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HOUSEHOLD FINANCES AND SOCIAL INTERACTION: BAYESIAN ANALYSIS OF HOUSEHOLD PANEL DATA

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We investigate the relationship between social interaction and household finances using the British Household Panel Survey. We explore the relationship between a wide range of aspects of household finances and social interaction, rather than focusing on one particular facet of household finances, such as the holding of stocks and shares. We develop a Bayesian statistical framework to simultaneously explore both sides of the household balance sheet—liabilities and assets. Additionally, we allow the influence of social interaction on household finances to be time dependent, enabling us to model the effects of social interaction from a dynamic perspective. We also develop a two-part model to jointly investigate the influence of social interaction on the amount of different types of debt and financial assets held conditional on holding the different types of debt and assets. Our analysis suggests that social interaction is associated with households holding larger amounts of debt and assets.

JEL Codes: C11, D12, D14

Keywords: assets, debt, household finances, social interaction

1. Introduction and Background

There is a growing body of empirical literature analyzing the implications of social capital and social interaction in the economy. For example, at the microeconomic level, there has been interest in the relationship between social interaction, social capital, and socio-economic outcomes such as educational attainment and employment (see, e.g., Glaeser *et al.*, 2002; Brown and Taylor, 2009); whilst at the macroeconomic level, the debate has focused on the relationship between social capital and economic growth (see, e.g., Knack and Keefer, 1997; Algan and Cahuc, 2010). Recent work has conjectured that social interaction and social capital might influence financial decision-making at the individual or

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household level focusing on stock market participation. Such an effect could occur through word-of-mouth or observational learning (e.g., Banerjee, 1992; Ellison and Fudenberg, 1995), operating via the diffusion of information relating to, for example, stock market opportunities or how to actually participate in the stock market (Hong *et al*., 2004). Such channels of learning are arguably particularly relevant in the context of financial assets which are relatively complicated to acquire, such as stocks and shares. Thus, the decision to invest in financial assets, as well as the type of assets to invest in, may be influenced by the decisions of and advice from work colleagues, friends, and family. Hong *et al*. (2004) present evidence supporting a positive association between social interaction (measured by church attendance and interaction with neighbors) and stock market participation in the U.S. Furthermore, this relationship is found to be more pronounced for individuals who reside in communities characterized by higher stock market participation rates. Similarly, Ivkovic and Weisbenner (2007) report a positive relationship between a household's stock purchases and those made by neighbors. Brown *et al*. (2008) establish a causal link between an individual's decision to own stocks and the average stock market participation of the individual's community. Moreover, the latter result is found to be stronger within more social communities, as measured by whether households are likely to be asked by neighbors for advice. In a similar vein, Guiso *et al*. (2008) explore the relationship between trust and stock market participation and find that less trusting individuals are less likely to purchase stocks. More recently, Christelis *et al*. (2010) find that socially active households are more likely to own shares.

The aim of this paper is to explore the implications of social interaction for household financial decision-making in recognition of the fact that the household financial portfolio is more than just the holding of stocks and shares, which has been the primary focus of the existing literature. Given the heterogeneous nature of financial assets in terms of, for example, the associated financial risk and complexity, one might conjecture that the influence of social interaction may vary across the different types of assets. In addition, we allow for the opposite side of the household balance sheet, which has attracted limited interest in the existing literature in this area, namely household debt. It is apparent that social interaction may potentially have implications for household debt: as argued by Georgarakos *et al*. (2010), more sociable households may be more likely to receive financial support from family or friends if faced with financial difficulties.[1] To be specific, we explore the relationship between social interaction and a wide range of aspects of the financial portfolio. We make a methodological contribution to the existing literature by developing a Bayesian approach to model this relationship within a joint framework. Our joint modeling approach is highly flexible, allowing social interaction to exert different influences on the different aspects of the financial portfolio yet allowing for the potential interdependence between them. Our

[1]These possibilities were also noted by Putnam (2000, p. 312), in his comprehensive review of civic life and social capital in the U.S., who states that: "social networks may also provide emotional and financial support for individuals." More recently, Georgarakos *et al*. (2014), using data drawn from a Dutch household survey, find that the higher is the perceived income of the social circle, the greater is the likelihood that individuals will borrow and, conditional on borrowing, the greater is the amount borrowed.

