Sheffield Economic Research Paper Series

SERP Number: 2012022

ISSN 1749-8368

Sarah Brown
Pulak Ghosh
Karl Taylor

The Existence and Persistence of Household Financial Hardship

September 2012

Department of Economics
University of Sheffield
9 Mappin Street
Sheffield
S1 4DT
United Kingdom
www.shef.ac.uk/economics

The Existence and Persistence of Household Financial Hardship

Sarah Brown[a], Pulak Ghosh[b] and Karl Taylor[a]

[a]*Department of Economics*
University of Sheffield
9 Mappin Street
Sheffield S1 4DT
Great Britain

[b]*Department of Quantitative Methods and Information Systems*
Indian Institute of Management
Bangalore
India

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. We model missing observations in the panel in order to allow for such attrition. Our findings 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 in previous time periods can play in mitigating current financial problems.

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

Acknowledgements: We are very grateful to Steve McIntosh, Gurleen Popli and seminar participants at the Centre for Finance, Credit and Macroeconomics, University of Nottingham, for excellent comments and advice. We are grateful to the Data Archive at the University of Essex for supplying the *British Household Panel Survey* waves 1 to 18. The normal disclaimer applies.

October 2012

1. Introduction and Background

The recent financial crisis has revealed the financial vulnerability that a significant number of households face in many developed economies such as the UK and the US, with households simultaneously holding relatively high levels of debt and 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 job loss, a fall in real wages or changes in their personal circumstances such as divorce or changes in household expenditure and financial commitments due to, for example, having children.[1] Households experiencing such changes in their financial situation may encounter problems in meeting their financial obligations leading to financial problems and hardship.

Although there is a growing empirical literature exploring households' financial portfolios (see, for example, Guiso et al., 2002, for a comprehensive review of this area), 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, for a comprehensive review of this area). 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

[1] In a similar vein, Love (2010) finds evidence suggesting that marital status and children influence household portfolio decisions.

analysis of household 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. Firstly, we model a wide range of household financial problems within a joint framework, allowing for correlation in the random effects across the different types of financial problems. 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 model missing observations in the panel in order to allow for such attrition. These three contributions are discussed in detail below.

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 problem within a joint framework. Hence, our joint modelling approach 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. 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. We adopt a wider approach than the existing literature and explore a range of financial problems, including housing payment problems, to allow for the fact that financial hardship is a multi-dimensional concept. 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. 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, Anderloni et al. (2011) adopt such an approach based on cross-sectional Italian household survey data, whereby they use principal components analysis to create a financial vulnerability index drawing on both subjective and objective measures of financial vulnerability such as problems paying utility bills and unsuccessful credit applications. Similarly, 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.

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 inclusion of the lagged dependent variables) allows for state dependence. Allowing for the dynamic aspect to household finances is important: as stated by Campbell (2006), households have to plan over long, yet finite, horizons. 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 reporting that they do so 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. In contrast, we model missing observations in the panel using a multinomial logit model where we distinguish between 'intermittent missing' where a household could be missing, for example, for just one year but then may re-enter the sample in later years and 'monotone missing,' where, once a missing observation is observed for a household, the household is always missing from the sample from this year onwards. We distinguish between two types of missing observations since the reasons behind a household completely dropping out of the panel may differ from those behind a household being observed intermittently over the course of the panel.

The rest of the paper is structured as follows. Our modelling framework incorporating these three potentially important contributions to the existing literature on household finances is detailed in Section 2. The data employed in our empirical analysis is described in Section 3 with the results of the empirical analysis discussed in Section 4. Finally, Section 5 concludes the paper.

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^{th} financial problem of the i^{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 multinomial logit model. The final step entails the construction of the joint likelihood of the financial problems of all households in the sample.

Let $y_{kit} \in \{0,1\}$ be the incidence of the $k(= 1,2, \ldots, K)^{\text{th}}$ financial problem of the $i(= 1,2, \ldots, I)^{\text{th}}$ household at time $t(= 1,2, \ldots, T)$. 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, $\boldsymbol{X}_{kit}$, 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 l^{th} 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., $b_i = (b_{1i} b_{2i}, \ldots, b_{Ki})^T \sim N(0, \sum)$.

The model described by equations (1) and (2) exploits the panel structure of the household level 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 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 k^{th} financial problem and the l^{th} $(l = 1,2, \dots, k-1, k+1, \dots, K)$ 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, 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_{ik} 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:

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

$$\text{logit}(p_{ki0}) = \boldsymbol{X}_{ki0}^{T}\gamma_k + \theta_k v_{ik} \tag{4}$$

where $\boldsymbol{X}_{ki0}^{T}$ are pre-sample values of covariates.

