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FINANCIAL HARDSHIP AND SAVING BEHAVIOUR: BAYESIAN ANALYSIS OF BRITISH PANEL DATA

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Abstract: We explore whether a protective role for savings against future financial hardship exists using household level panel data. We jointly model the incidence and extent of financial problems, as well as the likelihood of having secured debt and the amount of monthly secured debt repayments, allowing for dynamics and interdependence in both of the two-part outcomes. A two-part process is important given the considerable inflation at zero when analysing financial problems. The model is estimated using a flexible Bayesian approach with correlated random effects and the findings suggest that: (i) saving on a regular basis mitigates both the likelihood of experiencing, as well as the number of, future financial problems; (ii) state dependence in financial problems exists; (iii) interdependence exists between financial problems and secured debt, specifically higher levels of mortgage debt are associated with an increased probability of experiencing financial hardship.

Key Words: Bayesian Modelling; Financial Hardship; Saving; Zero Inflation.

JEL Classification: C11; D12; D14; R20.

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1. Introduction

Since the 2008 global financial crisis, the low levels of savings held at the household level in many countries has led to considerable concern amongst policymakers regarding the potential financial vulnerability faced by households (Garon, 2012). Savings provide a financial buffer in the event of adverse events from washing machine and car break-downs (i.e. expenditure shocks) through to illness and job loss (i.e. income shocks). Recent evidence from the Money Advice Service (2016) indicates that 4 out of 10 working-age individuals in the UK have less than £100 available in savings at a given point in time, which suggests limited funds to draw upon in the event of financial problems. Indeed, as stated by the House of Lords Select Committee on Financial Exclusion (2017), p.12 'a loss of income from job loss, reduced working hours or ill health may be eased by saving.' Furthermore, they report that the ratio of household saving to income has been falling since 2010 from 11.5% in the third quarter of 2010 to 4.9% in the first quarter of 2015. Moreover, in June 2017, according to the Office for National Statistics (ONS), the savings ratio reached a new record low, at 1.7% from January to March, down from 3.3% in the previous quarter. Low savings may lead to increased demand for high cost lending products, e.g. payday loans, which may exacerbate financial problems and lead to persistence in financial distress over time.

The relationship between saving behaviour and financial distress is clearly complex and, although an extensive literature exploring saving behaviour exists, limited attention has been paid in the economics literature to understanding the implications of a lack of savings. We contribute to existing knowledge by evaluating the implications of saving on a regular basis for future financial wellbeing. Specifically, we contribute to the existing literature by exploring the protective role of saving in the context of a large nationally representative UK data set.

The extensive literature on household saving explores the complex motivations for saving (see the comprehensive review by Browning and Lusardi, 1996). The motives for saving, which differ across households as well as over time for a given household, are likely to be interrelated. As stated by Le Blanc et al. (2016), 'ultimately, reasons for saving are not necessarily mutually exclusive,' p.18. Although the general consensus amongst policymakers appears to be that individuals are not saving enough for either the short-term or the long term, only a limited number of studies in the economics literature have explored the implications of saving for future financial wellbeing. Given that it has been long established in the economics literature that life cycle theories on household consumption and saving behaviour predict that households will consume savings and assets when faced with financial hardship (see, for example, Browning and Crossley 2001, and Modigliani and Brumberg 1954), it seems interesting to explore from an empirical perspective whether and to what extent holding savings provides a buffer against future financial adversity.

We aim to explore the effect of regular saving behaviour on future financial hardship using household level panel drawn from the British Household Panel Survey and Understanding Society. In order to allow for the fact that mortgage payments represent one of the main financial commitments of households, we model financial problems and mortgage payments jointly to allow for their potential interdependence. In addition, we make a methodological contribution by developing a flexible Bayesian framework which allows for the considerable inflation at zero when analysing financial problems in the context of a large scale nationally representative survey, i.e. a significant number of households do not experience financial hardship. Within our flexible Bayesian framework, we also allow for persistence in experiencing financial problems, which has been commented on in existing studies. Bayesian modelling techniques have only been applied to household finances in a small number of papers (see, for example, Brown et al., 2014, 2015, 2016). Given that the Bayesian approach allows flexible modelling in complex applications, such an approach seems to be ideally suited to modelling such financial behaviour.

2. Background

A small yet growing literature exists exploring household financial hardship using nationally representative household surveys (see, for example, Brown et al., 2014, and Giarda, 2013). However, with the exception of a small number of US studies (e.g. McKernan et al., 2009, Mills and Amick, 2010, and Gjertson, 2016), an explicit link has not been made in such studies to the potential protective role of saving in mitigating financial hardship. In contrast, these US studies highlight the potential protective role of saving amongst samples of low income households. For example, McKernan et al. (2009) use data from the 1996 and 2001 US Survey of Income and Programme Participation, which oversamples low income households, to explore whether assets reduce material hardship following an adverse event. Their descriptive statistics reveal that when asset poor families experience an adverse event, they are approximately 2 to 3 times more likely to experience deprivation than non-asset poor families. Such findings are supported by their regression analysis of a sample of families experiencing a negative event which suggests that, after controlling for income, asset poor families are 14 percentage points more likely to experience deprivation than non-asset poor families. Interestingly, they also find that approximately 40% of families experiencing negative events reduce their liquid assets. Mills and Amick (2010) use the same data source to explore whether holding modest amounts of liquid assets provides protection against financial hardship for low income households. For households in the lowest income quintile, their results suggest that holding liquid assets of up to $1,999 relative to holding zero assets reduces the incidence of material hardship by 5.1 percentage points.

In a similar vein, Collins and Gjertson (2013) analyse data from the Annie E. Casey Foundation's Making Connections project, which is a longitudinal study of families residing in disadvantaged neighbourhoods in 10 US cities. Their findings suggest that families that do save for an emergency are less likely to experience as many material hardships as those households which do not save, thereby providing further evidence of the protective role of saving amongst low income households. Although such studies are not able to discern the nature of causality, they do highlight some interesting associations between saving behaviour and subsequent financial hardship which warrant further investigation. More recently, Gjertson (2016), also using data from the Annie E. Casey Foundation's Making Connections project, presents evidence supporting a protective role for small amounts of saving against future financial hardship for this non-representative sample of low income US households. Thus, households holding even small amounts of saving may have a financial buffer against future shocks. Furthermore, the regression analysis of longitudinal data highlights the dynamic aspect of household finances with those households who saved for emergencies experiencing less financial hardship three years later.

Establishing a financial buffer for adverse effects has been found to be an important motivation for saving in large scale nationally representative data sets. For example, Le Blanc et al. (2016), who explore household saving behaviour in 15 euro-area countries, using the Household Finance and Consumption Survey 2010-11, find that 'saving for unexpected events' is reported to be the most important saving motive at the euro-area level by 53 percent of respondents. Furthermore, the importance of this saving motive is found to be prevalent across all countries regardless of institutional differences and differences in welfare systems. Similar findings supporting the importance of precautionary saving motives are reported by Kennickell and Lusardi (2005) using the US Survey of Consumer Finances.

We contribute to the existing literature by exploring whether a protective role for saving against future financial hardship exists beyond the US. Households holding even small amounts of saving may have a financial buffer against future shocks, such as changes in work or overtime hours (which is likely to increase with the growth in non-standard forms of employment and zero-hours contracts) as well as poor health, which may affect ability to work. As stated by Despard et al. (2016), 'households without sufficient savings are at greater risk for material hardship,' p.4. Existing work in this area, summarised above, has focused on US data and has tended to explore small non-representative samples of low income households. We will contribute to the existing literature by exploring the protective role of savings in the UK within the wider population and test empirically whether regular savings behaviour is inversely associated with future financial hardship. Although it is apparent that a lack of savings may be highly problematic for low income households with relatively small unexpected expenses leading to financial distress, it is also the case that non low income households may also suffer from a lack of savings with unexpected expenditure shocks or income decreases leading to problems meeting financial commitments and servicing debt. Indeed, McKernan et al. (2009) find that asset holding plays an important role in mitigating material hardship at all income levels.

3. Data

We investigate the existence, intensity and persistence of financial hardship in the UK, focusing on the protective role of saving, using longitudinal data over nearly a twenty period, from the 1990s to 2016. This is explored at the household level using the British Household Panel Survey (BHPS) and its successor Understanding Society, the UK Household Longitudinal Survey (UKHLS). The BHPS took place from 1991 through to 2008 and was replaced by the UKHLS in 2009. Both surveys are nationally representative large scale panel data sets containing detailed information on economic and social-demographic characteristics. The BHPS comprises approximately 10,000 annual individual interviews, with the same individuals interviewed in successive waves. In the first wave of the UKHLS, over 50,000 individuals were interviewed from 2009 through to 2011 and correspondingly in the latest wave available, wave 6, around 45,000 individuals were interviewed between 2014 and 2016. A subset of individuals in the UKHLS can be linked to the BHPS thus making a relatively long panel survey. We also use information recorded in the *Youth Survey*, as discussed in detail below, since some respondents were surveyed during their childhood.

After matching the BHPS and UKHLS together and incorporating lags, the estimation sample is over the period 1998 through to 2016. We focus upon a sample of 2,751 individuals who are the head of household or are identified as the individual responsible for making financial decisions within the household (referred to as the head of household hence forth). These individuals are observed over time yielding an unbalanced panel comprising 13,132 observations, where they are present in the panel for 7 years, on average, and we focus on individuals aged between 17 and 35, as discussed further below.

We consider how saving behaviour influences both the incidence and the extent of household financial problems. From 1996 onwards information on the following types of financial hardship are available in the data: problems paying for accommodation; problems with loan repayments (non-mortgage debt); problems keeping home adequately warm; difficulty in being able to pay for a week's annual holiday; difficulty in being able to replace worn-out furniture; ability to buy new rather than second hand clothing; ability to eat meat, chicken, fish every second day; and ability to have friends or family for a drink or meal at least once a month. Figure 1 shows the distribution of the number of household financial problems, where around 60% of the sample report no problems over the period and 40% report between 1 to 6 or more financial problems over the period. Information is also available in the data on whether the household has a mortgage and, if so, the last monthly payment made. Mortgages in the UK can be held from age 18 onwards. Hence, for heads of household aged less than 18, the mortgage will be held by a different household member. Figure 2 shows the distribution of the natural logarithm of monthly mortgage debt repayments where around 50% of the sample did not have secured debt. Hence, both financial problems and monthly mortgage repayments have a preponderance of zeros which is important to take into account in the empirical analysis. Conditional on holding secured debt, the distribution of monthly repayments is approximately normally distributed and so we model the level of secured debt repayments as a continuous variable. On the other hand, the number of financial problems, conditional on experiencing financial hardship, is regarded as a count outcome and, hence, we employ a Poisson estimator. The proposed modelling approach is developed in Section 4 below.

