frailty Correlated Default.’ Journal of Finance, 64, 2089-123.

Duygan-Bump, B. and C. Grant (2009) ‘Household Debt Repayment Behaviour: What Role do Institutions play?’ Economic Policy, January, 107-40.

Eraker, B., Johannes, M. and N. Polson (2003) ‘The Impact of Jumps in Volatility and Returns.’ Journal of Finance, 58, 1269–1300.

Garon, S. (2012) Beyond Our Means: Why America Spends While the World Saves. Princeton University Press.

Gelfand, A. E. and A. F. M. Smith (1990) ‘Sampling-Based Approaches to Calculating Marginal Densities.’ Journal of the American Statistical Association, 85, 398-409.

Giarda, E. (2013) ‘Persistency of Financial Distress Amongst Italian Households: Evidence from Dynamic Models for Binary Panel Data.’ Journal of Banking and Finance, 37, 3425-34.

Greene, W. (2012) Econometric Analysis. International Edition, 7th Edition, Prentice Hall.

Guiso, L., Haliassos, M. and Jappelli, T. (2002) Household Portfolios. MIT Press.

Heckman, J. J. (1981a) ‘Statistical Models for Discrete Panel Data.’ In C. F. Manski and D. McFadden (Eds.) Structural Analysis of Discrete Data with Econometric Applications, London, MIT Press.

Heckman, J. (1981b) ‘The Incidental Parameter Problem and the Problem of Initial Conditions in Estimating a Discrete-Time Discrete Data Stochastic Process.’ In C. F. Manski and D. McFadden (Eds.) Structural Analysis of Discrete Data with Econometric Applications, London, MIT Press.

Honoré, B. E. and E. Kyriazidou (2000) ‘Panel Data Discrete Choice Models with Lagged Dependent Variables.’ Econometrica, 68, 839-74.

Hoogerheide, L., Block, J. H. and R. Thurik (2012) ‘Family Background Variables as Instruments for Education in Income Regressions: A Bayesian Analysis.’ Economics of Education Review, 31, 515-23.

Jenkins R., Bhugra D., Bebbington P., Brugha T., Farrell M., Coid J., Fryers T., Weich S., Singleton N., and H. Meltzer (2008) ‘Debt, Income and Mental Disorder in the General Population.’ Psychological Medicine, 38, 1485–93.

Kass, R. and A. Raftery (1995) ‘Bayes Factors.’ Journal of the American Statistical Association, 90, 773-95.

Kempson, E., McKay, S. and M. Willets (2004) ‘Characteristics of Families in Debt and the Nature of Indebtedness.’ Department of Work and Pensions Research Report 211.

Korteweg, A. (2012) ‘Markov Chain Monte Carlo Methods in Corporate Finance.’ In P. Damien, P. Dellaportas, N. Polson, and D. Stephens (Eds.), MCMC and Hierarchical Models, Oxford University Press.

Little, R. J. A. (1985) ‘A Note about Models for Selectivity Bias.’ Econometrica, 53, 1469-74.

Little, R. J. A. (1995) ‘Modeling the Drop-out Mechanism in Longitudinal Studies.’ Journal of the American Statistical Association, 90, 1112-21.

Lopes, H. F. and C. M. Carvalho (2007) ‘Factor Stochastic Volatility with Time-Varying Loadings and Markov Switching Regimes.’ Journal of Statistical Planning and Inference, 137, 3082-91.

Lunn, D., Spiegelhalter, D., Thomas, A. and N. Best (2009) ‘The BUGS Project: Evolution, Critique and Future Directions.’ Statistics in Medicine, 28, 3049-67.

May, O. and M. Tudela (2005) ‘When is Mortgage Indebtedness a Financial Burden to British Households? A Dynamic Probit Approach.’ Bank of England Working Paper Number 277.

Office for National Statistics (2009) A Profile of Worklessness. Painting Pictures of Place Series – Topic Profiles. http://www.ons.gov.uk/ons/rel/regional-trends/painting-pictures-of-place-series---topic-profiles/worklessness-topic-profile/index.html

Robert, C. and Casella, G. (1999) Monte Carlo Statistical Methods. Springer, New York.

Schräpler, J.-P. (2004) ‘Respondent Behaviour in Panel Studies: A Case Study for Income-Nonresponse by Means of the German-Socio Economic Panel (SOEP).’ Sociological Methods and Research, 33, 118-56.

Taylor, M. P. (2011) ‘Measuring Financial Capability and its Determinants Using Survey Data.’ Social Indicators Research, 102, 297-314.

Taylor, M. P., S. P. Jenkins and A. Sacker (2011) ‘Financial Capability and Psychological Health.’ Journal of Economic Psychology, 32, 710-23.