2.2 Modelling Missing Observations

Due to missing data, some information for some households is unavailable. If the missing information is unrelated to the survey, 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.

Let R_{it} be a missing value indicator that takes three values as follows:

$$R_{it} = \begin{cases} 0 & \text{if } y_{it} \text{ is observed at time t} \\ 1 & \text{if } y_{it} \text{ is intermittent missing at time t} \\ 2 & \text{if } y_{it} \text{ drops out at time t} \end{cases} \quad (5)$$

The missing data mechanism is assumed to depend on the history of measurement up to and including the t^{th} observation, i.e.,

$$P(R_{it} = r|H_{it}) = P_t(H_{it}, y_{it}; \varphi) \quad (6)$$

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.

We model the probability of missing data via an AR(1) process as follows,

$$\eta_{it1} = \lambda^1 + \sum_{k=1}^{K} \theta_k^1 \, y_{kit} + \sum_{k=1}^{K} \delta_k^1 \, y_{ki,t-1}.$$

and

$$\eta_{it2} = \lambda^2 + \sum_{k=1}^{K} \theta_k^2 \, y_{kit} + \sum_{k=1}^{K} \delta_k^2 \, y_{ki,t-1}.$$

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. Note that, when $\theta_k \neq 0$ or $\delta_k \neq 0$, the missing observation is informative. The parameters θ and δ relate the intermittent missing cases and the drop outs, respectively, to the response process. The missing data mechanism is modelled as a multinomial regression with three states (Albert and Follmann, 2003) as follows:

$$P\big(R_{it} = r|H_{it}, R_{i,t-1} \neq 2\big) = P_{itr} \begin{cases} \frac{1}{1+\sum_{r=1}^{2}\exp(\eta_{itr})}, & r = 0 \\ \frac{\exp(\eta_{itr})}{1+\sum_{r=1}^{2}\exp(\eta_{itr})}, & r = 1,2 \end{cases} \tag{7}$$

The missing data mechanism is non-ignorable when θ and δ take non-zero values. Also, 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 ith household can be written as:

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

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

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

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

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:

$$L_i(\boldsymbol{R}_i|\boldsymbol{y}_i, \boldsymbol{b}_i; \Omega_2) = \prod_{t=1}^{n_i}(1 - P_{it1} - P_{it2})^{I(R_{it}=0)}\, P_{it1}^{I(R_{it}=1)} P_{it2}^{I(R_{it}=2)} \tag{10}$$

where n_i is the last observation prior to the missing data and $I(R_{it} = r)$ are indicator functions, which take the value of one when the condition is met.

Finally, $L_i(\boldsymbol{b}_i)$ is the likelihood of the multivariate normal random effects with 0 mean, i.e. $L_i(\boldsymbol{b}_i) \propto \exp\frac{1}{|\Sigma|}\exp\big(\boldsymbol{b}_i^T\Sigma^{-\boldsymbol{1}}\boldsymbol{b}_i\ \big)$. We then obtain the unconditional likelihood function for household i as follows:

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

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:

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

We use a Bayesian Markov Chain Monte Carlo (MCMC) method for parameter estimations for three main reasons. 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). Note that to estimate our proposed joint model, one would have to develop a two stage estimation procedure, which may not be consistent and may increase the standard errors in estimating the parameters. Secondly, the Bayesian strategy enables us to examine the entire posterior distribution of the parameters, and to avoid dependence on asymptotic properties to assess the sampling variability of the parameter estimates. Finally, our approach allows us to 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 financial 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

3.1 The Dependent Variables

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.[2] 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

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

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. The total number of observations in the panel is 123,432 observations. The households can be split into three categories: those households observed in the panel for each of the 12 years, which comprises 1,669 households; those households with intermittent missing observations, where they could be missing, for example, for just one year but then may re-enter the sample in later years, which comprises 7,405 households; and, those households, who are monotone missing, where, once a missing observation is observed for a household, the household is always missing from the sample from this year onwards, which comprises 1,212 households.[3] Hence, out of the total number of observations, 16% (20,028 observations) represent the households which are always in the panel, 72% (88,860 observations) represent the households with intermittent missing observations and 12% (14,544 observations) represent the households with monotone missing observations.

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*,

[3] In this case, the household must be observed for at least one year over the period 1997 to 2008.