Our focus lies in exploring the protective role of saving on a regular basis. A distinction is made in the existing literature between passive and active saving, where active saving relates to money set aside to be used in the future and passive saving refers to wealth accumulation due to asset appreciation. Active saving has been explored from an empirical perspective by a small number of studies, including for the UK: Guariglia (2001); Yoshida and Guariglia (2002); Guariglia and Rossi (2004); and Brown and Taylor (2016). Our measure of monthly saving, which is akin to active saving, is based on responses to the following question: "*Do you save any amount of your income, for example, by putting something away now and then in a bank, building society, or Post Office account other than to meet regular bills? About how much, on average, do you manage to save a month?*" We explore three alternative measures of the head of household's saving behaviour: the average amount of monthly saving in the previous year; a binary indicator of saving on a monthly basis in the previous year; and fitted values for monthly saving in the previous year based on instrumenting saving behaviour on whether the head of household saved as a child. The latter approach is based on Brown and Taylor (2016) and uses information recorded in the *Youth Survey*, which asks children aged 11-15 '*what do you usually do with your money?*' The possible responses were: *save to buy things*; *save and not spend*; and *spend immediately*. Saving as a child has been found to be a strong predictor of saving behaviour as an adult. Hence, our data set comprises relatively young adults as our estimation approach requires observing the head of household as a youth and also as an adult. Furthermore, in the UK, financial problems are typically more prevalent amongst the young, see Kempson et al. (2004), Atkinson et al. (2006), Brown et al. (2014) and Taylor (2011). In addition, the House of Lords Selection Committee on Financial Exclusion (2017) reports that young people are more susceptible to financial exclusion. Indeed, the report shows that 51% of 18-24 year olds are worried about money on a regular basis and that 1 in 5 individuals in this age group have experienced financial problems as a result of poor credit ratings.

In the empirical analysis, we include a comprehensive number of control variables in matrix $\boldsymbol{X}$ (defined below). These include head of household characteristics such as gender; white; age; highest educational attainment - specifically degree, other high educational qualification, A levels, GCSE/O levels, or any other qualification, with no qualifications as the omitted category; labour market status, i.e. employee, self-employed or unemployed, out of the labour market is the reference category; and self-reported health status, specifically whether in excellent, good or fair health, where poor and very poor health comprise the reference group. We also control for: the natural logarithm of monthly household equivalised income; the natural logarithm of annual household expenditure on water, gas and electricity; the natural logarithm of total monthly household expenditure on non-durable goods; region; and year.

Summary statistics are provided in Table 1 Panels A and B. Panel A provides summary statistics on the dependent variables, whilst Panel B reports descriptive statistics for the covariates. All monetary variables are measured in constant prices deflated to 1997 prices. Conditional on reporting financial problems, the average number reported is 1.90, whilst conditional on having mortgage debt, the last monthly payment is 2.94 log units, which is approximately £564.14, see Table 1 Panel A. Around 38% of the sample saved in the previous year and the average monthly amount saved was 1.68 log units, which equates to £59.90. Approximately 49% of heads of household are males, 10% have a degree as their highest educational qualification, and 53% are employees, see Table 1 Panel B.

4. Methodology

The Bayesian estimator which we develop allows us to examine inflation at zero for both household financial problems and monthly secured debt repayments, as well as examining the number of problems (conditional on facing financial hardship) and the level of secured debt repayments (conditional on having a mortgage), whilst also allowing for state dependence and interdependence between outcomes. Of primary interest in our analysis is the role that saving behaviour has in terms of mitigating both the likelihood and extent of future financial problems.

Our key dependent variable, the number of financial problems, takes integer values from 0 to 6. Given the considerable inflation at zero, we use a zero-inflated Poisson model for financial problems. The monthly mortgage repayment, on the other hand, is a continuous variable with a point mass at zero representing no mortgage. Hence, we also develop a semi-continuous model for monthly mortgage payments. The results which follow in Section 5 are robust to using a wider definition of housing costs which includes monthly mortgage payments and monthly rent. Furthermore, given the well-documented life cycle patterns associated with household finances, age may not have a linear relationship with the dependent variables. Hence, we model the relationships with head of household's age as nonlinear spline effects. Finally, given the number of explanatory variables, we develop a shrinkage prior to account for the high dimensionality of the regression model. The rest of this section presents our Bayesian approach designed to account for the issues summarised above.

4.1 Model Specification: A Semi-parametric Joint Model

Our joint model consists of three components, specifically: a semi-parametric Poisson hurdle mixed model for the number of financial problems, our key outcome variable of interest; a semi-parametric semi-continuous model for monthly mortgage payments; and, finally, a Dirichlet process (DP) for the joint distribution of the latent random effects from the Poisson hurdle and the semi-continuous models.

Modelling the number of financial problems – zero-inflated Poisson model

Let Y_{ht}^{f} be the number of financial problems reported by the h^{th} household in the t^{th} year, $h = 1,2,\dots,N, t = 1,2,\dots,T$, where N represents the number of households in the sample, and T denotes the number of years. In the context of reported financial problems, a large number of zeros are observed in Y_{ht}^{f}. Following Lambert (1992), Hall (2000), Dagne (2004) and Ghosh et al. (2006), we further assume that for each observed event count, Y_{ht}^{f}, there is an unobserved random variable for the state of financial distress, U_{ht}, where $P(U_{ht} = 0) = p_{ht}^{f}$ if Y_{ht}^{f} comes from the degenerate distribution, and $P(U_{ht} = 1) = 1 - p_{ht}^{f}$ if Y_{ht}^{f}~Poisson (λ_{ht}):

$$Y_{ht}^{f} = \begin{cases} 0 & \text{with probability } p_{ht} \\ \text{Poisson}(\lambda_{ht}) & \text{with probability } (1 - p_{ht}) \end{cases} \tag{1}$$

where $\text{Poisson}(\lambda_{ht})$ is defined by the density function $P\left(Y_{ht}^{f} = y_{ht}^{f}\right) = \exp(-\lambda_{ht})\lambda_{ht}^{y_{ht}^{f}}/y_{ht}^{f}!$. It should be noted that both the degenerate distribution and the Poisson process can produce zero observations. Such a formulation is often referred to as the zero-inflated Poisson (ZIP) distribution. It then follows that

$$\Pr\left(Y_{ht}^{f} = 0\right) = p_{ht}^{f} + \left(1 - p_{ht}^{f}\right)\exp(-\lambda_{ht}) \tag{2}$$

$$\Pr\left(Y_{ht}^{f} = y_{ht}^{f}\right) = \left(1 - p_{ht}^{f}\right)\left\{\exp(-\lambda_{ht})\,\lambda_{ht}^{y_{ht}^{f}}/y_{ht}^{f}!\right\}, \quad y_{ht} = 1,2,\dots \tag{3}$$

One could conceptualize the degenerate distribution as representing a "no financial problem" state with probability, p_{ht}^{f}, while the Poisson process represents an "active financial problem" state with λ_{ht} being the mean annual number of financial problems.

Since the annual event counts are simultaneously influenced by the state that the household is in during the year and the annual event rate given that it is in an "active" state, we consider simultaneous modelling of both λ_{ht} and p_{ht}^{f}. We assume the following logistic and log-linear regression models for p_{ht}^{f} and λ_{ht} to accommodate covariates and random effects as follows:

$$Y_{ht}^{f} \sim \left(1 - p_{ht}^{f}\right) 1_{\left(Y_{ht}^{f}=0\right)} + p_{ht}^{f} \text{Poisson}(\lambda_{ht}) 1_{\left(Y_{ht}^{f} \geq 0\right)} \tag{4}$$

$$\text{logit}\left(p_{ht}^{f}\right) = \gamma_1 y_{h,t-1}^{f} + \varsigma_1 y_{h,t-1}^{m} + \psi_1 S_{h,t-1}^{A} + \boldsymbol{X}_{ht}^{\prime} \beta_1 + g^{p}(\text{age}_{ht}) + b_{h1} \tag{5}$$

$$\log(\lambda_{ht}) = \gamma_2 y_{h,t-1}^{f} + \varsigma_2 y_{h,t-1}^{m} + \psi_2 S_{h,t-1}^{A} + \boldsymbol{X}_{ht}^{\prime} \beta_2 + g^{\lambda}(\text{age}_{ht}) + b_{h2} \tag{6}$$

where γ_1, γ_2 are the autoregressive coefficients for lag effect of order 1 of y_{ht}^{f} and ς_1, ς_2 are the autoregressive coefficients for the lag effect of order 1 of the other dependent variable, mortgage payments, y_{ht}^{m}, capturing interdependence. The inclusion of such lags is particularly important given the persistence in financial problems over time reported in the existing literature. Saving behaviour is lagged by a year and is represented by $S_{h,t-1}^{A}$ with associated parameters ψ_1 and ψ_2. The lag is introduced to explore whether savings insulate against future financial hardship. In addition, from a modelling perspective, this approach serves to reduce the potential for reverse causality since as argued by Angrist and Pischke (2009), savings predate the outcome variables. As stated above, we compare the protective role of saving using three alternative measures: the amount saved; the incidence of saving; and fitted values where savings are instrumented using information on saving behaviour of the head of household as a child (this is discussed further in Section 5). The covariates in $\boldsymbol{X}$ are as defined above and have the associated regression coefficients β_1 and β_2 in the respective equations for the incidence of financial problems and the number of financial problems. The b_{h1} and b_{h2} are the random effects of p_{ht}^{f} and λ_{ht}, respectively. We discuss the distribution of the random effects terms below.