Bayesian approach allows us to simultaneously model more financial decisions than in the existing literature. In addition, in order to model continuous measures of debt and asset holding, we develop a two-part model to allow for the holding of zero assets and debt. Finally, in contrast to the existing literature, which has generally focused on cross-section data, we exploit panel data which allows us to make an additional contribution by allowing the effect of social interaction on household finances to be time dependent. Hence, we model the effects of social interaction from a dynamic perspective.

In terms of jointly modeling the probability of holding six different types of debt and six different types of financial assets, our results suggest that the effect of social interaction on household finances is not just restricted to share ownership, with positive effects found for both assets and liabilities, that is, both sides of the balance sheet. However, there are differences with respect to the size of the influence of social interaction on the various components of household finances analyzed. Similarly, in terms of jointly modeling the continuous outcomes in the two-part model, that is, the value of unsecured debt, secured debt, non-housing financial assets, and housing assets, social interaction is found to positively influence the probability of holding each liability and asset, that is, a non-zero value, and, conditional on holding the particular liability or asset, social interaction increases the amount of each type of debt and asset held.

2. Empirical Framework

We explore the relationship between household finances and social interaction in the context of two different statistical frameworks. First, we model the relationship between household finances and social interaction by developing a multivariate logit model distinguishing between the joint holding of six different types of assets and six different types of debt. We then focus on the relationship between social interaction and the amount of the assets and liabilities held by specifying a framework whereby we jointly model the amount of unsecured debt, the amount of secured debt, the value of housing assets, and the value of non-housing financial assets held at the household level, conditional on holding the particular type of asset or liability.[2,3] A joint modeling approach to modeling household debt and assets has been adopted by Brown *et al.* (2013), who explore the relationship between attitudes toward risk and household debt. Their findings support an inverse relationship.

[2]In our sample, 63 percent of households hold both financial assets and debt, which, as expected, varies over the life cycle. The following percentages indicate the proportion of households holding both assets and debt with a head of household aged 18–24, 25–34, 35–44, 45–54, and 55 and over: 5, 24, 35, 27, and 9 percent, respectively.

[3]The simultaneous holding of debt and assets, which has been observed in many developed countries, has attracted considerable attention in the existing theoretical literature on household finances. In particular, the "credit card debt puzzle" is well known in the literature, where households simultaneously revolve credit card debt whilst holding liquid financial assets (see, e.g., Gross and Souleles, 2002). The widespread evidence indicating that households simultaneously hold debt and financial assets suggests that a joint approach is appropriate for modeling household financial portfolios.

With respect to the holding of assets and/or debt, let $y_{kit} \in \{0; 1\}$ denote the incidence of holding the $k(= 1, 2, \ldots, K)^{\text{th}}$ financial asset or type of debt, where $K = 12$, by the $i(= 1, 2, \ldots I)^{\text{th}}$ household at time $t(= 1, 2, \ldots, T)$. We model each of the y_{kit} as having a binary distribution with the probability of incidence denoted by p_{kit} and, in turn, we model the p_{kit} using a logit link function. Thus, we assume that household i's joint holding of assets and debt is governed by the following stochastic process:

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

(2) $$\text{logit}(p_{kit}) = \boldsymbol{X}_{kit}^{T}\beta_k + \alpha_{kt}SI_{kit} + b_{ki},$$

where $\boldsymbol{X}_{kit}$ represents the vector of explanatory variables (detailed below), and SI_{kit} denotes social interaction, where the coefficient on the social interaction measure is assumed to be time dependent. The time varying parameter, α_{kt}, which is allowed to vary each year, is an important feature of our contribution (see Dangl and Halling, 2012). This coefficient may change for a variety of reasons, such as the occurrence of unexpected events or changes in the financial situation of the household. Thus, we develop a flexible framework that allows for such changes. In addition, the time varying coefficients improve the predictive power of a model (see West and Harrison, 1997). Therefore, we assume that the parameter α_{kt} has a first order random walk prior as follows:

(3) $$\alpha_{kt} = \alpha_{k,t-1} + e_{kt},$$

with $e_{kt} \sim N(0, \tau_e)$. Thus, the vector α_{kt} consists of unobservable time varying regression coefficients and the coefficients are exposed to random shocks e_{kt} that are normally distributed with a mean of zero and variance, τ_e.[4] This structure allows us to model the effect of social interaction on the holding of different types of assets and debt dynamically by estimating the time-dependent social interaction effect. It is important to note that this prior does not require us to assume that all α_{kt} have the same values as the previous $\alpha_{k,t-1}$. Rather, our approach assumes that they come from a common distribution with the mean being equal to the effect of previous exposure, and allows us to estimate the exposure effect at each point in time dynamically. Note that, if the variance τ_e equals zero, then the regression coefficients α_{kt} are constant over time. Thus, our model nests the specification of constant regression coefficients.

Finally, 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, that is, $\boldsymbol{b}_i = (b_{1i}, b_{2i}, \ldots, b_{12i})^T \sim N_{12}(0, \Sigma)$.

We also jointly model the four continuous variables, that is, unsecured debt, secured debt, the value of housing assets, and the value of non-housing financial assets held at the household level. One particular issue relates to the fact that there

[4]For the first parameter, the base distribution is assumed.

are a large proportion of zeros observed in the data, especially in the context of financial assets. A small number of studies exploring multiple financial decisions based on non-Bayesian methods model the demand for different assets via a two-step approach in order to correct for selectivity. For example, King and Leape (1998) estimate a model for U.S. household portfolio allocation with 11 aggregate asset and liability classifications, whilst Perraudin and Sorensen (2000) aggregate asset and liability holding into stocks, bonds and money. More recently, Christelis *et al*. (2011) explore three investment choices, namely, direct stock holding, investment in mutual funds, and retirement accounts using a multivariate probit model with selection.

The four continuous variables that we analyze are clearly characterized by a two-part nature, that is, a combination of a point mass at zero and a positively skewed distribution for the values exceeding zero. Such data is sometimes referred to as semi-continuous. In order to model unsecured debt, secured debt, non-housing financial assets, and housing assets, we develop a two-part Bayesian model, where the first part models the probability that an outcome is non-zero and the second part models the value of an outcome given that it is greater than zero. Specifically, denote the amount of debt or value of assets of a household by Y. A two-part model for the probability distribution of Y consists of: (i) modelling the probability of $Y > 0$ (using in our case a logistic model); and (ii) separately modelling the distribution of $Y|Y > 0$. A convenient choice is to assume that $[\log(Y)|Y > 0]$ follows a normal distribution. The second part of the two-part model describes the conditional mean of the response given that it is non-zero.[5] The four continuous variables are denoted as follows: unsecured debt (y_{1it}), secured debt (y_{2it}), the value of non-housing financial assets (y_{3it}), and the value of housing assets held at the household level (y_{4it}). Let y_{kit} be the k^{th} dependent variable of the i^{th} household in the t^{th} year. Let R_{kit} be a latent random variable such that:

$$R_{kit} = \begin{cases} 0, & \text{if} \quad y_{kit} = 0 \\ 1, & \text{if} \quad y_{kit} > 0, \end{cases} \tag{4}$$

where

$$\text{prob}(R_{kit} = r_{kit}) = \begin{cases} 1 - p_{kit}, & \text{if} \quad r_{kit} = 0 \\ p_{kit}, & \text{if} \quad r_{kit} = 1. \end{cases} \tag{5}$$

Further, let $s_{kit} \equiv [y_{kit}|R_{kit} = 1]$ denote the positive debt or assets of the i^{th} household in the t^{th} year from the k^{th} variable.