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 affected. In Sections 3.2 to 3.5 below, we define the control variables included in our empirical analysis. 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 drawn on with respect to the selection of control variables. We largely follow Böheim and Taylor (2000), Duygan-Bump and Grant (2009) and May and Tudela (2005) and include controls for a relatively standard set of socio-economic characteristics.

3.2 Control Variables: Dynamics – Allowing for Persistence

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 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 inter-dependence 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.

3.3 Control Variables: Demographic Characteristics

With respect to demographic characteristics, we control for the following head of household characteristics: being male; being white; being married; 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 and no educational qualification (the omitted category);[4] labour market status, i.e. employed, self-employed, unemployed, retired and out of the labour market (the omitted category); and, finally, self-assessed health 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

[4] GCSE level qualifications are taken after eleven years of formal compulsory schooling and approximate to the U.S. honours high school curriculum. The A level qualification is a public examination taken by 18 year olds over a two year period studying between one to four subjects and is the main determinant of eligibility for entry to higher education in the UK.

included as additional regressors in the second stage along with the observed value of self-assessed health, the potentially endogenous regressor.[5]

3.4 Control Variables: Household and Financial Characteristics

With respect to household characteristics, we control for: 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.

3.5 Control Variables: Regional and Business Cycle Influences

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. Finally, we control for year to capture any changes in the financial and economic climate over the time period. Summary statistics relating to the explanatory variables incorporated in our econometric analysis are presented in Table 1B in the Appendix.

4. Results

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 24.02, 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 4). Positive correlations are found to exist between all of the financial

[5] We model self-assessed health (SAH) as a random effects ordered probit model, with the standard set of socio-economic characteristics as well as measures of specific health problems as controls. The results, which accord with the existing literature, are available on request.

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.

4.1 The Missing Observations Selection Model

Table 2 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 both the probability of monotone missing values and the probability of intermittent missing values are experiencing affordability issues with respect to heating and purchasing meat and fish on a regular basis in both the current and the previous time period, experiencing affordability issues regarding clothing in the current period and the inability to save on a monthly basis in the previous time period. Noticeably, intermittent missing values are also influenced by experiencing problems with loan repayments and the affordability of annual holidays in both the current and the previous time periods indicating the importance of distinguishing between the two types of missing observations.

4.2 Persistence and Interdependence across Financial Problems

In Table 3 Panels A to C in the Appendix, we present the results from estimating the system of nine logit equations of financial hardship. Table 3 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 card 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.

There is considerable heterogeneity in terms of state dependence as evidenced by the shaded lead diagonal in Table 3 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 $\exp(\hat{\alpha}_{kk}) = \exp(0.585)$ and is equal to 1.79. This finding is consistent with other studies, 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).

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. 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 a finding 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.

4.3 Financial Problems and Demographic Characteristics

In Table 3 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 positively associated with the probability of experiencing difficulties paying for accommodation, the probability of experiencing problems repaying loans as well as the probability of experiencing financial problems related to paying for heating, an annual holiday, new furniture, clothes and entertaining friends or family on a monthly basis. Having a white head of household, on the other hand, is inversely associated with the probability of experiencing problems with loan repayments as well as experiencing problems with affording an annual holiday or replacing worn-out furniture. Having a married head of household is inversely associated with experiencing financial problems (although the only categories to attain statistical significance are affordability issues with respect to 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, where OR= $\exp(\hat{\beta}_k) = \exp(0.206)$ =1.23. 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.[6] Interestingly, having a head of household aged 35

[6] 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.

to 44 is also positively related to 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.

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 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 associated 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 the only age category, 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$= \exp(\hat{\beta}_k) = \exp(-0.154) = 0.86$.

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$= \exp(\hat{\beta}_k) = \exp(-0.188) = 0.83$.

Turning to self-assessed health status, it is apparent that the estimated coefficients on the first stage residuals are positive and statistically significant for all types of financial problems (with the exception of affordability issues relating to annual holidays) as well as inability to save on a monthly basis, indicating that self-assessed health 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= $\exp(\hat{\beta}_k) = \exp(0.212) = 1.24$. Noticeably, having an unemployed head of household is positively associated with experiencing all eight types of financial problem. 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= $\exp(\hat{\beta}_k) = \exp(-0.215) = 0.81$. This is not an income effect as income sources are included as separate controls, as discussed below.

4.4 Financial Problems and Household and Financial Characteristics

In Table 3 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= $\exp(\hat{\beta}_k) = \exp(-0.029) = 0.97$ and, similarly, for non labour income, OR= $\exp(\hat{\beta}_k) = \exp(-0.087) = 0.92$. It is also 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 contrast, 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 may reflect a wealth effect associated with home ownership.