Given that the life cycle effects of household finances have been long established, the effects of some covariates, viz., age_{ht}, on p_{ht}^{f} and λ_{ht}, may not be linear. Thus, the effects of the head of household's age are modelled by unspecified non-parametric functions $g^{p}(\mathrm{age}_{ht})$ and $g^{\lambda}(\mathrm{age}_{ht})$. These unknown smoothing functions reflect the nonlinear effects of this covariate. We approximate the spline function $g(\mathrm{age}_{ht})$, suppressing the superscripts, by a piecewise polynomial of degree τ. The knots $\widetilde{\omega} = (\widetilde{\omega}_1, \widetilde{\omega}_2, \dots, \widetilde{\omega}_m)$ are placed within the range of age_{ht}, such that $\min(\mathrm{age}_{ht}) < \widetilde{\omega}_1 < \widetilde{\omega}_2 < \cdots < \widetilde{\omega}_m < \max(\mathrm{age}_{ht})$. Then $g(\mathrm{age}_{ht})$ is approximated by

$$g(\mathrm{age}_{ht}) = \nu_1 \mathrm{age}_{ht} + \nu_2 \mathrm{age}_{ht}^2 + \cdots + \nu_\tau \mathrm{age}_{ht}^\tau + \sum_{c=1}^{C} u_c \gamma_c (\mathrm{age}_{ht} - \widetilde{\omega}_c)_+^\tau \qquad (7)$$

where $X_+ = x$ if $x > 0$, and 0 otherwise, $\nu = (\nu_1, \dots, \nu_\tau)$, $\widetilde{\omega}$ are vectors of regression coefficients in the polynomial regression spline. Note that there is no intercept in the polynomial regression to avoid lack of identification. We assume $u_c \sim^{idd} N(0, \sigma_u^2)$; $h = 1, \dots, C$.

In the above formulation, one of the important issues is the choice of the number of knot points and where to locate them. Following Ruppert (2002) and Crainiceanu et al. (2005), we consider a number of knots that is large enough (typically 5 to 20) to ensure desired flexibility, and $\widetilde{\omega}_k$ is the sample quantiles of age_{ht} corresponding to probability $k/(m+1)$, but the results hold for other choices of knots. In our empirical application, the function of age is modelled with m=20 knots chosen so that the k^{th} knot is the sample quantile of age corresponding to probability $k/(m+1)$. However, if there are too few knots or they are poorly located, estimates may be biased, while too many knots will inflate the local variance. Thus, to avoid overfitting, following Smith and Kohn (1996), we incorporate selector indices, γ_c, that allow the spline coefficients to be included or excluded and that are defined for each knot. The γ_c are then drawn independently from a Bernoulli prior, viz., $\gamma_c \sim \mathrm{Bernoulli}(0.5)$. By introducing this, we can select a subset of well supported knots from a larger space. For each knot point u_c, the γ_c will weight the importance of a particular knot point. In the entire set-up, $\nu_1, \dots, \nu_\tau$, are the fixed effect regression parameters, and the u_c's are the random coefficients. The spline smoother corresponds to the optimal predictor in a mixed model framework assuming $u_c \sim^{idd} N(0, \sigma_u^2)$; $h = 1, \dots, C$.

Modelling monthly mortgage payments – a semi-continuous model

As stated above, although our primary focus lies in analysing the relationship between regular saving behaviour and future financial problems, given that mortgage payments arguably represent one of the most important financial commitments held by households, our modelling structure allows for the interdependence between financial problems and mortgage payments. Hence, in this section, we present a semi-continuous model for longitudinal data relating to the amount of monthly mortgage payments. Since in some years the household may not hold a mortgage and hence will make no monthly repayments, this dependent variable is also characterised by a mixture of zero and positive continuous observations. To formulate a model for the mortgage amount, let Y_{ht}^{m} be the monthly mortgage payment of household h at year t.

Let R_{ht} be a random variable which denotes having monthly mortgage payments where,

$$R_{ht} = \begin{cases} 0, & \text{if } Y_{ht}^{m} = 0 \\ 1, & \text{if } Y_{ht}^{m} > 0 \end{cases} \tag{8}$$

with conditional probabilities

$$\Pr(R_{ht} = r_{ht}) = \begin{cases} 1 - p_{ht}^{m}, & \text{if } r_{ht} = 0 \\ p_{ht}^{m}, & \text{if } r_{ht} = 1. \end{cases} \tag{9}$$

For such semi-continuous data, we introduce an analogous semi-continuous model consisting of a degenerate distribution at zero and a positive continuous distribution, such as a lognormal (LN), for the nonzero values as follows:

$$Y_{ht}^{m} \sim (1 - p_{ht}^{m})^{1-r_{ht}} \{p_{ht}^{m} \times N(\log(Y_{ht}^{m}); \mu_{ht}^{m}, \sigma^2)\}^{r_{ht}} \tag{10}$$

$$\text{logit}(p_{ht}^{m}) = \gamma_3 y_{h,t-1}^{m} + \varsigma_3 y_{h,t-1}^{f} + \psi_3 S_{h,t-1}^{A} + \boldsymbol{X}'_{ht}\eta_1 + h^{p}(\text{age}_{ht}) + b_{h3} \tag{11}$$

$$\mu_{ht} = \gamma_4 y_{h,t-1}^{m} + \varsigma_4 y_{h,t-1}^{f} + \psi_4 S_{h,t-1}^{A} + \boldsymbol{X}'_{ht}\eta_2 + h^{\mu}(\text{age}_{ht}) + b_{h4} \tag{12}$$

where, r_{ht} is an indicator as defined above, μ_{ht}^{m} and σ^2 are the mean and variance of $\log(Y_{ht}^{m})$, respectively. The model given by equations (11, 12) is a semi-parametric counterpart of the correlated two-part model proposed for modelling financial problems. Saving behaviour $S_{h,t-1}^{A}$ is included as a lag for the aforementioned reasons.

Correlation structure and heterogeneity – joining the models

Both models detailed above contain information about household behaviour and are, therefore, inter-related. To obtain the complete picture and to account for the heterogeneity across households, we combine these effects by correlating the multiple outcomes. However, since these outcomes are measured on a variety of different scales (viz., binary, Poisson, log-normal), it is not possible to directly model the joint predictors' effects due to the lack of any natural multivariate distribution for characterising such dependency. A flexible solution is to model the association between the different responses by correlating the random heterogeneous effects from each response. In our joint modelling approach, random effects are assumed for each response process and the different processes are associated by imposing a joint multivariate distribution on the random effects. Such a model not only provides a covariance structure to assess the strength of association between the responses, but also borrows information across the outcomes and offers an intuitive way of describing the dependency between the responses.

Let $\boldsymbol{b}_h = (b_{h1}, b_{h2}, b_{h3}, b_{h4})'$ be the vector representing the random effects associated with the h^{th} household. Typically, a parametric normal distribution is considered for $\boldsymbol{b}_h$: however, the choice of normality is often due to computational tractability, an assumption which may not always hold in reality. In addition, it provides limited flexibility because it is unimodal. This may result in misleading inferences relating to the magnitude of effects and the nature of heterogeneity. One common approach entails using a finite mixture of normal distributions as an alternative choice. However, rather than handling the very large number of parameters resulting from finite mixture models with a large number of mixands, it may be more straightforward to work with an infinite dimensional specification by assuming a random mixing distribution which is not restricted to a specific parametric family. Following Li and Ansari (2014), we propose here an enriched class of models that can capture heterogeneity in a flexible yet structured manner. In the context of the proposed class of models, an unknown distribution G of the random effects is assumed to be random and a DP is placed on the distribution of G. Then, the model for $\boldsymbol{b}_h$ can be written as

$$\boldsymbol{b}_h \sim G, \quad G \sim \mathrm{DP}(\alpha G_0) \tag{13}$$

where α is a positive scalar precision parameter and G_0 is a parametric baseline distribution. With such a non-parametric modelling of the random effects, the entire model turns out to be a semi-parametric model. We assume a multivariate normal distribution for G_0, i.e. $G_0 \sim \boldsymbol{N}(\boldsymbol{0}, \Sigma)$. Realisations of the DP are discrete with probability one, implying that the estimated $\boldsymbol{b}_h$ that will be drawn from G will be grouped into a cluster, thus allowing for possible multimodality in the distribution of $\boldsymbol{b}_h$. The discrete nature of the DP is apparent from the popular stick-breaking formulation pioneered by Sethuraman (1994). The stick-breaking formulation implies that $G \sim DP(\alpha G_0)$ is equivalent to

$$G = \sum_{q=1}^{\infty} \pi_q^D \delta_{\boldsymbol{b}_q}, \quad \boldsymbol{b}_q \sim G_0, \quad \text{and} \quad \sum_{q=1}^{\infty} \pi_q^D = 1 \tag{14}$$

where G is a mixture of countably but infinite atoms, and these atoms are drawn independently from the base distribution G_0, and $\delta_{\boldsymbol{b}}$ is a point mass at $\boldsymbol{b}$. An atom is like a cluster (i.e. a sub-group of random effects), $\boldsymbol{b}_q$ is the value of that cluster and all random effects in a cluster share the same $\boldsymbol{b}_q$. In equation 14, $\pi_q^D = V_h \prod_{l<q}(1 - V_l)$, which is formulated from a stick-breaking process, with $V_q \sim \mathrm{Beta}(1, \alpha)$, is the probability assigned to the q^{th} cluster. For small values of α, $V_q \to 1$ and thus $\pi_q^D \to 1$, assigning all probability weight to a few clusters and thus the G is far from G_0. On the contrary, for large values of α, the number of clusters can be as many as the number of random effects implying that the sampled distribution of G is close to the base distribution of G_0. For practicality, researchers use a finite truncation to approximate G, i.e. $G \sim \sum_{q=1}^{Q} \pi_q^D \delta_{\boldsymbol{b}_q}$.