We model the probability p_{kit} (i.e., the "binary part") using a random intercept logistic model and the logarithm of the non-zero continuous observations s_{kit} (i.e., the "continuous part") using a normal distribution as follows:

$$\text{logit}(p_{kit}) = \boldsymbol{X}_{kit}^{T}\beta_{k}^{p} + \alpha_{kt}^{p} SI_{kit} + b_{ki}^{p}, \tag{6a}$$

[5]Note that two-part point mass mixture data are data where the zeros observed are true zeros, that is, not holding assets or debts.

(6b) $$\log(s_{kit}) \sim N\left(\mu_{kit}, \sigma_k^2\right),$$

(6c) $$\mu_{kit} = \boldsymbol{X}_{kit}^T \beta_k^s + \alpha_{kt}^s SI_{kit} + b_{ki}^s,$$

where, $\boldsymbol{b}_i = \left(b_{1i}^p, b_{1i}^s, b_{2i}^p, b_{2i}^s, b_{3i}^p, b_{3i}^s, b_{4i}^p, b_{4i}^s\right)^T \sim N_8(0, \Sigma)$.

Conditional on the random effects $\boldsymbol{b}_i$, the likelihood for the i^{th} household is a product of the data and the random effects as follows:

(7) $$L_i(\boldsymbol{y}_i | \boldsymbol{b}_i; \Omega) \cdot L_i(\boldsymbol{b}_i),$$

where $L_i(\boldsymbol{y}_i|\boldsymbol{b}_i; \Omega)$ is the conditional likelihood. For the multivariate logit model, this is given by:

(8) $$L_i(\boldsymbol{y}_i | \boldsymbol{b}_i; \Omega) = \prod_{k=1}^{K} \prod_{t=1}^{T} p_{kit}^{y_{kit}} (1 - p_{kit})^{1-y_{kit}}.$$

And, for the multivariate continuous outcome model, the conditional likelihood is given by:

(9) $$L_i(\boldsymbol{y}_i | \boldsymbol{b}_i; \Omega) \propto \prod_{k=1}^{K} \prod_{t=1}^{T} (1 - p_{kit})^{(1-r_{kit})} \left\{p_{kit} \cdot \mathrm{LN}\left(y_{kit}; \mu_{kit}, \sigma_k^2\right)\right\}^{r_{kit}},$$

where LN denotes the log-normal density.

In modeling the binary outcomes, Ω are the parameters from equation (2), whilst, for modeling continuous outcomes, Ω are the parameters from equation (6). For the two-part model, from equation (6), $L_i(\boldsymbol{b}_i)$ is the likelihood of the multivariate normal random effects with 0 mean, that is, $L_i(\boldsymbol{b}_i) \propto \exp\frac{1}{|\Sigma|}\exp\left(\boldsymbol{b}_i^T \Sigma^{-1} \boldsymbol{b}_i\right)$. We then obtain the unconditional likelihood function for household i as follows:

(10) $$L_i(\boldsymbol{y}_i | \Omega) = \int L_i(\boldsymbol{y}_i, | \boldsymbol{b}_i, \Omega)\, L_i(\boldsymbol{b}_i)\, d\boldsymbol{b}_i.$$

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 given by:

(11) $$logL = \sum_i \log(L_i(\boldsymbol{y}_i | \Omega)).$$

We use a Bayesian Markov Chain Monte Carlo (MCMC) method for parameter estimation for three main reasons. First, our Bayesian estimation procedure, with the incorporation of the recent development of the MCMC method (Gelfand and Smith, 1990; Robert and Casella, 1999; Korteweg, 2012), 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. Second, 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.