Terza, J. V., Basu, A. and P. J. Rathouz (2008) ‘Two-Stage Residual Inclusion Estimation: Addressing Endogeneity in Health Econometric Modeling.’ Journal of Health Economics, 27, 531-43.

TABLE 1A: Correlation Matrix

	frob1	frob2	fprob3	fprob4	fprob5	fprob6	fprob7	fprob8	nosave
frpob1	1								
fprob2	0.186 *	1							
fprob3	0.087 *	0.045 *	1						
fprob4	0.229 *	0.189 *	0.158 *	1					
fprob5	0.208 *	0.149 *	0.198 *	0.432 *	1				
fprob6	0.148 *	0.093 *	0.174 *	0.299 *	0.336 *	1			
fprob7	0.119 *	0.082 *	0.175 *	0.229 *	0.230 *	0.263 *	1		
fprob8	0.169 *	0.117 *	0.145 *	0.357 *	0.311 *	0.281 *	0.297 *	1	
nosave	0.105 *	0.056 *	0.046 *	0.172 *	0.122 *	0.089	0.067 *	0.098 *	1

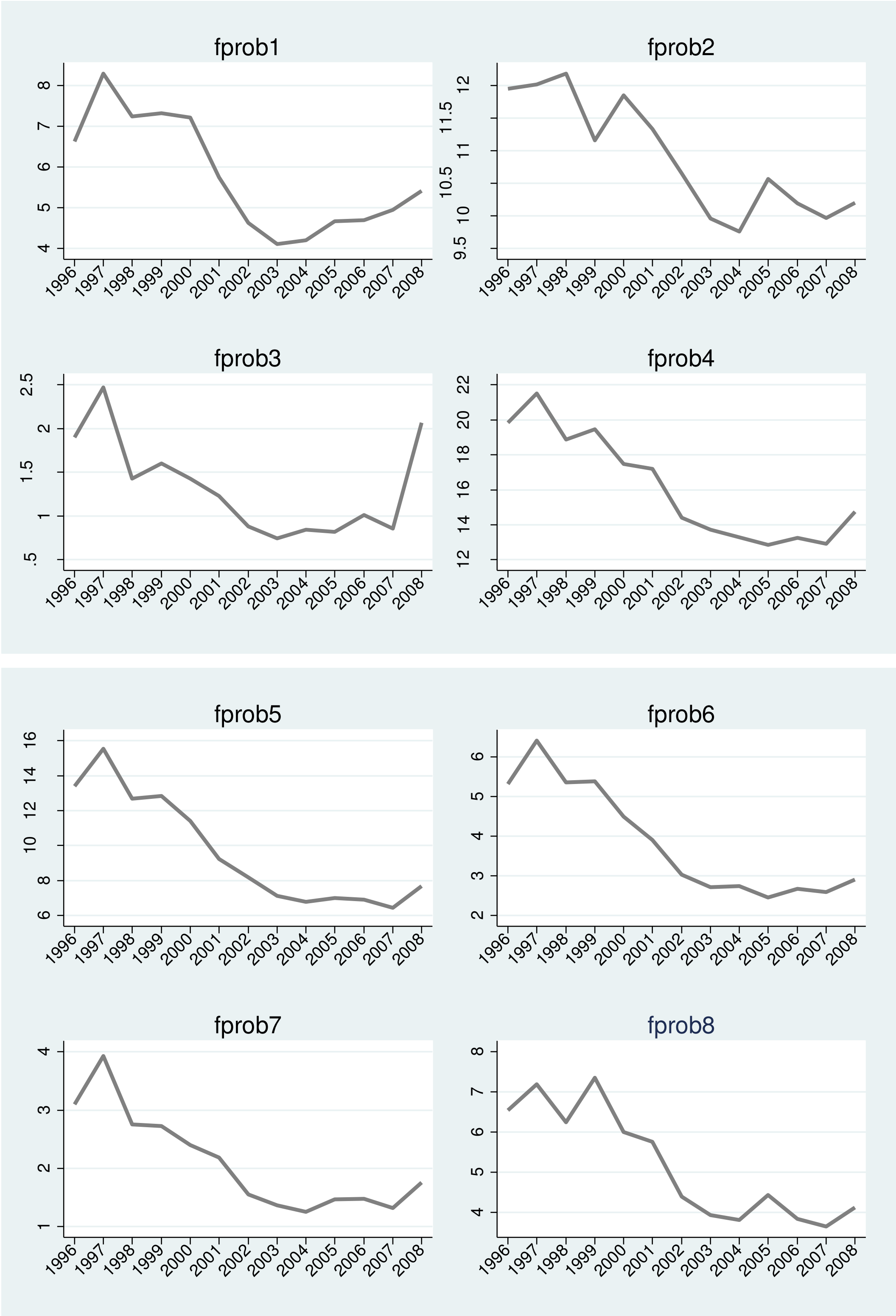
Notes: (i) * denotes statistical significance at the 5% level. (ii) Percentages of heads of household reporting problems faced during the past 12 months with respect to: fprob1=difficulties paying for accommodation; fprob2=repaying loans; fprob3=being able to keep home adequately warm; fprob4=being able to pay for a week's annual holiday; fprob5=replacing worn-out furniture; fprob6=buying new clothes; fprob7=eating meat, chicken, fish every second day; and fprob8=having family/ friend's for a drink or a meal at least once a month.