While the above formulation appears appropriate, there is an issue of identifiability within it in the sense that, although the prior expectation of the mean of G is 0, the posterior expectation can be non-zero and, thus, can bias inference (Yang et al., 2010; Li et al., 2011). In parametric hierarchical models, it is standard practice to place a mean constraint on the latent variable distribution for the sake of identifiability and interpretability. In a nonparametric DP, Yang et al. (2010) proposed using an entered DP to tackle the identifiability issue. Li et al. (2011) have shown the utility of entered DP in modelling heterogeneity in choice models. Following Yang et al. (2010) and Li et al. (2011), we centre the DP to have zero mean. We estimate the mean and variance of the process, i.e., μ_G^j and Σ_G^j at the j^{th} Bayesian Markov Chain Monte Carlo (MCMC) iteration as follows

$$\mu_G^j = \sum_{q=1}^{Q} V_q^j \prod_{l<q}\left(1 - V_l^j\right)\boldsymbol{b}_q^j \tag{15}$$

$$\Sigma_G^j = \sum_{q=1}^{Q} V_q^j \prod_{l<q}\left(1 - V_l^j\right)\left(\boldsymbol{b}_q^j - \mu_G^j\right)\left(\boldsymbol{b}_q^j - \mu_G^j\right)' \tag{16}$$

where V_q^j and $\boldsymbol{b}_q^j$ are the posterior samples from the uncentered process defined in equation 14 and $\left(\boldsymbol{b}_q^j - \mu_G^j\right)$ is the centered estimate for random effects at the j^{th} iteration. The above entered DP implies that $\mathrm{E}(\boldsymbol{b}_h|G = 0)$ and $\mathrm{Var}(\boldsymbol{b}_h|G = \Sigma_G)$.

4.2 Bayesian Methods

Under the joint model described by equations 4, 5, 6, 8, 10, 11 and 12, the likelihood of the observed data for the h^{th} household, denoted by $\boldsymbol{Y}_{h1}, \dots, \boldsymbol{Y}_{hN}$, with $\boldsymbol{Y}_{ht} = \left(Y_{ht}^f, Y_{ht}^m\right)'$ for $t = 1, \dots, T$, based on the parameter set Ω and the random effects $\boldsymbol{b}_h$ is proportional to

$$L_i(\Omega, \boldsymbol{b}_h|\boldsymbol{Y}_{h1}, \dots, \boldsymbol{Y}_{hT}) = \prod_{t=1}^{T}\left[\left(1 - p_{ht}^f\right)\right]^{I\left[y_{ht}^f=0\right]} \times \left[\frac{p_{ht}^f {\mu_{ht}^f}^{y_{ht}^f} e^{-\mu_{ht}^f}}{y_{ht}^f!\left(1 - e^{-\mu_{ht}^f}\right)}\right]^{1-I\left[y_{ht}^f=0\right]}$$

$$\times \left(1 - p_{ht}^m\right)^{1-r_{ht}}\{p_{ht}^m \times \mathrm{LN}(y_{ht}^m; \mu_{ht}^m; \sigma^2)\}^{r_{ht}} \times f(\boldsymbol{b}_h) \tag{17}$$

To complete the Bayesian specification of the model, we assign priors to the unknown parameters in the above likelihood function. For the regression coefficients $\beta_1, \beta_2, \eta_1, \eta_2, \psi_1, \dots, \psi_4$, we assume shrinkage priors. We have a large number of covariates and, thus, a shrinkage prior will be beneficial. We use a LASSO prior on these sets of parameters. Suppressing the subscripts and assuming that each coefficient is a vector of order $k \times 1$, β_k, and where the shrinkage parameters are denoted by the τ's, we use a LASSO prior as follows:

$$\beta_k|\sigma^2, \tau_1^2, \dots, \tau_p^2 \sim N_p(0, \sigma^2\boldsymbol{D}_\tau) \tag{18a}$$

$$\text{where } \boldsymbol{D}_\tau = \mathrm{diag}(\tau_1^2, \dots, \tau_{P'}^2) \tag{18b}$$

$$\tau_1^2, \dots, \tau_{P'}^2 \sim \prod_{p=1}^{P'} \frac{\lambda^2}{2}\exp\left(-\frac{1}{2}\lambda\tau_p^2\right) \tag{19}$$

$$\lambda^2 \sim \mathrm{Gamma}(a, b) \tag{20}$$

$\sigma^2 \sim \pi(\sigma^2) = \frac{1}{\sigma^2}$ (21)

For the rest of the regression parameters, we assume a normal prior, the spline coefficients (ν) are also assigned a normal density prior; for each variance parameter, we assume an inverse-gamma (IG) prior and for the variance-covariance matrix in the baseline distribution of G, we assume an inverse Wishart prior; and finally, for the total mass α of the DP, we assume a uniform distribution.

4.3 Model Selection and Model Fit

In order to assess our model, we compare it with a variety of different nested models as follows. We analyse deviance information criteria (DIC) proposed by Spiegelhalter et al. (2002), Log-pseudo marginal likelihood (LPML) and Bayesian p-values to determine the best model. We also compute the Log-Pseudo Marginal Likelihood (LPML) as an additional model selection criteria and Posterior Predictive P-value for model fit.

Let $\boldsymbol{D} = (Y^f, Y^m)$ be the observed data, θ be the set of parameters and $\boldsymbol{b}$ is the set of latent random effects variables. DIC in its basic form is given by:

$\mathrm{DIC}(\boldsymbol{D}) = \overline{\boldsymbol{D}(\theta)} + p_{\boldsymbol{D}} = -4E_\theta[\log p(\boldsymbol{D}|\theta)|\boldsymbol{D}] + 2\log p[\boldsymbol{D}|\mathrm{E}_\theta(\theta|\boldsymbol{D})]$

However, in our setting, with the latent variable $\boldsymbol{b}$, $p(\boldsymbol{D}|\theta)$ is not a closed form. Hence, we follow the approach in Jiang et al. (2015) and Celeux et al. (2006), and calculate $\mathrm{DIC}(\boldsymbol{D})$, by first considering the DIC measure with "complete data" with $\boldsymbol{b}$ and then integrating out the observed $\boldsymbol{b}$.

$E_b\{\mathrm{DIC}(\boldsymbol{D}, \boldsymbol{b})\} = -4E_\theta[\log p(\boldsymbol{D}, \boldsymbol{b}|\theta)|\boldsymbol{D}, \boldsymbol{b}] + 2\log p[\boldsymbol{D}, \boldsymbol{b}|E_\theta(\theta|\boldsymbol{D}, \boldsymbol{b})]$

Integrating out $\boldsymbol{b}$ leaves

$\mathrm{DIC} = \mathrm{DIC}(\boldsymbol{D}) = E_b\big[-4E_\theta[\{\log p(\boldsymbol{D}, \boldsymbol{b}|\theta)|\boldsymbol{D}\} + 2\log\{\boldsymbol{D}, \boldsymbol{b}|E_\theta(\theta|\boldsymbol{D}, \boldsymbol{b})\}]\big]$ (22)

$= -4E_{\boldsymbol{b},\theta}\{\log p(\boldsymbol{D}, \boldsymbol{b}|\theta)|\boldsymbol{D}\} + 2E_{\boldsymbol{b}}[\log\{\boldsymbol{D}, \boldsymbol{b}|E_\theta(\theta|\boldsymbol{D}, \boldsymbol{b})\}|\boldsymbol{D}]$ (23)

where integration over $\boldsymbol{b}$ is obtained via numerical methods (Jiang et al., 2015). The smaller the DIC values the better the model is.

In addition to the DIC measure, we also compute $p\big(Y_h^f, Y_h^m \big| Y_{-h}^f, Y_{-h}^m\big)$, see Geisser and Eddy (1979), which is the posterior density of $\big(Y_h^f, Y_h^m\big)$ for household h conditional on the observed data with a single data point deleted. This value is known as the conditional predictive ordinate (CPO), see Gelfand et al. (1992) and Jiang et al. (2015), which has been widely used for model diagnostics and assessment. For the h^{th} household, the CPO statistic according to the model is defined as:

$$\mathrm{CPO}_h = p\left(Y_h^f, Y_h^m \middle| Y_{-h}^f, Y_{-h}^m\right) = E_\theta\left[p\left(Y_h^f, Y_h^m|\theta\right)\middle|Y_{-h}^f, Y_{-h}^m\right] \tag{24}$$

where $-h$ denotes the exclusion from the data of household h. $p\left(Y_h^f, Y_h^m|\theta\right)$ is the sampling density of the model evaluated at the h^{th} observation. The expectation above is taken with respect to the posterior distribution of the model parameters, θ, given the cross validated data $\left(Y_{-h}^f, Y_{-h}^m\right)$. For household h, the CPO_h can be obtained from the MCMC samples by computing the following weighted average:

$$\widehat{\mathrm{CPO}}_h = \left(\frac{1}{S}\sum_{s=1}^{S}\frac{1}{f\left(Y_h^f, Y_h^m|\theta^{(m)}\right)}\right)^{-1} \tag{25}$$

where S is the number of simulations. $\theta^{(s)}$ denotes the parameter samples at the s^{th} iteration. A large CPO value indicates a better fit. A useful summary statistic of the CPO_h is the LPML, defined as $\mathrm{LPMP} = \sum_{h=1}^{N}\log\left(\widehat{\mathrm{CPO}}_h\right)$. Models with greater LPML values represent a better fit. To assess the goodness of fit of the models, we also compute the Bayesian p-value/posterior predictive p-value (Gelman et al., 2004), which measures the discrepancy between the data and the model by comparing a summary χ^2 statistic of the posterior predictive distribution with the true distribution of the data. Values close to 0.5 are considered to be a good fit, as then the observed pattern is likely to be seen in replications of the data under the true model.

The following section discusses the results from estimating the model, in particular the estimated parameters in equations (5-6) and (11-12). Our key focus is on: (i) whether saving acts as a buffer against future financial problems, i.e. focusing on the ψ's, a priori, we expect saving to have a protective role against future hardship, hence $\psi_1, \psi_2 < 0$; (ii) whether state dependence is apparent in observed financial problems, where the key parameters of interest are the γ's; (iii) finally, whether there is interdependence between secured debt holding and financial problems, where the parameters of interest are the ς's.

5. Results

The results from estimating the model detailed in Section 4 are presented in Tables 2 and 3. Table 2 shows the correlation in the unobservable effects across the equations, i.e. the variance – covariance matrix. Where statistically significant, both the variance and covariance terms are positive. For example, positive correlations are found to exist in the unobservable effects between the extent of financial problems and secured debt payments. The findings of interdependence across the different parts of the empirical model support the joint modelling framework: ignoring such effects would result in less efficient estimates.