4.5 Financial Problems and Regional and Business Cycle Influences

In Table 3 Panel C in the Appendix, we present the results associated with regional and business cycle effects and how they influence financial problems. 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 may reflect high economic inactivity rates over the period relative to London,[7] 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 all eight types of financial problems, with the largest coefficient estimated for problems paying for accommodation. In contrast, residing in Scotland is positively related to six of the eight financial problems, with statistically significant associations found for problems paying for accommodation and loan repayments.

[7] See UK Office for National Statistics (ONS) (2009).

Interestingly, differences are also found for regions which are geographically close. For example, residing in West Yorkshire is positively associated with experiencing six of the eight financial problems, where statistically insignificant effects are found in the case of affordability issues with respect to annual holidays 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. 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.

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.

Our findings reveal that the influence of individual and household characteristics varies across the different types of financial problems. The life cycle effects are particularly interesting with the findings suggesting that individuals aged 35 to 44 are likely to encounter a range of financial problems including both housing payment problems and loan repayment problems. Income, on the other hand, both earned and unearned, appears to be an important influence on the probability of being able to save on a monthly basis, indicating that economic and financial factors play an important role in the ability of households to set aside money to be used following adverse changes in their economic situation. Finally, there are notable regional differences in the extent to which households experience financial problems, as well as in the type of problems encountered. In general, financial problems appear to be more prevalent outside of the London region.

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. 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.

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.

Anderloni, L., Bacchiocchi, E. and D. Vandone (2011) 'Household Financial Vulnerability: An Empirical Analysis.' DIPECO Universita Degli Studi Di Milano Working Paper Number 2011-2.

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(3), 388-403.

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

Campbell, J. Y. (2006) 'Household Finance.' *The Journal of Finance*, LXI, 1553-1604.

Duffie, D., Eckner, A, Horel, G. and L. Saita (2009) 'Frailty correlated default.' *Journal of Finance*, 64 (5), 2089-2123.

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.

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.

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.

Love, D. A. (2010) 'The Effects of Marital Status and Children on Savings and Portfolio Choice.' *Review of Financial Studies*, 23, 385-432.

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.

Taylor, M. P. (2011) 'Measuring Financial Capability and its Determinants Using Survey Data.' *Social Indicators Research*, 102(2), 297-314.

Taylor, M. P., S. P. Jenkins and A. Sacker (2011) 'Financial Capability and Psychological Health.' *Journal of Economic Psychology*, 32(5), 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(3), 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

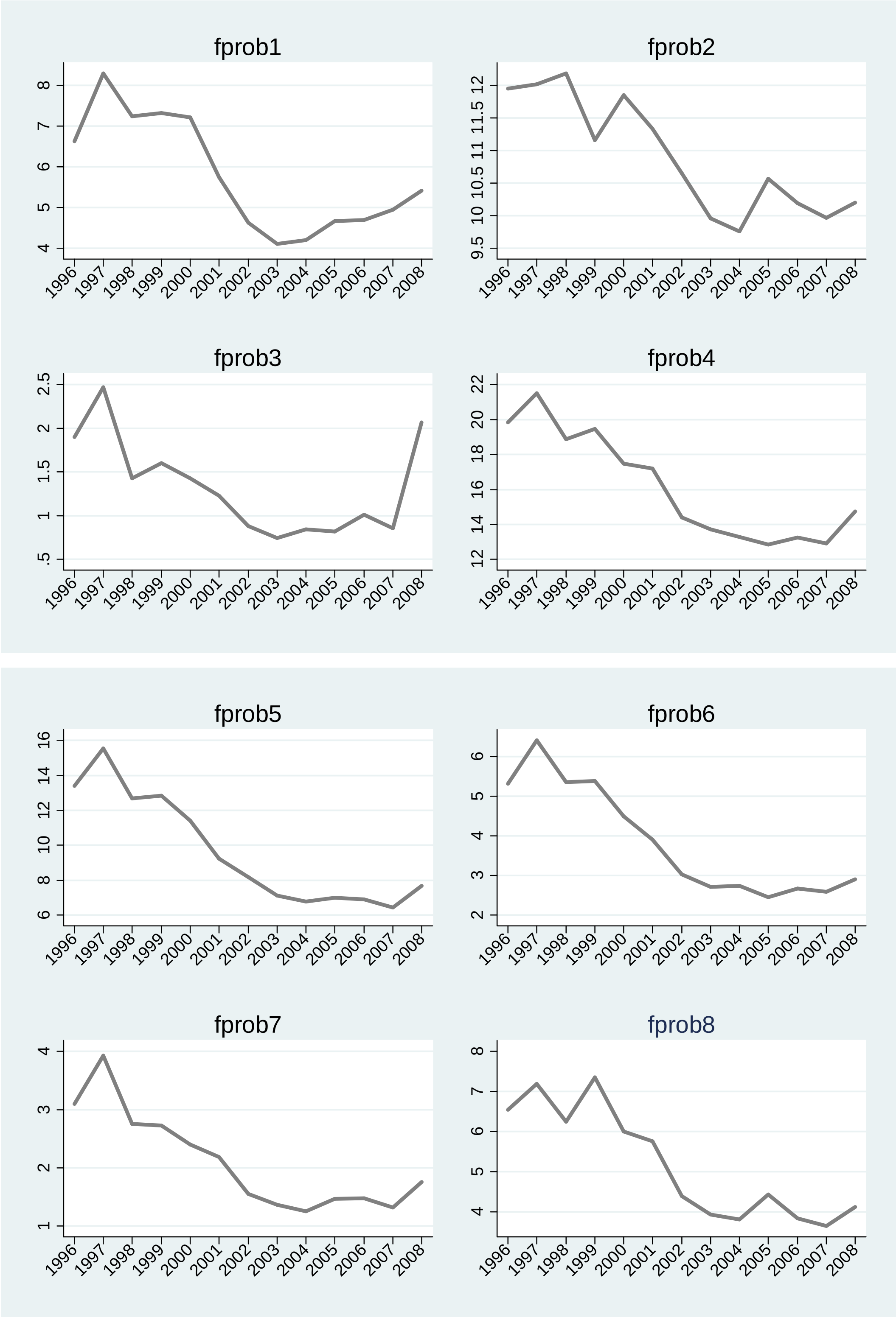
Notes: * denotes statistical significance at the 5% level.