TABLE 1B: Summary Statistics for the Independent Variables

	VARIABLE DEFINITION	MEAN
Male	=1 if male, 0=female	0.681
White	=1 if white ethnicity, 0=otherwise	0.893
Aged 18-24 [i]	=1 if aged 18 to 24, 0=otherwise	0.021
Aged 25-34 [i]	=1 if aged 25 to 34, 0=otherwise	0.143
Aged 35-44 [i]	=1 if aged 35 to 44, 0=otherwise	0.209
Aged 45-54 [i]	=1 if aged 45 to 54, 0=otherwise	0.186
Aged 55-64 [i]	=1 if aged 55 to 64, 0=otherwise	0.163
Aged 65-74 [i]	=1 if aged 65 to 74, 0=otherwise	0.140
Aged 75-84 [i]	=1 if aged 75 to 84, 0=otherwise	0.109
Married [ii]	=1 if currently married or cohabiting, 0=otherwise	0.518
Sep. or Div. [ii]	=1 if currently separated or divorced, 0=otherwise	0.157
Widowed [ii]	=1 if currently widow or widower, 0=otherwise	0.141
Labour Income	Natural logarithm of household labour income	7.167
Other Income	Natural logarithm of household non labour income	4.170
Degree [iii]	=1 if highest education degree, 0=otherwise	0.134
Teach/Nursing [iii]	=1 if highest education teaching/nursing, 0=otherwise	0.273
A Level [iii]	=1 if highest education A level, 0=otherwise	0.088
GCSE [iii]	=1 if highest education GCSE (O level), 0=otherwise	0.143
Other [iii]	=1 if highest education all other levels, 0=otherwise	0.079
Health: Poor [iv]	=1 if current health poor, 0=otherwise	0.091
Health: Good [iv]	=1 if current health good, 0=otherwise	0.232
Health: V. Good [iv]	=1 if current health very good, 0=otherwise	0.434
Health: Excellent [iv]	=1 if current health excellent, 0=otherwise	0.212
Health Residuals	Generalised health residuals	0.690
Spouse Employed	=1 if spouse employee/self-employed, 0=otherwise	0.366
Employed [v]	=1 if currently employee, 0=otherwise	0.486
Self-Employed [v]	=1 if currently self-employed, 0=otherwise	0.088
Unemployed [v]	=1 if currently unemployed but looking for work, 0=otherwise	0.023
Retired [v]	=1 if currently retired, 0=otherwise	0.297
No. of Adults	Number of other adults in household	0.910
No. of Children	Number of children in household	0.521
Own Home	=1 if home owned outright or on a mortgage, 0=otherwise	0.717
South East [vi]	=1 if currently lives in South East, 0=otherwise	0.124
South West [vi]	=1 if currently lives in South West, 0=otherwise	0.061
East Anglia [vi]	=1 if currently lives in East Anglia, 0=otherwise	0.029
East Midlands [vi]	=1 if currently lives in East Midlands, 0=otherwise	0.057
West Midlands [vi]	=1 if currently lives in West Midlands, 0=otherwise	0.023
Rest W. Midlands [vi]	=1 if currently lives in rest of West Midlands, 0=otherwise	0.034
Gr. Manchester [vi]	=1 if currently lives in Greater Manchester, 0=otherwise	0.026
Merseyside [vi]	=1 if currently lives in Merseyside, 0=otherwise	0.014
North West [vi]	=1 if currently lives in North East, 0=otherwise	0.031
South Yorkshire [vi]	=1 if currently lives in South Yorkshire, 0=otherwise	0.018
West Yorkshire [vi]	=1 if currently lives in West Yorkshire, 0=otherwise	0.022
Rest of Yorkshire [vi]	=1 if currently lives in rest of Yorkshire and Humberside, 0=otherwise	0.022
Tyne & Wear [vi]	=1 if currently lives in Tyne and Wear, 0=otherwise	0.016
Rest of the North [vi]	=1 if currently lives in rest of North, 0=otherwise	0.026
Wales [vi]	=1 if currently lives in Wales, 0=otherwise	0.151
Scotland [vi]	=1 if currently lives in Scotland, 0=otherwise	0.172