Table 3 provides Bayesian posterior mean estimates (BPMEs) and is split into three panels. Panel A provides BPMEs and their associated statistical significance for head of household and household level controls. In Panel B of Table 3, BPMEs are given for regional and business cycle effects. Finally, Table 3 Panel C provides the key parameter estimates of interest, i.e. those BPMEs associated with: the role of saving, the ψ's; dynamics, the γ's; and interdependence across equations for each of the outcomes, the ς's. Each panel of Table 3 is split into four columns: the first two columns relate to financial problems, our primary outcome of interest, the probability of being in financial hardship and the number of problems reported, respectively; and the final two columns show the estimates for secured debt, namely the probability of having secured debt and the monthly mortgage repayments, respectively. In addition to identifying correlation in the unobservables, the flexibility of the two-part process is also evident when comparing the influence of the explanatory variables across the binary and the non-binary parts of the model, where in what follows it can be seen that some explanatory variables exert different influences across the two parts.

Initially, we discuss the role of head of household and financial covariates focusing on the results in Table 3 Panel A. Households with male heads have higher monthly mortgage payments than their female counterparts but are less likely to experience financial problems. This latter finding is consistent with the existing literature, e.g. Brown et al. (2014) for the UK, Gjertson (2016) for the US and Giarda (2013) for Italy. Households with a white head are less likely to hold mortgage debt but conversely have a higher probability of reporting financial problems. The role of education is mixed, where, in general, effects are only evident for the most qualified heads of household. Specifically, those households with a head who has a degree as their highest educational attainment are less likely to face financial hardship and report fewer problems compared to those with no qualifications. This does not reflect an income effect as income is controlled for directly. This finding may reflect the possibility that highly educated heads of household are likely to be more financially literate and capable of managing their household finances, see Lusardi and Mitchell (2014). The 'Odds Ratio' (OR) is given by $\exp(\hat{\beta}_{1k}) = \exp(-0.231)$ and is equal to 0.79. Hence, the relative probability of a household with a head with a degree currently reporting financial problems is 21 percentage points lower compared to those with no qualifications. In contrast, those with only GCSE qualifications have a lower (higher) probability of having mortgage debt (financial problems).

With respect to labour market status, the relative probability of household with an employed head having mortgage debt is around 19 percentage points higher compared to a household with a head who is out of the labour market, given the OR= $\exp(\hat{\beta}_{1k}) = \exp(0.177) = 1.19$. Households with a self-employed head have fewer financial problems and lower monthly mortgage repayments. Compared to households with a head reporting very poor or poor health, effects are evident for both secured debt and financial hardship. In accordance with the existing literature (e.g. Bridges and Disney, 2005), a positive association is found between a head of household being in poor health and household debt. The results show that households with a head reporting good health have a lower probability of facing financial problems.

Perhaps surprisingly there is no effect of real equivalized monthly income on either secured debt or financial problems. This might be because the income effect is captured to some extent by the controls for the head of household's highest educational attainment and labour market status, as well as the lagged dependent variables (we comment on the latter below). We also condition the outcomes on household expenditure on utilities and non-durable goods. A priori, we might envisage that higher utility bills and expenditure on goods would increase financial problems. However, the results show that higher utility bills are associated with a higher incidence of financial problems but conversely a lower number of financial problems, whilst expenditure on non-durable goods such as food is positively associated with the number of financial problems reported, which is consistent with prior expectations.

Figures 3 and 4 show the effects of the head of household's age, illustrated by spline function graphs of age on each outcome. The shaded grey area represents the 95 percent credible interval. Figure 3A shows the association between the head of household's age and the probability of reporting a financial problem, and Figure 3B reveals the relationship between age and the number of problems reported at the household level. Whilst financial problems have been found to be more prevalent for those under 30 compared to other age groups in the existing literature, e.g. Atkinson et al. (2006), within this group Figure 3A reveals that there is clear evidence that the likelihood of a household experiencing financial problems increases monotonically with the head of household's age. Conversely, whilst the head of household's age has a significant effect on the number of financial problems reported at the household level, as can be seen from Figure 3B, the effects are very similar for each age – peaking at around 21 and 31 – but are small in terms of magnitude (with BPME of around 0.05) at less than 1 percentage point per year. Figure 4 reveals that life cycle effects exist for secured debt. The probability of a household having a mortgage falls up to the head of household's age of 24 and then increases, peaking at 30, see Figure 4A, whilst the level of the monthly mortgage repayments increases monotonically with the head of household's age, which is consistent with the findings of Brown and Taylor (2008) who examine the mortgage-income gearing ratio across countries. The results herein show the importance of allowing for the non-linear effects of age on the outcomes, where the spline function reveals evidence of life cycle effects within this sample of young household heads.

In Table 3 Panel B, we present the results associated with regional and business cycle effects, where for the former London is the reference category and for the latter pre-2000 is the omitted period. Focusing on secured debt, there is heterogeneity across regions in terms of the likelihood of a household holding secured debt and the amount of monthly mortgage repayments. For example, households in the North East are less likely to have a mortgage (compared to those in London), and those in Wales have the lowest monthly mortgage repayments: OR= $\exp(\hat{\beta}_{1k}) = \exp(-0.394) = 0.67$, approximately 33 percentage points lower than London. There are generally no significant differences across regions for either the incidence or the extent of financial hardship, with the exception that households in Scotland (the North East) have fewer (more) financial problems than those living in London. The finding of more financial problems in the North East may reflect high economic inactivity rates over the period relative to London, see UK Office for National Statistics (ONS, 2009). The business cycle effects are interesting, in that there are significant differences by year after 2002 (compared to pre-2000) for secured debt with monthly mortgage repayments increasing monotonically over time, this is an effect over and above inflation since monetary values are held at constant prices. In contrast for financial problems, only after the 2008 financial crisis period has the incidence and extent of household financial hardship increased. For example, in 2012 a household was, OR= $\exp(\hat{\beta}_{1k}) = \exp(0.596) = 1.81$, approximately 81 percentage points more likely to experience a financial problem compared to pre-2000, ceteris paribus. In terms of the number of problems conditional on facing hardship, the estimated BPME equates to having an extra half problem. This is found by multiplying the mean number of financial problems, see Table 1 Part A, by the Odds Ratio, i.e. OR= $\exp(\hat{\beta}_{1k}) = \exp(0.24) = 1.27$, so $1.27 \times 1.91 = 2.43$ which is 0.52 problems higher than the average.

In Table 3 Panel C, the results focus on the key covariates of interest: the role of saving; dynamics and the existence of state dependence; and interdependence between outcomes. Focusing initially on secured debt, there is evidence of state dependence, where a 1% increase in mortgage debt in the previous year is associated with around a 2 percentage point increase in current monthly mortgage repayments (i.e. OR= $\exp(\hat{\gamma}_4) = \exp(0.018) = 1.02$), which is consistent with existing evidence, e.g. Burrows (1997). Households which experienced financial problems in the previous year have higher levels of monthly mortgage repayments, i.e. $\hat{\varsigma}_4 > 0$. With respect to financial problems, there is also evidence of positive state dependence, which is consistent with findings in the existing literature, e.g. Giardi (2013) and Brown and Taylor (2014). The 'Odds Ratio' shows that households which experienced financial hardship in the previous year are nearly twice as likely, 85 percentage points, to currently report a financial problem, i.e. OR= $\exp(\hat{\gamma}_1) = \exp(0.614) = 1.85$. Having had mortgage debt in the previous year increases the probability of currently having financial problems, i.e. $\hat{\varsigma}_1 > 0$, which is consistent with Gjertson (2016), but is inversely related to the extent of financial hardship, i.e. $\hat{\varsigma}_2 < 0$. This finding might reflect a housing tenure effect in that those who own a home via a mortgage may face fewer financial problems due to the wealth effect associated with home ownership, e.g. Taylor (2011).

We now consider whether past savings behaviour plays a protective role or buffer against currently experiencing financial problems. The parameters on the amount saved in the previous year are negative, i.e. $\hat{\psi}_1, \hat{\psi}_2 < 0$. For example, a 1% increase in savings in the previous year is associated with 15 percentage point lower probability of currently having a financial problem and reduces the number of financial problems by approximately 6 percentage points, e.g. OR= $\exp(\hat{\psi}_2) = \exp(-0.064) = 0.94$. These findings are consistent with the existing international literature which has revealed a protective role of savings against financial hardship, e.g. Collins and Gjertson (2013), Mills and Amick (2010), both for the US, Giardi (2013) for Italy, and the study by Le Blanc et al. (2016) which revealed that a key motive for saving in European countries was for unexpected events. In contrast to existing studies, our modelling framework separates each outcome into a two-part process, i.e. the probability of having a financial problem and the number of financial problems revealing that saving influences both the incidence and extent of financial problems. It is apparent that our findings suggest that the level of savings has a large effect on reducing the likelihood of the household experiencing financial problems, hence acting as a financial buffer.

Table 4 shows the results of estimating alternative specifications: (i) in model 2, the amount saved last year is instrumented on the head of household's saving behaviour during childhood and parental characteristics (including their financial expectations); (ii) in model 3, the amount saved is replaced by a binary indicator which reflects saving in the previous year, to explore whether the incidence of saving is important regardless of the amount; and (iii) in model 4, we instrument the incidence of saving in the previous year.

To model saving behaviour, we follow Brown and Taylor (2016) and use information recorded in the *Youth Survey*, which provides information on the head of household's saving behaviour as a child. For the latter, children were asked '*what do you usually do with your money?*' The possible responses were: *save to buy things*; *save and not spend*; and *spend immediately*. We create a binary indicator S_h^C, which shows whether the individual saved as a child, and we then model their saving behaviour as an adult, as follows: $S_h^A = \boldsymbol{Z}_h{}'\boldsymbol{\phi} + S_h^C + \mathbf{EXP}_h^{P}{}'\boldsymbol{\pi} + \nu_h$, where S_h^A is either a binary indicator (i.e. whether they saved as an adult in the previous period) or the natural logarithm of savings in the previous period. The vector of controls, $\boldsymbol{Z}_h$, includes permanent income (constructed following the approach of Kazarosian, 1997) and its volatility, and $\mathbf{EXP}_h^P$ is a vector of the financial expectations of the child's parent (who is the head of household). The results from modelling savings behaviour reveal that the probability and level of savings are positively associated with: whether the individual saved during childhood; the financial expectations of their parent, in particular financial pessimism; and permanent income and its volatility. Full results are given in Table A1.

In Table 4, for brevity, we only report the key parameters of interest, i.e. those associated with savings behaviour (the ψ's), dynamics (the γ's) and interdependence (the ς's). Panels A through to C report the BPMEs for models 2 to 4 respectively. Clearly, throughout each panel, the dynamic effects and interdependence between financial problems and secured debt are very similar in terms of magnitude of the BPMEs to that of model 1 shown in Table 3.