TABLE 1B: Summary Statistics for the Independent Variables

	VARIABLE DEFINITION	MEAN
Male	=1 if male, 0=female	0.319
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	=1 if currently married or cohabiting, 0=otherwise	0.518
Labour Income	Natural logarithm of household labour income	7.167
Other Income	Natural logarithm of household non labour income	4.170
Degree [ii]	=1 if highest education degree, 0=otherwise	0.134
Teach/Nursing [ii]	=1 if highest education teaching/nursing, 0=otherwise	0.273
A Level [ii]	=1 if highest education A level, 0=otherwise	0.088
GCSE [ii]	=1 if highest education GCSE (O level), 0=otherwise	0.143
Other [ii]	=1 if highest education other level, 0=otherwise	0.079
Health: Poor [iii]	=1 if current health poor, 0=otherwise	0.091
Health: Good [iii]	=1 if current health good, 0=otherwise	0.232
Health: V. Good [iii]	=1 if current health very good, 0=otherwise	0.434
Health: Excellent [iii]	=1 if current health excellent, 0=otherwise	0.212
Health Residuals	Generalised health residuals	0.690
Employed [iv]	=1 if currently employee, 0=otherwise	0.486
Self-Employed [iv]	=1 if currently self employed, 0=otherwise	0.088
Unemployed [iv]	=1 if currently unemployed but looking for work, 0=otherwise	0.023
Retired [iv]	=1 if currently retired, 0=otherwise	0.297
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 [v]	=1 if currently lives in South East, 0=otherwise	0.124
South West [v]	=1 if currently lives in South West, 0=otherwise	0.061
East Anglia [v]	=1 if currently lives in East Anglia, 0=otherwise	0.029
East Midlands [v]	=1 if currently lives in East Midlands, 0=otherwise	0.057
West Midlands [v]	=1 if currently lives in West Midlands, 0=otherwise	0.023
Rest W. Midlands [v]	=1 if currently lives in rest of West Midlands, 0=otherwise	0.034
Gr. Manchester [v]	=1 if currently lives in Greater Manchester, 0=otherwise	0.026
Merseyside [v]	=1 if currently lives in Merseyside, 0=otherwise	0.014
North West [v]	=1 if currently lives in North East, 0=otherwise	0.031
South Yorkshire [v]	=1 if currently lives in South Yorkshire, 0=otherwise	0.018
West Yorkshire [v]	=1 if currently lives in West Yorkshire, 0=otherwise	0.022
Rest of Yorkshire [v]	=1 if currently lives in rest of Yorkshire and Humberside, 0=otherwise	0.022
Tyne & Wear [v]	=1 if currently lives in Tyne and Wear, 0=otherwise	0.016
Rest of the North [v]	=1 if currently lives in rest of North, 0=otherwise	0.026
Wales [v]	=1 if currently lives in Wales, 0=otherwise	0.151
Scotland [v]	=1 if currently lives in Scotland, 0=otherwise	0.172