To complete the Bayesian specification of the model, we must assign priors to the unknown parameters. Since we have no prior information from, for example, historical data or experiments, we take the usual route and assign conjugate priors to the parameters. We assume a standard normal prior for the regression coefficients, β_k, that is, $\pi(\beta_k) \sim N(\mu_k, \sigma_k^2)$, and an inverse Wishart prior for the variance–covariance matrix, where π denotes the prior. We assume a Wishart distribution for the inverse of a variance–covariance matrix, where $W_q(\rho, S)$ is a q-dimensional Wishart distribution with ρ degrees of freedom and a mean of ρS^{-1}. For our analysis, diffuse priors can be chosen so that the analysis is dominated by the data likelihood. For the coefficients of social interaction, α_{kt}, we assume a random walk prior as in Dangl and Halling (2012). Thus, the prior on α_{kt} can be written as follows:

$$(12) \qquad \pi(\alpha_{k1}, \alpha_{k2}, \dots, \alpha_{kT})^T \sim \pi(\alpha_{k1}) \prod_{k=2}^{T} \pi(\alpha_{kt}) = N(0, \tau_e^2) \prod_{k=2}^{T} N(\alpha_{k,t-1}, \tau_e^2).$$

The joint posterior distribution of the parameters of the models conditional on the data are obtained by combining the likelihood and the prior densities using Bayes theorem:

$$(13) \qquad f(\Omega, \mathbf{b}|y) \propto \sum_i \log(L_i(\boldsymbol{y}_i|\Omega)) \cdot \prod_k \pi(\beta_k) \cdot \prod_k \pi(\alpha_{k1}) \prod_{k=2}^{T} \pi(\alpha_{kt}) \pi(\Sigma).$$

The posterior distributions are analytically intractable. However, the models described above can be fitted using MCMC methods such as the Gibbs sampler (Gelfand and Smith, 1990). Since the full conditional distributions are not standard, a straightforward implementation of the Gibbs sampler using standard sampling techniques may not be possible. However, sampling methods can be performed using adaptive rejection sampling (ARS; Gilks and Wild, 1992) and the Metropolis–Hastings algorithm.

We construct a test of parameter significance by calculating the Bayes factor (see Kass and Raftery, 1995; Greene, 2012). This is constructed by formulating the null hypothesis H_0 that all of the slope parameters of the model are simultaneously equal to zero against the alternative hypothesis H_1 that the former is not true. The Bayes factor has been used in existing finance literature to compare the quality of fit between competing models (see, e.g., Eraker *et al.*, 2003; 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 $B_{01} \cdot (p(H_0)/p(H_1))$, where B_{01} is the Bayes factor for comparing the two hypotheses. Based upon the observed data, the Bayes factor is given as:

$$B_{01} = \frac{f(\boldsymbol{y}|\boldsymbol{X}, H_0)}{f(\boldsymbol{y}|\boldsymbol{X}, H_1)} = \frac{\int p(\boldsymbol{y}|\boldsymbol{X}, \beta_0)\pi_0(\beta_0)d\beta_0}{\int p(\boldsymbol{y}|\boldsymbol{X}, \beta_1)\pi_1(\beta_1)d\beta_1}, \tag{14}$$

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. For both of the models estimated, we also explore whether the dynamic specification in social interaction, see equation (3), is preferred to a static specification. Bayes factors are constructed formulating the null hypothesis H_0 that $\alpha_{kt} = \alpha_k$, that is, the influence of social interaction is static against the alternative hypothesis H_1 that the former is not true, where $\alpha_{kt} \neq \alpha_k$.

3. Data

Our empirical analysis is based on the British Household Panel Survey (BHPS), a survey conducted by the Institute for Social and Economic Research comprising approximately 10,000 annual individual interviews. The existing literature has generally focused on stock market participation in the context of the U.S. To our knowledge, this is the first paper to explore the relationship between social interaction and household finances for the U.K., which is surprising in the context of the changes in stock market participation and financial asset holding in the U.K. over the last three decades with, for example, the widely publicized privatization of public utilities such as British Telecom (see, e.g., Banks and Tanner, 2002). For wave one, interviews were carried out during the autumn of 1991. The same households are re-interviewed in successive waves—the last available being 2008. Detailed information on debt and asset holding is available in three waves: 1995, 2000, and 2005. Hence, these three waves are the primary focus of our empirical analysis, which is based on a balanced panel. There are 4,089 households in each year yielding a total of 12,267 observations.