The protective role of savings in mitigating the likelihood of future financial problems and the extent of such hardship is also evident when the amount saved is instrumented, see Table 4 Panel A, in that $\hat{\psi}_1, \hat{\psi}_2 < 0$. The effects are magnified compared to model 1, where a 1% increase in savings in the previous year is associated with a 23 percentage point lower probability of currently having a financial problem, i.e. OR= $\exp(\hat{\psi}_1) = \exp(-0.267) = 0.77$. The influence of the amount saved on the extent of financial problems is similar to that of model 1 at around 5 percentage points, i.e. OR= $\exp(\hat{\psi}_2) = \exp(-0.046) = 0.95$. Table 5 reports the DIC and LPML for each model, revealing that model 2, where the amount saved is instrumented is preferred in terms of fit in comparison to model 1 given that it has a lower DIC value and larger LPML. Replacing the amount of savings with the incidence of saving in the previous year shows that the incidence of past saving, regardless of the amount, reduces both the probability of having a financial problem by 27 percentage points (OR= $\exp(\hat{\psi}_1) = \exp(-0.319) = 0.73$) and the number of financial problems by 11 percentage points (OR= $\exp(\hat{\psi}_2) = \exp(-0.113) = 0.89$), see Table 4 Panel B. Hence, the act of saving can help to mitigate financial hardship. These effects remain when the likelihood of saving is instrumented, as can be seen from Table 4 Panel C, although the magnitudes fall to 24 and 4 percentage points, respectively. Consistent with the results of model 1 shown in Table 3, past saving behaviour has a larger effect on reducing the incidence of financial hardship rather than on the extent or number of financial problems faced. Again the instrumented specification is preferred in terms of model fit given the lower DIC value and larger LPML when comparing models 3 and 4, see Table 5. Across each of the four models, the posterior p-values are close to 0.5, which shows that each specification provides good fit thereby endorsing our modelling approach.

6. Conclusion

We have explored whether savings provide a buffer against future financial hardship using British panel data. Our findings suggest that savings provide a financial buffer in the event of future hardship and are consistent with evidence from the US, which has generally been based on non-representative samples of low income families. In addition to contributing to the existing literature by exploring British panel data, we have made by a methodological contribution by developing a flexible Bayesian framework to examine the two-part process behind financial hardship, specifically the incidence and extent of financial problems, as well as allowing for the two-part process behind important financial commitments such as mortgage debt. Our modelling approach, which allows for correlated random effects, identifies interdependence between financial hardship and secured debt and between each of the associated two-part processes. The analysis also allows for persistence over time in financial problems revealing clear evidence of dynamic effects and the existence of interdependence between the outcomes.

To summarise, our results show persistence in experiencing financial problems over time as well as the role that saving on a regular basis can play in mitigating future financial problems. Our findings relate to the widespread concern amongst policymakers in a number of countries regarding the relatively low levels of household saving. The protective role of saving established by our empirical analysis is an important finding given the evidence from the House of Lords Selection Committee on Financial Exclusion (2017) indicating that young adults are more likely to face financial exclusion. Our analysis also highlights the need to enhance financial literacy and promote the importance of 'putting money aside'. Indeed, influencing saving behaviour during childhood, i.e. in the formative years, may ultimately help to reduce the prevailing levels of financial vulnerability and stress experienced by households later in the life cycle.

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FIGURE 1: Number of financial problems

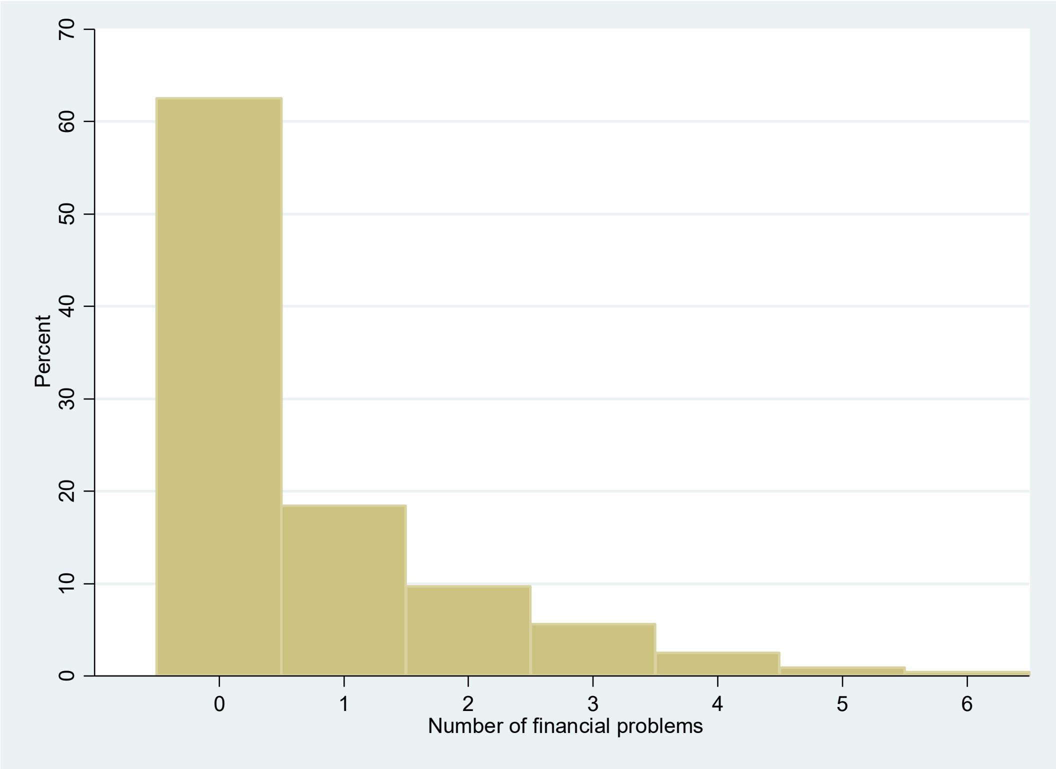


FIGURE 2: Natural logarithm of monthly mortgage repayments

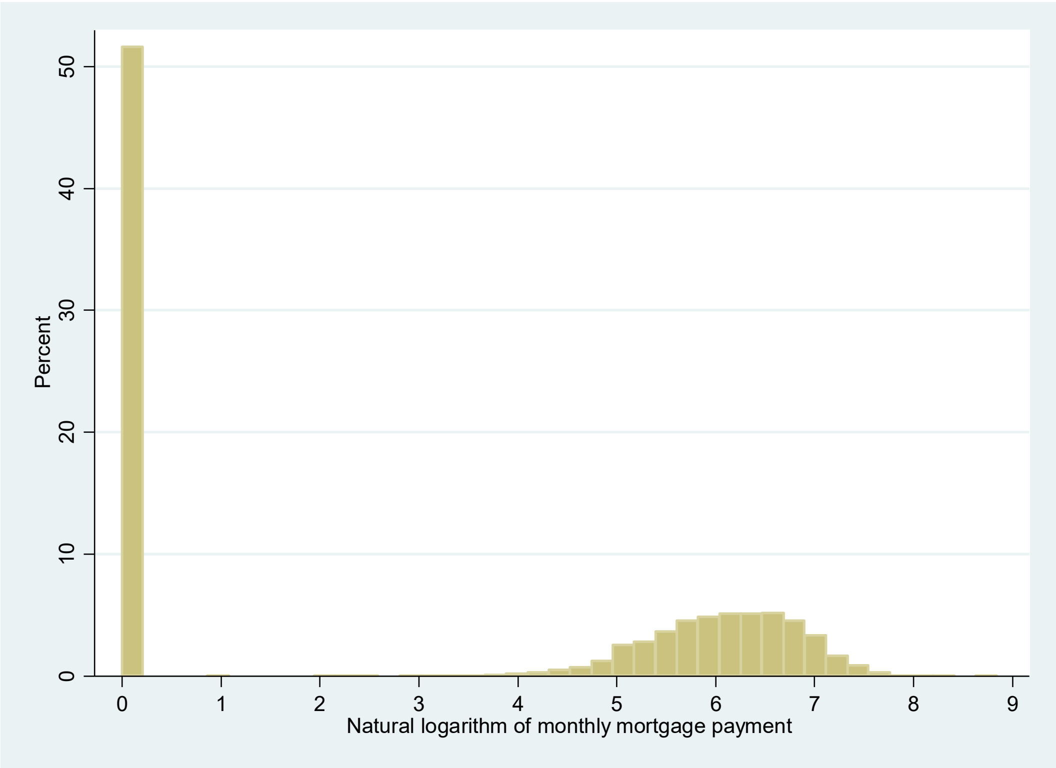
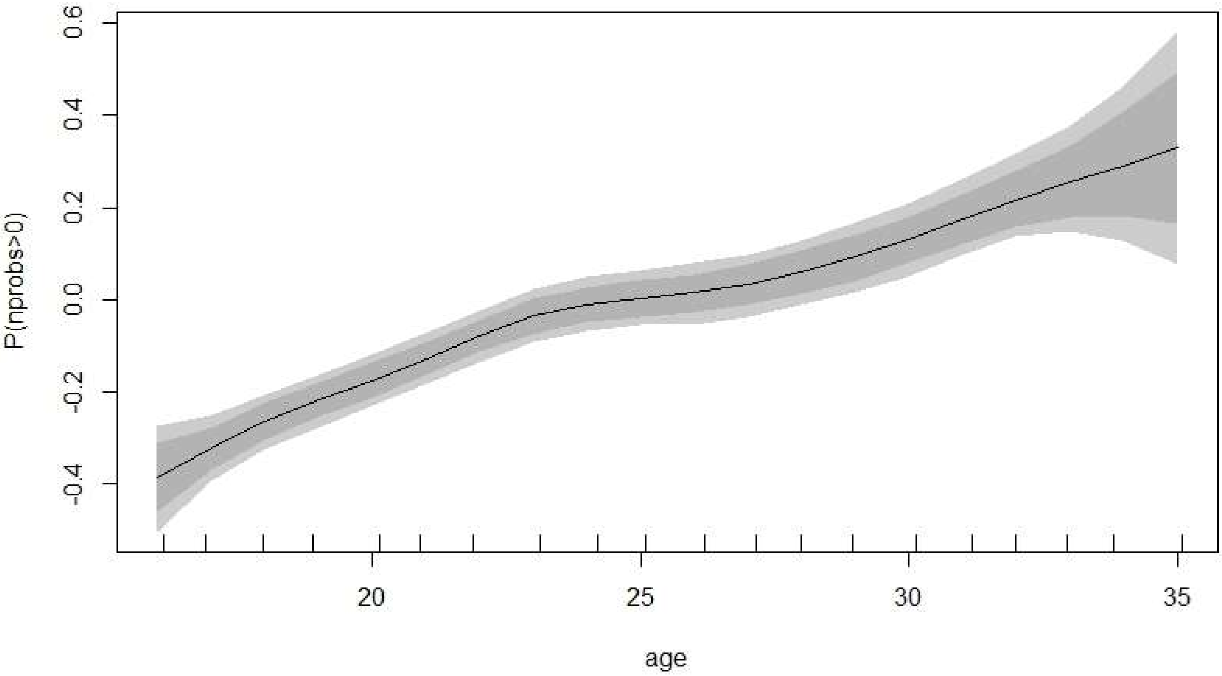
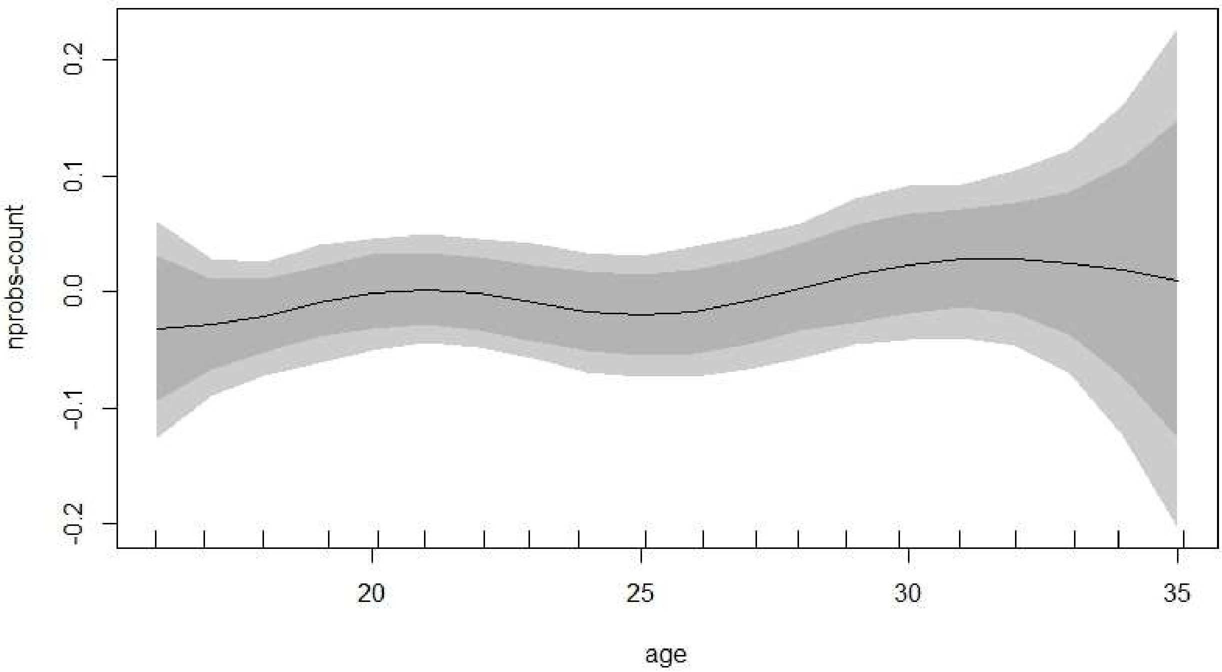