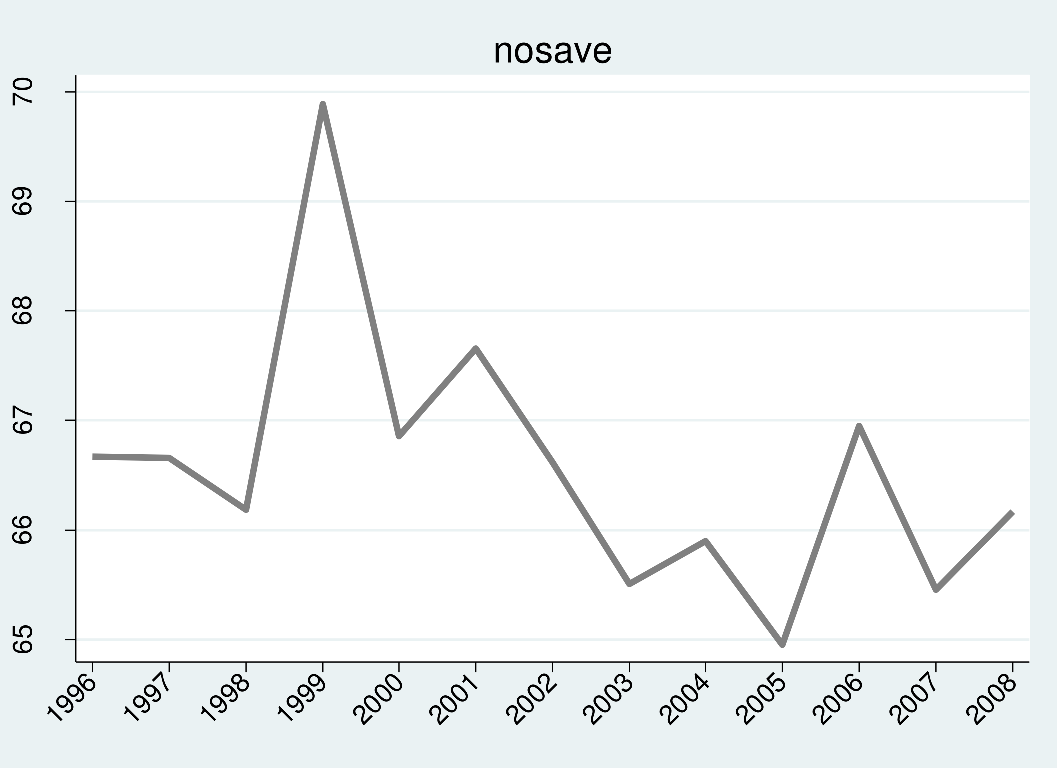
Notes: (i) the omitted age category is 85 and above; (ii) the omitted category is never married; (iii) the omitted highest education category is no education; (iv) the omitted health category is very poor health; (v) the omitted labour force status category is out of the labour market; (vi) the omitted region is inner and outer London.