Our measure of social interaction, SI_{kit}, is based on active club membership, constructed from the responses to a series of questions asking individuals whether they are currently active in a range of clubs/groups, namely: a political party; trade unions; an environmental group; a parents'/school association; a tenants'/residents' group or neighborhood watch; a religious group or church organization; a voluntary services group; any other community or civic group; a social club/working men's club; sports club; women's institute/townswomen's guild; or any other group or organization. Our focus on active membership follows Putnam (2000, p. 580), who argues that:

> . . . formal "card-carrying" membership may not accurately reflect actual involvement in community activities. An individual who "belongs to" half a dozen community groups may actually be active in none. What really matters from the point of view of social capital and civic engagement is not merely nominal membership, but active and involved membership.

Hence, we use the responses to the questions described above in order to proxy the social interaction of the individual, who in our analysis is the head of household, by constructing an index of the number of clubs that the individual is currently active in, where the index runs from zero clubs to four plus clubs. Our measure of social interaction based on club membership accords with that frequently used in the existing literature (see, e.g., Putnam, 2000; Glaeser *et al.*, 2002; Brown and Taylor, 2009).[6]

With respect to the holding of debt and assets modeled via the joint framework of 12 equations, we distinguish between six types of debt: hire purchase agreements; personal loans from banks, building societies, or other financial institutions; credit cards; loans from private individuals; overdrafts; and other debt including catalogue or mail purchase agreements and student loans. With respect to financial assets, we again distinguish between six types: national savings certificates, national savings, building society and insurance bonds; premium bonds;[7] unit/investment trusts; personal equity plans; shares; and other investments, government or company securities.[8] We explore the hypothesis that the effect of social interaction will vary across the different types of assets and debt held, with larger effects expected in the case of the more complicated financial instruments, such as stocks and shares.

For the continuous variables relating to household liabilities, we model the total amount of unsecured debt across the six categories detailed above and the total amount of secured debt, which relates to the outstanding mortgages on property. With respect to assets, we model the total value of assets held across the six categories described above as well as the current value of property.[9] As the distributions of the continuous variables are highly skewed, following Gropp *et al.* (1997), we specify logarithmic dependent variables. For households reporting zero values, the dependent variables are recoded to zero, since there are no reported values between zero and unity. Thus, to summarize, we explore the hypothesis that social interaction influences the amount of assets and debt held, as well as whether social interaction has different influences across the four components of the household balance sheet.

Table A1, Panel A in the online Appendix provides sample statistics of debt holding in the form of hire purchase agreements, credit cards, personal loans, overdrafts, loans from private individuals, or other types of debt. Clearly, over the period 1995 to 2005, the least common type of unsecured debt held was a loan from a private individual at 1.3 percent, whilst, in contrast, approximately 19 percent

[6]Our measure of social interaction is lagged since, as argued by Angrist and Pischke (2009), such an approach reduces the potential for reverse causality with social interaction being measured *ex ante*, that is, it predates the outcome variable, that is, in this case, the type of debt or assets held. The matching is as follows: 1994 club membership to 1995 debt or assets; 1999 club membership to 2000 debt or assets; and 2003 club membership to 2005 debt or assets.

[7]Premium bonds are a financial product offered by the National Savings and Investments of the U.K. Government, where, instead of interest payments, investors have the chance to win tax-free prizes. Hence, this type of financial asset is quite distinct from the other assets in terms of its return.

[8]Unfortunately, information regarding the amount held in each debt and asset category is unavailable.

[9]In our sample, 41 percent of households hold unsecured debt and 57 percent of households hold mortgage debt, whilst only 29 percent of households hold non-housing financial assets compared to 80 percent of households holding housing assets.