FIGURE 3A: Head of household age effects and the probability of having financial problems



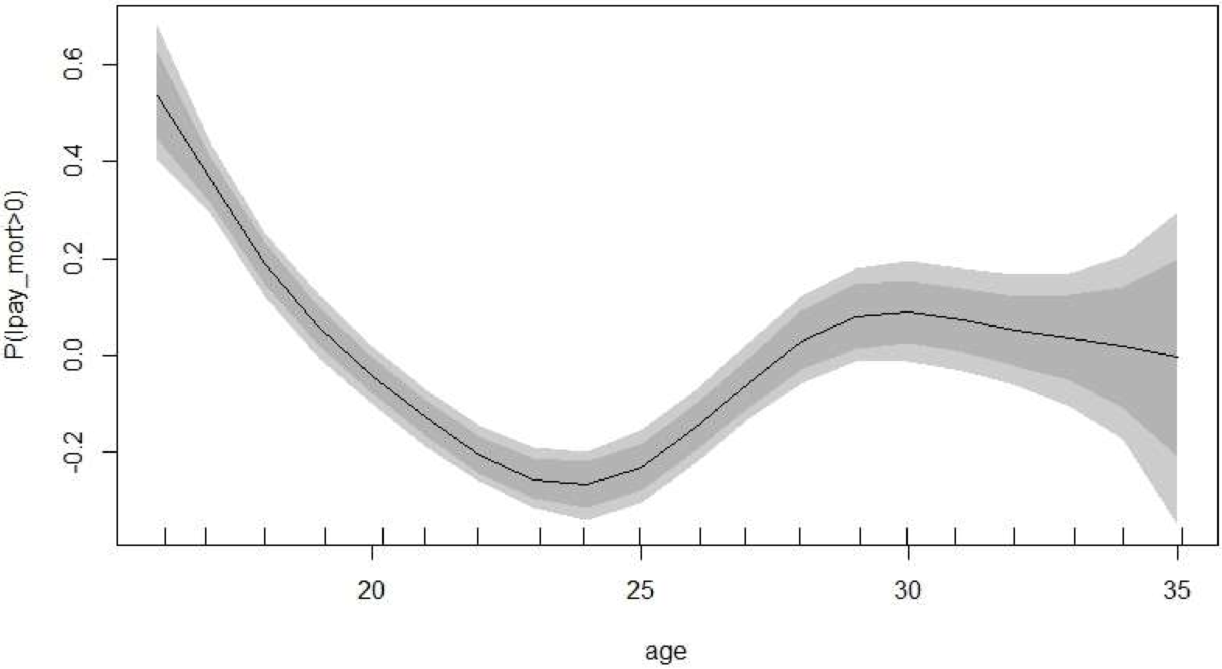
Note the vertical axis shows BPME for the probability of having financial problems.

FIGURE 3B: Head of household age effects and the number of financial problems



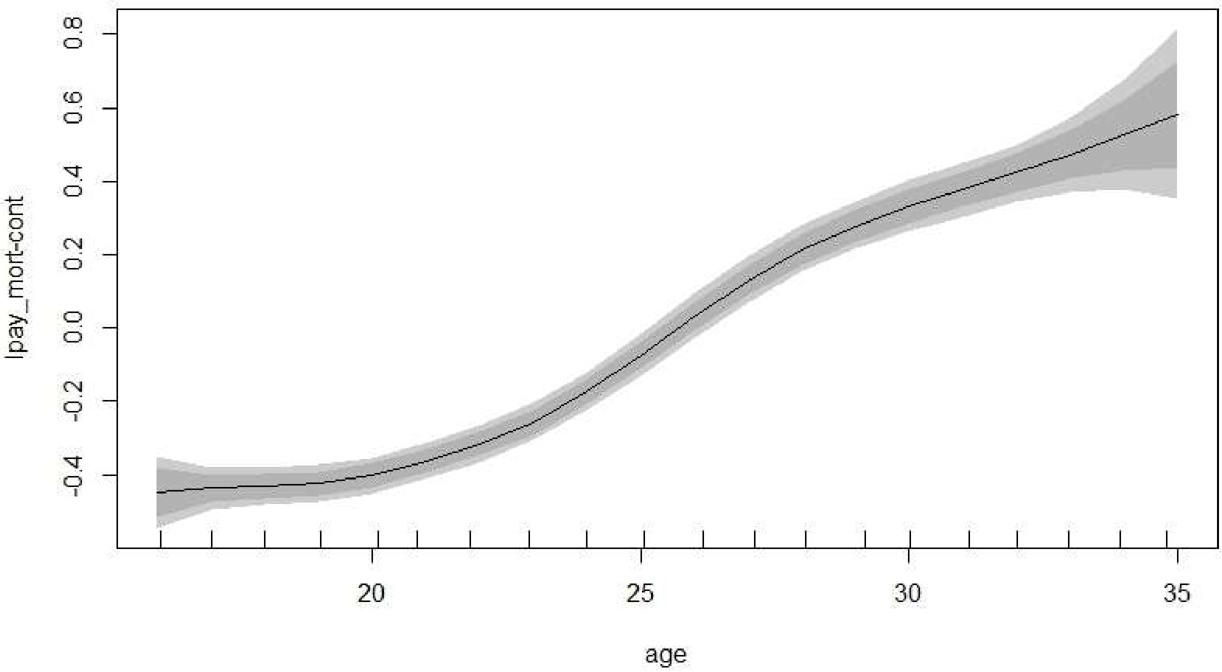
Note the vertical axis shows BPME for the number of financial problems.

FIGURE 4A: Head of household age effects and the probability of having mortgage debt at the household level



Note the vertical axis shows BPME for the probability of having mortgage debt.

FIGURE 4B: Head of household age effects and the natural logarithm of the amount of monthly household mortgage debt repayments



Note the vertical axis shows BPME for the log level of monthly mortgage debt repayments.