FIGURE 1A: Indicators of Financial Hardship – Percentage Reporting a Problem



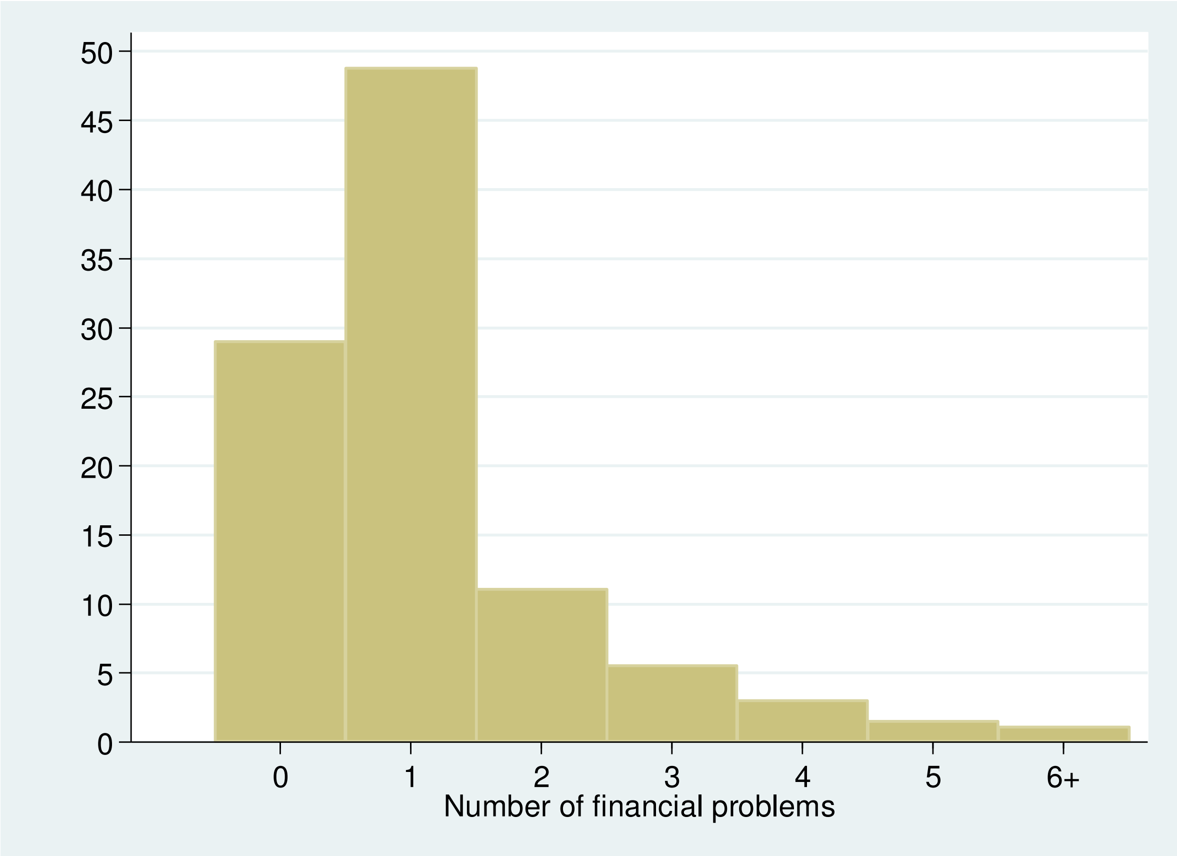
Notes: Percentages of heads of household reporting problems faced during the past 12 months with respect to: fprob1=difficulties paying for accommodation; fprob2=repaying loans; fprob3=being able to keep home adequately warm; fprob4=being able to pay for a week's annual holiday; fprob5=replacing worn-out furniture; fprob6=buying new clothes; fprob7=eating meat, chicken, fish every second day; and fprob8=having family/ friend's for a drink or a meal at least once a month.

FIGURE 1B: Percentage of Households Reporting No Regular Monthly Savings



Note: The percentage of heads of household not able to save on a monthly basis (nosave).

FIGURE 1C: Histogram of the Number of Types of Financial Problems



Note: this is the sum of fprob1 through to fprob8 and nosave.

TABLE 2: Variance – Co-variance Matrix

	frob1	frob2	fprob3	fprob4	fprob5	fprob6	fprob7	fprob8	nosave
frpob1	0.354 *	0.328 *	0.196 *	0.447 *	0.478 *	0.399 *	0.214 *	0.372 *	0.269 *
fprob2		0.341 *	0.193 *	0.425 *	0.458 *	0.402 *	0.212 *	0.354 *	0.151 *
fprob3			0.123 *	0.255 *	0.271 *	0.237 *	0.125 *	0.212 *	0.104 *
fprob4				0.587 *	0.616 *	0.526 *	0.279 *	0.479 *	0.291 *
fprob5					0.667 *	0.557 *	0.296 *	0.512 *	0.332 *
fprob6						0.520 *	0.265 *	0.433 *	0.105 *
fprob7							0.145 *	0.230 *	0.083 *
fprob8								0.405 *	0.258 *
nosave									0.957 *

Notes: (i) * denotes statistical significance at the 5% level. (ii) Percentages of heads of household reporting problems faced during the past 12 months with respect to: fprob1=difficulties paying for accommodation; fprob2=repaying loans; fprob3=being able to keep home adequately warm; fprob4=being able to pay for a week's annual holiday; fprob5=replacing worn-out furniture; fprob6=buying new clothes; fprob7=eating meat, chicken, fish every second day; and fprob8=having family/ friend's for a drink or a meal at least once a month.