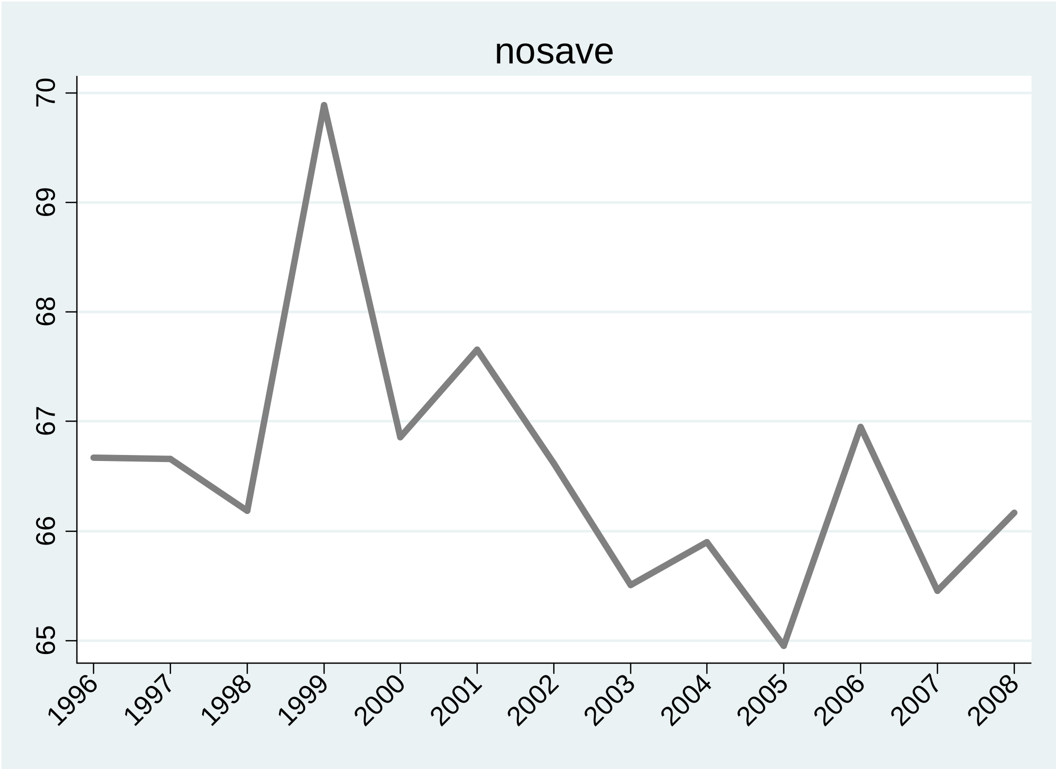
Notes: (i) the omitted age category is 85 and above; (ii) the omitted highest education category is no education; (iii) the omitted health category is very poor health; (iv) the omitted labour force status category is out of the labour market; (v) the omitted region is inner and outer London.

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



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

TABLE 2: Missing Data Selection Model

	Missing: intermittent		Missing: monotone	
	BPME		BPME	
fprob1	0.025		-0.124	
fprob1[t-1]	0.016		-0.282	*
fprob2	0.269	*	0.089	
fprob2[t-1]	0.259	*	0.043	
fprob3	2.434	*	2.489	*
fprob3[t-1]	2.362	*	2.385	*
fprob4	0.305	*	0.225	
fprob4[t-1]	0.279	*	0.214	
fprob5	0.072		0.086	
fprob5[t-1]	0.095		0.089	
fprob6	0.446	*	0.613	*
fprob6[t-1]	0.281		0.377	
fprob7	1.992	*	2.100	*
fprob7[t-1]	1.884	*	1.953	*
fprob8	0.285		0.373	*
fprob8[t-1]	0.186		0.240	
nosave	-0.079		-0.383	*
nosave[t-1]	-0.200	*	-0.426	*
OBS	123,432			

Notes: (i) * denotes statistical significance at the 5% level. (ii) BPME denotes Bayesian posterior mean estimates.