TABLE 1: Summary statistics

	MEAN	STD. DEV	MIN	MAX
PANEL A: Dependent variables				
Number of financial problems	0.716	1.155	0	6
Whether financial problems	0.375	–	0	1
Number of financial problems conditional upon non-zero	1.907	1.133	1	6
Natural logarithm mortgage	2.939	3.083	0	8.842
Whether secured debt	0.484	–	0	1
Natural logarithm mortgage conditional upon non-zero	6.071	0.784	0.933	8.842
PANEL B: Control variables				
Whether saved last year, $S_{h,t-1}^{A}$	0.375	–	0	1
Natural logarithm of savings last year, $S_{h,t-1}^{A}$	1.678	2.272	0	8.135
Male	0.487	–	0	1
White	0.884	–	0	1
Age	21.079	3.709	17	35
Degree	0.104	–	0	1
Other higher qual., e.g. teaching or nursing	0.190	–	0	1
A levels	0.296	–	0	1
GCSE/O level	0.196	–	0	1
Any other qualification	0.058	–	0	1
Employee	0.530	–	0	1
Self-employed	0.022	–	0	1
Unemployed	0.084	–	0	1
Excellent health	0.249	–	0	1
Good health	0.510	–	0	1
Fair health	0.135	–	0	1
Natural logarithm monthly equivalized income	7.618	1.200	0.627	10.909
Natural logarithm annual utilities	6.179	2.315	0	9.164
Natural logarithm expenditure non-durable goods	5.837	1.097	0	8.257
Heads of Household (h)		2,751		
Observations (ht)		13,132		

TABLE 2: MODEL 1 – Variance-covariance matrix

VAR (binary financial problems) $\sum_{1,1}$	0.060	*
COV (binary financial problems and number of financial problems) $\sum_{1,2}$	-0.028	*
COV (binary financial problems and binary secured debt) $\sum_{1,3}$	-0.131	
COV (binary financial problems and log secured debt) $\sum_{1,4}$	0.323	*
VAR (number of financial problems) $\sum_{2,2}$	0.049	*
COV (number of financial problems and binary secured debt) $\sum_{2,3}$	0.180	*
COV (number of financial problems and log secured debt) $\sum_{2,4}$	0.478	*
VAR (binary secured debt) $\sum_{3,3}$	0.955	*
COV (binary secured debt and log secured debt) $\sum_{3,4}$	2.369	*
VAR (log secured debt) $\sum_{4,4}$	6.306	*

* denotes statistical significance at the 5 per cent level.

TABLE 3: MODEL 1 – Estimated Bayesian marginal effects (posterior means) of the independent variables upon outcomes

	FINANCIAL PROBLEMS		SECURED DEBT	
PANEL A: Head of household and Household Controls	Probability non-zero $\Pr(Y_{ht}^{f} \neq 0)$	Number (count >0) $\log(\lambda_{ht})$	Probability non-zero $\Pr(Y_{ht}^{m} \neq 0)$	Log amount >0 $\log(Y_{ht}^{m})$
Male	-0.299 *	-0.016	-0.017	0.058 *
White	0.158 *	-0.159 *	-0.499 *	-0.020
Degree	-0.231 *	-0.235 *	-0.067	-0.023
Other higher qual., e.g. teaching or nursing	-0.096	-0.051	-0.108	-0.056
A levels	-0.133	-0.068	-0.116	-0.074 *
GCSE/O level	0.158 *	-0.021	-0.231 *	-0.044
Any other qualification	0.397 *	0.012	0.096	-0.051
Employee	-0.031	0.019	0.177 *	-0.009
Self-employed	-0.017	-0.067 *	0.065	-0.049 *
Unemployed	-0.047	-0.118	-0.134	0.082
Excellent health	0.120	0.068	0.136	-0.096 *
Good health	-0.365 *	-0.068	-0.489 *	-0.042
Fair health	-0.202 *	-0.111 *	-0.382 *	-0.053
Natural logarithm monthly equivalized income	0.035	-0.007	-0.228	-0.017
Natural logarithm annual utilities	0.143 *	-0.068 *	-1.389 *	0.189 *
Natural logarithm expenditure non-durable goods	0.028	0.067 *	-0.315 *	-0.016
Heads of household (h)		2,751		
Observations (ht)		13,132		

* denotes statistical significance at the 5 per cent level.

TABLE 3 (Cont.): MODEL 1 – Estimated Bayesian marginal effects (posterior means) of the independent variables upon outcomes

PANEL B: Regional and Business Cycle Controls	FINANCIAL PROBLEMS Probability non-zero $\Pr(Y_{ht}^{f} \neq 0)$	FINANCIAL PROBLEMS Number (count >0) $\log(\lambda_{ht})$	SECURED DEBT Probability non-zero $\Pr(Y_{ht}^{m} \neq 0)$	SECURED DEBT Log amount >0 $\log(Y_{ht}^{m})$
Scotland	-0.076	-0.173 *	0.155 *	0.130 *
Wales	0.112	0.041	-0.664 *	-0.394 *
North East	0.059	0.111 *	-0.707 *	-0.290 *
North West	0.181	-0.058	-0.695 *	-0.355 *
East Midlands	0.173	-0.099	-0.451 *	-0.138 *
West Midlands	0.087	-0.053	-0.747 *	-0.227 *
East of England	0.144	-0.005	-0.869 *	-0.218 *
South East	0.010	-0.124	-0.426 *	-0.033
South West	0.095	0.094	-0.448 *	0.033
2000	-0.038	0.087	-0.379 *	-0.027
2001	0.029	0.085	0.221	0.133 *
2002	-0.176	-0.067	0.315 *	0.153 *
2003	-0.154	-0.172 *	0.306 *	0.194 *
2004	-0.091	-0.046	0.706 *	0.261 *
2005	-0.156	-0.075	0.695 *	0.407 *
2006	0.018	-0.073	0.908 *	0.538 *
2007	0.004	-0.009	1.198 *	0.637 *
2008	0.026	-0.052	1.238 *	0.746 *
2010	0.153	0.057	1.447 *	0.819 *
2012	0.596 *	0.133 *	1.705 *	0.768 *
2014	0.384 *	0.240 *	1.894 *	0.853 *
2015	0.252 *	0.100	1.946 *	0.917 *
Heads of household (h)	2,751			
Observations (ht)	13,132			

* denotes statistical significance at the 5 per cent level.

TABLE 3 (Cont.): MODEL 1 – Estimated Bayesian marginal effects (posterior means) of the independent variables upon outcomes

	FINANCIAL PROBLEMS		SECURED DEBT	
PANEL C:	Probability non-zero	Number (count >0)	Probability non-zero	Log amount >0
Dynamics, Interdependence and Savings	$\Pr(Y_{ht}^{f} \neq 0)$	$\log(\lambda_{ht})$	$\Pr(Y_{ht}^{m} \neq 0)$	$\log(Y_{ht}^{m})$
Natural logarithm of savings last year, $S_{h,t-1}^{A}$	-0.161 *	-0.064 *	-0.078 *	0.001
Financial problems last year, $y_{h,t-1}^{f}$	0.614 *	0.167 *	-0.012	0.017 *
Natural logarithm of mortgage debt last year, $y_{h,t-1}^{m}$	0.027 *	-0.019 *	-0.449 *	0.018 *
Heads of household (h)	2,751			
Observations (ht)	13,132			

* denotes statistical significance at the 5 per cent level.

TABLE 4: Estimated Bayesian marginal effects (posterior means) for key covariates – Alternative specifications

	FINANCIAL PROBLEMS		SECURED DEBT	
	Probability non-zero $\Pr(Y_{ht}^{f} \neq 0)$	Number (count >0) $\log(\lambda_{ht})$	Probability non-zero $\Pr(Y_{ht}^{m} \neq 0)$	Log amount >0 $\log(Y_{ht}^{m})$
PANEL A: MODEL 2 – Amount saved, instrumented				
Instrumented natural logarithm savings last year, $\hat{S}_{h,t-1}^{A}$	-0.267 *	-0.046 *	-0.391 *	0.016
Financial problems last year, $y_{h,t-1}^{f}$	0.613 *	0.164 *	-0.025	0.017 *
Natural logarithm of mortgage debt last year, $y_{h,t-1}^{m}$	-0.017 *	-0.015 *	-0.430 *	0.018 *
PANEL B: MODEL 3 – Whether saved last year				
Whether saved last year, $S_{h,t-1}^{A}$	-0.319 *	-0.113 *	-0.139 *	0.003
Financial problems last year, $y_{h,t-1}^{f}$	0.613 *	0.168 *	-0.017	0.017 *
Natural logarithm of mortgage debt last year, $y_{h,t-1}^{m}$	-0.024 *	-0.020 *	-0.453 *	0.018 *
PANEL C: MODEL 4 – Whether saved last year, instrumented				
Instrumented whether saved last year, $\hat{S}_{h,t-1}^{A}$	-0.278 *	-0.042 *	-0.443 *	0.019
Financial problems last year, $y_{h,t-1}^{f}$	0.617 *	0.164 *	-0.024	0.018 *
Natural logarithm of mortgage debt last year, $y_{h,t-1}^{m}$	-0.016 *	-0.015 *	-0.443 *	0.018 *
Heads of household (h)		2,751		
Observations (ht		13,132		

Notes: (1) * denotes statistical significance at the 5 per cent level. (2) Full results for models 2-4 are available from the authors on request.

TABLE 5: Model selection

MODEL	DIC	LPML
1: Amount saved last year	30,642	-16,011
2: Amount saved, instrumented	30,508	-15,660
3: Whether saved last year	30,821	-16,195
4: Whether saved last year, instrumented	30,525	-15,891

TABLE A1: Instrumenting the head of household's saving behaviour

	MEAN	WHETHER SAVED LAST MONTH	LOG AMOUNT SAVED LAST MONTH
Male	0.487	0.012	0.135
White	0.884	0.017	-0.001
Age	21.079	-0.405 *	-1.357 *
Age squared	444.324	0.008 *	0.026 *
Degree	0.104	0.315 *	1.233 *
Other higher qual., e.g. teaching or nursing	0.190	0.290 *	1.091 *
A levels	0.296	0.159 *	0.601 *
GCSE/ O level	0.196	0.240 *	0.806 *
Any other qualification	0.058	-0.031	-0.136
Household size	3.609	0.002	0.017
Whether married	0.121	0.076	0.161
Employee	0.530	0.274 *	1.264 *
Self-employed	0.022	0.075	0.668 *
Unemployed	0.084	-0.628 *	-1.434 *
Excellent health	0.249	-0.043	-0.182
Good health	0.510	-0.077	-0.330
Fair health	0.135	-0.117 *	-0.468 *
Financially optimistic parent (observed during childhood)	0.468	0.037	0.102
Financially pessimistic parent (observed during childhood)	0.085	0.261 *	1.008 *
Natural logarithm permanent income	5.426	0.152 *	0.625 *
Variance in permanent income	1.211	0.071 *	0.267 *
Whether ever saved during childhood	0.641	0.258 *	0.992 *

* denotes statistical significance at the 5 per cent level.