TABLE 3: Missing Data Selection Model

	BPME	
Missing[t-1]	1.700	*
fprob1	0.181	
fprob1[t-1]	0.166	
fprob2	0.645	*
fprob2[t-1]	1.996	*
fprob3	2.112	*
fprob3[t-1]	2.230	*
fprob4	0.189	
fprob4[t-1]	1.639	*
fprob5	-0.191	
fprob5[t-1]	0.911	
fprob6	0.729	
fprob6[t-1]	-1.019	
fprob7	1.903	*
fprob7[t-1]	0.616	
fprob8	1.088	*
fprob8[t-1]	0.343	
nosave	1.098	*
nosave[t-1]	4.471	*
change in interviewer	1.071	*
change in interviewer[t-1]	3.514	*
OBS	123,432	

Notes: (i) * denotes statistical significance at the 5% level. (ii) BPME denotes Bayesian posterior mean estimates. (iii) Percentages of heads of household reporting problems faced during the past 12 months with respect to: fprob1=difficulties paying for accommodation; fprob2=repaying loans; fprob3=being able to keep home adequately warm; fprob4=being able to pay for a week's annual holiday; fprob5=replacing worn-out furniture; fprob6=buying new clothes; fprob7=eating meat, chicken, fish every second day; and fprob8=having family/ friend's for a drink or a meal at least once a month.

TABLE 4: Results from the Multivariate Dynamic Logit Model

PANEL A: Lagged Dependent Variable and Interdependence Between Financial Problems

	fprob1	**fprob2**	**fprob3**	**fprob4**	**fprob5**	**fprob6**	**fprob7**	**fprob8**	**nosave**
	BPME	BPME	BPME	BPME	BPME	BPME	BPME	BPME	BPME
Intercept	-2.152 *	-2.567 *	-3.133 *	-1.089 *	-1.957 *	-2.745 *	-3.341 *	-2.598 *	1.661 *
fprob1[t-1]	0.401 *	0.132	0.161	-0.043	-0.048	-0.014	0.112	0.100	0.143
fprob2[t-1]	0.251 *	0.578 *	-0.087	0.078	0.054	-0.054	0.118	-0.129	0.021
fprob3[t-1]	-0.194 *	0.078	0.075	-0.073	-0.151	-0.066	-0.048	-0.048	-0.052
fprob4[t-1]	0.076	0.033	-0.125	0.413 *	0.114	0.143 *	-0.132	0.150	0.069
fprob5[t-1]	0.063	-0.210 *	0.124	-0.051	0.446 *	0.012	0.051	0.040	0.021
fprob6[t-1]	-0.042	-0.053	0.009	-0.037	-0.066	0.133	0.161 *	-0.180 *	-0.079
fprob7[t-1]	-0.090	-0.132	0.052	-0.053	-0.223 *	-0.089	0.092	-0.125	-0.085
fprob8[t-1]	-0.098	0.014	-0.062	0.016	0.070	0.099	-0.192 *	0.242 *	-0.059
nosave[t-1]	0.154 *	0.207 *	0.119 *	0.126 *	0.227 *	0.167 *	0.246 *	0.158 *	0.733 *
OBS					123,432				

Notes: (i) * denotes statistical significance at the 5% level. (ii) BPME denotes Bayesian posterior mean estimates. (iii) Percentages of heads of household reporting problems faced during the past 12 months with respect to: fprob1=difficulties paying for accommodation; fprob2=repaying loans; fprob3=being able to keep home adequately warm; fprob4=being able to pay for a week's annual holiday; fprob5=replacing worn-out furniture; fprob6=buying new clothes; fprob7=eating meat, chicken, fish every second day; and fprob8=having family/ friend's for a drink or a meal at least once a month.