TABLE 3: 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	-2.299 *	-2.505 *	-3.189 *	-1.183 *	-2.025 *	-2.711 *	-3.282 *	-2.632 *	1.798 *
fprob1[t-1]	0.401 *	0.123	0.166	-0.059	-0.057	-0.024	0.118	0.094	0.102
fprob2[t-1]	0.264 *	0.585 *	-0.093	0.073	0.077	-0.037	0.115	-0.092	-0.012
fprob3[t-1]	-0.178 *	0.073	0.078	-0.064	-0.135	-0.060	-0.045	-0.047	-0.056
fprob4[t-1]	0.077	0.030	-0.112	0.421 *	0.109	0.147	-0.124	0.174 *	0.090
fprob5[t-1]	0.048	-0.218	0.126	-0.059	0.452 *	0.024	0.035	0.072	0.001
fprob6[t-1]	-0.018	-0.050	0.011	-0.027	-0.053	0.150	0.173 *	-0.150	-0.026
fprob7[t-1]	-0.088	-0.125	0.073	-0.065	-0.200	-0.101	0.101	-0.150	-0.092
fprob8[t-1]	-0.101	0.000	-0.044	0.030	0.080	0.134	-0.181 *	0.265 *	-0.060
nosave[t-1]	0.129 *	0.194 *	0.158 *	0.165 *	0.253 *	0.260 *	0.238 *	0.207 *	0.715 *
OBS					123,432				

TABLE 3 (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	0.185 *	0.057	0.219 *	0.470 *	0.143 *	0.329*	0.132	0.266 *	-0.111
White	-0.124	-0.136 *	0.039	-0.200 *	-0.195 *	-0.085	-0.013	-0.151	-0.027
Aged 18-24	0.206 *	0.065	0.097	0.222 *	0.220 *	0.030	0.174 *	0.264 *	0.027
Aged 25-34	0.123	0.315 *	-0.023	0.203 *	0.204 *	0.037	0.167 *	0.123	-0.266
Aged 35-44	0.162 *	0.333 *	0.135	0.274 *	0.308 *	0.243 *	0.232 *	0.230 *	-0.154 *
Aged 45-54	0.007	0.148 *	0.139	0.202 *	0.099	-0.062	0.066	0.167 *	0.073
Aged 55-64	0.094	0.163 *	0.058	0.149	0.003	0.201 *	0.134	0.108	0.051
Aged 65-74	-0.209 *	0.095	0.187 *	0.036	-0.089	0.334 *	-0.013	0.167 *	0.061
Aged 75-84	0.078	-0.024	0.221 *	0.025	0.115	0.267 *	0.233 *	0.094	-0.029
Married	-0.023	-0.081	-0.090	-0.162	-0.362 *	-0.071	-0.150	-0.168 *	-0.042
Labour Income	-0.027	0.008	0.000	-0.039	-0.018	-0.016	-0.008	-0.037 *	-0.029 *
Other Income	0.015	0.039 *	-0.005	-0.038	0.006	-0.014	0.003	-0.011	-0.087 *
Degree	0.048	-0.020	0.068	-0.027	0.074	0.098	0.163 *	-0.006	-0.188 *
Teach/Nursing	0.052	0.170 *	0.046	0.072	0.043	-0.001	0.119	0.134	-0.213 *
A Level	0.164 *	0.005	0.140	0.025	0.142	0.183 *	0.221	0.088	-0.139
GCSE	0.113	0.022	0.033	0.188 *	0.114	0.092	0.144	0.129	-0.108
Other	0.037	0.124	0.039	0.191 *	0.048	0.142 *	0.022	0.259 *	0.103
Health: Poor	0.186 *	0.084	0.182 *	0.074	0.261 *	0.256 *	0.223 *	0.180 *	0.015
Health: Good	0.221 *	0.094	0.086	0.110	0.252 *	0.109	0.206 *	0.184 *	0.052
Health: V. Good	-0.036	0.061	-0.024	-0.039	0.084	0.193 *	0.009	-0.022	0.038
Health: Excellent	-0.051	-0.040	-0.025	-0.209 *	0.099	0.040	-0.016	-0.058	-0.027
Health Residuals	0.033 *	0.025 *	0.017 *	0.008	0.026 *	0.031 *	0.012 *	0.037 *	0.029 *
Employed	0.155 *	0.212 *	0.133	-0.089	-0.099	-0.079	0.147	0.089	-0.215 *
Self-Employed	0.244 *	0.070	0.098	0.004	0.022	-0.006	0.204 *	0.063	0.110
Unemployed	0.160 *	0.168 *	0.303 *	0.286 *	0.230 *	0.181 *	0.231 *	0.195 *	0.010
Retired	-0.099	-0.198 *	0.070	-0.276 *	0.007	-0.081	0.038	0.085	0.123
No of Children	0.104 *	0.212 *	0.119	0.242 *	0.174 *	0.132 *	0.041	0.137 *	0.047
Own Home	-0.212 *	-0.282 *	-0.089	-0.401 *	-0.183 *	-0.253 *	0.011	-0.179 *	-0.275 *
OBS					123,432				