TABLE 4 (CONT.): Results from the Multivariate Dynamic Logit Model

PANEL B: Demographic, Household and Financial Controls

	fprob1	**fprob2**	**fprob3**	**fprob4**	**fprob5**	**fprob6**	**fprob7**	**fprob8**	**nosave**
	BPME	BPME	BPME	BPME	BPME	BPME	BPME	BPME	BPME
Male	-0.175 *	-0.050	-0.204 *	-0.445 *	-0.121	-0.307 *	-0.127	-0.242 *	0.105
White	-0.156 *	-0.145 *	0.038	-0.227 *	-0.185 *	-0.081	0.006	-0.160 *	-0.045
Aged 18-24	0.201 *	0.077	0.095	0.209 *	0.224 *	0.041	0.183 *	0.281 *	0.035
Aged 25-34	0.123	0.327 *	-0.015	0.200 *	0.209 *	0.041	0.180 *	0.138	-0.268 *
Aged 35-44	0.152 *	0.331 *	0.136	0.260 *	0.305 *	0.244 *	0.239 *	0.210 *	-0.161 *
Aged 45-54	-0.003	0.150 *	0.136	0.193 *	0.107	-0.059	0.073	0.167 *	0.067
Aged 55-64	0.106	0.173 *	0.057	0.151 *	0.006	0.187 *	0.145	0.106	0.062
Aged 65-74	-0.212 *	0.096	0.188 *	0.038	-0.069	0.349 *	-0.015	0.169 *	0.051
Aged 75-84	0.054	-0.028	0.219 *	0.008	0.105	0.264 *	0.231 *	0.105	-0.028
Married	-0.026	-0.073	-0.080	-0.171 *	-0.362 *	-0.079	-0.148	-0.183 *	-0.030
Sep. or Div.	0.191	0.163	-0.076	0.025	0.120	-0.029	0.220	0.054	-0.025
Widowed	0.121	-0.021	-0.038	-0.024	0.118	-0.015	0.094	0.085	0.074
Labour Income	-0.027 *	0.011	0.002	-0.040 *	-0.021	-0.014	-0.008	-0.037 *	-0.028 *
Other Income	0.014	0.040 *	-0.004	-0.039 *	0.007	-0.013	0.004	-0.012	-0.084 *
Degree	0.041	-0.014	0.061	-0.025	0.076	0.110	0.189 *	-0.019	-0.169 *
Teach/Nursing	0.035	0.178 *	0.038	0.069	0.048	-0.004	0.136	0.133	-0.198 *
A Level	0.157 *	0.008	0.144	0.026	0.143	0.194 *	0.214 *	0.089	-0.120
GCSE	0.099	0.014	0.019	0.163 *	0.095	0.077	0.145	0.128	-0.117
Other	0.050	0.009	0.025	0.009	0.007	0.004	0.009	-0.028	0.021
Health: Poor	0.188 *	0.071	0.170 *	0.059	0.244 *	0.244 *	0.230 *	0.173 *	0.027
Health: Good	0.225 *	0.091	0.084	0.107	0.256 *	0.109	0.214 *	0.184 *	0.055
Health: V. Good	-0.036	0.051	-0.013	-0.042	0.083	0.197 *	0.012	-0.012	0.037
Health: Excellent	-0.061	-0.039	-0.025	-0.215 *	0.091	0.034	-0.003	-0.060	-0.023
Health Residuals	0.032 *	0.025 *	0.016	0.009	0.030 *	0.032 *	0.011	0.039 *	0.029 *
Spouse Employed	0.094	0.159 *	0.040	0.089	0.059	0.021	0.253 *	0.152	0.099
Employed	0.138 *	0.218 *	0.126	-0.094	-0.115	-0.091	0.148	0.089	-0.209 *
Self-Employed	0.243 *	0.076	0.092	-0.014	0.017	-0.007	0.209 *	0.067	0.115
Unemployed	0.161 *	0.151 *	0.307 *	0.286 *	0.221 *	0.184 *	0.231 *	0.182 *	0.023
Retired	-0.121	-0.176 *	0.073	-0.278 *	0.006	-0.078	0.042	0.107	0.145 *
No. of Adults	-0.036	0.006	0.056	-0.013	0.006	0.006	0.050	-0.018	-0.042
No. of Children	0.082 *	0.195 *	0.086	0.225 *	0.137 *	0.139 *	0.039	0.171 *	0.048
Own Home	-0.190 *	-0.275 *	-0.080	-0.381 *	-0.148 *	-0.237 *	0.037	-0.179 *	-0.268 *
OBS					123,432				

Notes: (i) * denotes statistical significance at the 5% level. (ii) BPME denotes Bayesian posterior mean estimates. (iii) Percentages of heads of household reporting problems faced during the past 12 months with respect to: fprob1=difficulties paying for accommodation; fprob2=repaying loans; fprob3=being able to keep home adequately warm; fprob4=being able to pay for a week's annual holiday; fprob5=replacing worn-out furniture; fprob6=buying new clothes; fprob7=eating meat, chicken, fish every second day; and fprob8=having family/ friend's for a drink or a meal at least once a month.