TABLE 3 (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	0.184 *	-0.112	-0.068	-0.007	0.141	0.110	0.028	-0.069
South West	0.252 *	0.206 *	0.161 *	0.024	0.270 *	0.264 *	0.324 *	0.265 *	0.051
East Anglia	0.118	0.050	0.122	0.096	0.055	0.134	0.134	0.135	-0.080
East Midlands	-0.029	0.068	0.251 *	0.199 *	0.116	0.236 *	0.159 *	0.080	-0.041
West Midlands	0.216 *	0.133	0.299 *	0.001	-0.016	0.128	0.083	0.071	-0.083
Rest W. Midlands	-0.006	-0.003	0.265 *	0.153	0.040	0.022	0.219 *	-0.061	-0.028
Gr. Manchester	0.140	0.160	0.302 *	0.040	0.073	0.088	0.055	0.110	0.104
Merseyside	0.154 *	-0.034	0.091	0.118	0.106	0.062	0.286 *	0.123	-0.106
North West	0.183 *	0.226 *	0.207 *	0.117	0.054	-0.097	0.163	0.050	0.048
South Yorkshire	0.089	0.152	0.283 *	0.050	0.071	0.274 *	-0.033	0.242 *	0.086
West Yorkshire	0.308 *	0.249 *	0.215 *	0.055	0.157 *	0.255 *	0.026	0.288 *	0.134
Rest of Yorkshire	0.279 *	0.181 *	0.217 *	0.261 *	0.176 *	0.219 *	0.225 *	0.208 *	0.135
Tyne & Wear	0.135	0.016	0.164 *	0.080	0.259 *	-0.020	0.202 *	0.138	0.024
Rest of the North	-0.002	0.225 *	0.245 *	0.094	0.113	0.371 *	0.200 *	0.078	0.089
Wales	0.182 *	0.244 *	0.128	0.266 *	0.184 *	0.136 *	0.182 *	0.235 *	-0.055
Scotland	0.156	0.090	0.256 *	0.285 *	0.197 *	0.152 *	0.322 *	0.320 *	0.095
1998	-1.015 *	-0.694 *	-2.068 *	-0.680 *	-0.773 *	-1.192 *	-2.174 *	-0.715 *	-0.468 *
1999	-1.143 *	-0.920 *	-1.904 *	-0.671 *	-0.652 *	-1.542 *	-2.017 *	-1.029 *	-0.381 *
2000	-0.897 *	-0.902 *	-2.982 *	-0.881 *	-0.780 *	-1.383 *	-2.271 *	-1.298 *	-0.396 *
2001	-1.135 *	-1.233 *	-2.329 *	-1.080 *	-0.968 *	-1.610 *	-2.260 *	-1.458 *	-0.200
2002	-1.190 *	-0.990 *	-2.386 *	-1.268 *	-1.036 *	-1.486 *	-3.080 *	-1.810 *	-0.129
2003	-1.164 *	-1.138 *	-2.580 *	-1.191 *	-1.082 *	-1.798 *	-2.456 *	-1.750 *	-0.164
2004	-1.464 *	-1.129 *	-1.927 *	-1.104 *	-1.342 *	-1.594 *	-2.234 *	-1.905 *	-0.255
2005	-1.236 *	-1.111 *	-2.073 *	-1.526 *	-1.502 *	-2.213 *	-3.034 *	-1.788 *	-0.588
2006	-1.371 *	-0.943 *	-3.333 *	-1.409 *	-1.566 *	-1.692 *	-2.659 *	-1.686 *	-0.170
2007	-0.897 *	-0.730 *	-2.819 *	-1.512 *	-1.668 *	-2.288 *	-2.971 *	-1.646 *	-0.466 *
2008	-1.243 *	-0.679 *	-1.470 *	-1.039 *	-1.562 *	-1.964 *	-2.541 *	-1.096 *	-0.455 *
OBS					123,432				

Notes: (i) * denotes statistical significance at the 5% level. (ii) BPME denotes Bayesian posterior mean estimates.

TABLE 4: 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: * denotes statistical significance at the 5% level.