TABLE 4 (CONT.): Results from the Multivariate Dynamic Logit Model

PANEL C: Regional and Business Cycle Controls

	fprob1		**fprob2**		**fprob3**		**fprob4**		**fprob5**		**fprob6**		**fprob7**		**fprob8**		**nosave**	
	BPME		BPME		BPME		BPME		BPME		BPME		BPME		BPME		BPME	
South East	0.100		0.180	*	-0.130		-0.076		-0.008		0.139		0.110		0.014		-0.073	
South West	0.262	*	0.208	*	0.161	*	0.027		0.268	*	0.272	*	0.321	*	0.259	*	0.052	
East Anglia	0.112		0.051		0.128		0.086		0.036		0.119		0.135		0.126		-0.078	
East Midlands	-0.038		0.089		0.257	*	0.196	*	0.095		0.243	*	0.153		0.075		-0.040	
West Midlands	0.224	*	0.130		0.292	*	0.015		-0.004		0.129		0.086		0.087		-0.102	
Rest W. Midlands	0.011		-0.002		0.261	*	0.160		0.026		0.022		0.205	*	-0.056		-0.029	
Gr. Manchester	0.124		0.154		0.289	*	0.047		0.040		0.062		0.045		0.106		0.101	
Merseyside	0.135		-0.027		0.103		0.120		0.107		0.060		0.283	*	0.126		-0.090	
North West	0.158		0.244	*	0.194	*	0.121		0.046		-0.098		0.181	*	0.041		0.083	
South Yorkshire	0.089		0.139		0.289	*	0.040		0.041		0.260	*	-0.032		0.242	*	0.088	
West Yorkshire	0.279	*	0.250	*	0.212	*	0.059		0.162		0.262	*	0.016		0.300	*	0.131	
Rest of Yorkshire	0.256	*	0.166	*	0.211	*	0.236	*	0.152		0.222	*	0.218	*	0.199	*	0.150	
Tyne & Wear	0.147		0.028		0.163	*	0.092		0.256	*	0.006		0.199	*	0.154		0.030	
Rest of the North	-0.018		0.211	*	0.229	*	0.089		0.112		0.388	*	0.191	*	0.083		0.097	
Wales	0.180	*	0.249	*	0.124		0.285	*	0.190	*	0.137		0.176		0.253	*	-0.051	
Scotland	0.160		0.113		0.243	*	0.296	*	0.195	*	0.153		0.325	*	0.314	*	0.104	
January	0.245		0.236		0.337		0.582	*	-0.120		0.017		0.379		0.085		-0.310	
February	-0.657		-0.199		1.373	*	-0.706		-0.286		-0.028		-0.792		-0.431		-0.600	
March	0.878		-0.396		0.189		-0.296		-0.433		-0.007		-1.066		-0.181		0.224	
April	-0.618		0.442		-0.649		-1.338	*	0.277		-0.021		0.181		-0.588		1.426	
May	-0.953		0.272		-1.440		1.656		0.118		0.014		1.311		0.439		-0.455	
September	0.017		-0.186	*	0.088		0.052		0.092		0.030		-0.145		0.067		-0.088	
October	-0.030		-0.099		0.175		0.012		0.065		0.008		-0.310	*	0.181		-0.048	
November	0.138		-0.071		0.283		-0.049		0.065		0.014		-0.133		-0.066		-0.120	
December	0.575		-0.316		-0.165		0.008		0.175		0.046		0.180		0.310		-0.145	
1998	-1.179	*	-0.623	*	-2.158	*	-0.744	*	-0.873	*	-1.231	*	-2.167	*	-0.886	*	-0.353	*
1999	-1.302	*	-0.858	*	-2.055	*	-0.718	*	-0.755	*	-1.566	*	-2.006	*	-1.201	*	-0.262	
2000	-1.053	*	-0.826	*	-3.109	*	-0.937	*	-0.870	*	-1.444	*	-2.254	*	-1.468	*	-0.273	
2001	-1.267	*	-1.172	*	-2.470	*	-1.131	*	-1.065	*	-1.654	*	-2.233	*	-1.649	*	-0.086	
2002	-1.310	*	-0.921	*	-2.491	*	-1.309	*	-1.128	*	-1.539	*	-3.082	*	-2.011	*	-0.001	
2003	-1.297	*	-1.082	*	-2.693	*	-1.249	*	-1.188	*	-1.836	*	-2.409	*	-1.914	*	-0.055	
2004	-1.601	*	-1.071	*	-2.067	*	-1.150	*	-1.440	*	-1.636	*	-2.250	*	-2.118	*	-0.128	
2005	-1.390	*	-1.044	*	-2.160	*	-1.565	*	-1.599	*	-2.289	*	-3.003	*	-1.990	*	-0.470	*
2006	-1.503	*	-0.871	*	-3.484	*	-1.454	*	-1.664	*	-1.733	*	-2.639	*	-1.887	*	-0.045	
2007	-1.022	*	-0.660	*	-2.908	*	-1.552	*	-1.783	*	-2.355	*	-2.986	*	-1.806	*	-0.341	
2008	-1.351	*	-0.628	*	-1.593	*	-1.070	*	-1.675	*	-2.013	*	-2.565	*	-1.237	*	-0.350	
OBS									123,432									

Notes: (i) * denotes statistical significance at the 5% level. (ii) BPME denotes Bayesian posterior mean estimates. (iii) Percentages of heads of household reporting problems faced during the past 12 months with respect to: fprob1=difficulties paying for accommodation; fprob2=repaying loans; fprob3=being able to keep home adequately warm; fprob4=being able to pay for a week's annual holiday; fprob5=replacing worn-out furniture; fprob6=buying new clothes; fprob7=eating meat, chicken, fish every second day; and fprob8=having family/ friend's for a drink or a meal at least once a month.