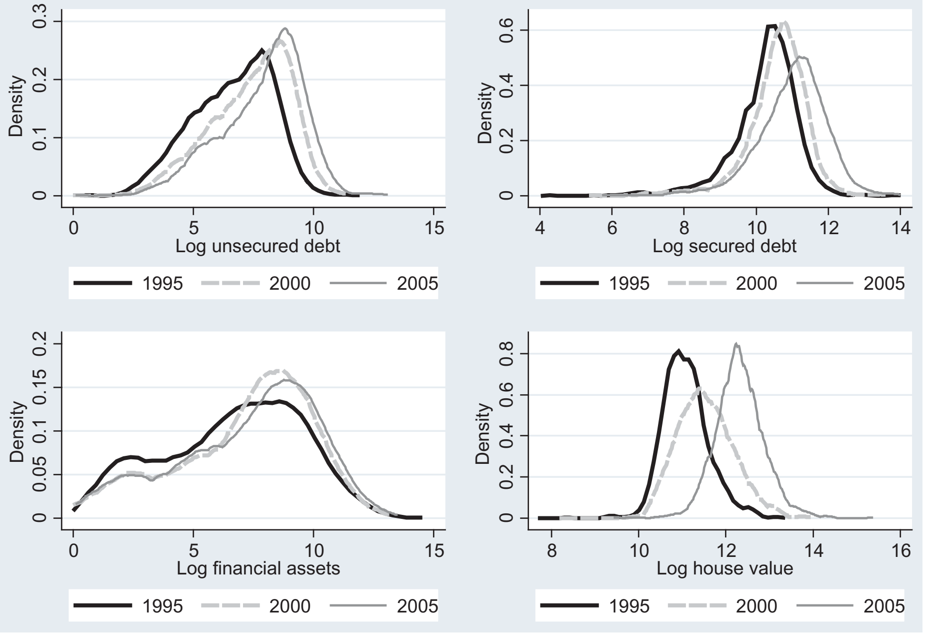

Figure 1. Distributions over Time of Log: Unsecured Debt, Secured Debt, Financial Assets, and House Value

held either credit card debt or a personal loan. The table also shows the percentage of financial asset holding in the form of stocks/shares, national savings, premium bonds, a unit trust, a personal equity plan, or other forms of financial assets. Over the ten-year period, the least common form of financial asset was national savings at 2.5 percent, whilst the most common types of investment were shares and premium bonds at 19 and 21 percent, respectively. Table A1, Panel B in the Appendix provides summary statistics for the continuous dependent variables in log levels and in monetary units. The average levels of unsecured debt and financial assets over the period were £1830 and £3721, respectively, whilst the levels of mortgage debt and house value were £33,627 and £126,858, respectively. Finally, Figure 1 presents distributional plots of the continuous variables, conditional on holding positive amounts, for 1995, 2000, and 2005. Whilst there appears to have been no shift in the distribution of financial assets over time, the distribution and mean of unsecured debt has shifted to the right, with individuals holding higher levels of debt over the time period.

The control variables include: age binary controls for whether the head of household is aged 18–24, 25–34, 35–44, or 45–54 (where aged 55 and above is the omitted category); a male head of household dummy variable; a dummy variable for whether the head of household is married or cohabiting; a binary indicator for whether the head of household is white; the natural logarithm of household labor income; the natural logarithm of other household income; binary controls for housing tenure, specifically whether the home is owned outright, owned on a mortgage, or rented (other tenure status is the omitted category);[10] binary controls for head of household's employment status, specifically whether he/she is employed, self-employed, or unemployed (retired, full time student, maternity leave, and government training form the omitted category); the number of children and the number of adults in the household; a binary control for whether the head of household is in good or excellent health (poor health is the reference group); and the highest level of educational attainment of the head of household, distinguishing between degree level, nursing or teaching qualifications, Advanced (A) levels, General Certificate of Secondary Education (GCSEs)),[11] other educational qualifications, and no educational qualifications (the omitted category). We also control for whether the individual reads a national newspaper on a daily basis. The reason for including this control is that it may act as a signal of awareness of current affairs and, potentially, a route for spreading information and thereby making individuals more aware of financial products and investment opportunities, as well as the general prevailing economic and financial climate. Similarly, in an attempt to provide a proxy for access to information, we condition on whether the individual has a computer in the home and also whether a computer was purchased in the last 12 months, that is, whether the potential to access information has increased recently.[12] Finally, we include controls for 17 regions, with London being the omitted category. In Table A2 in the Appendix, summary statistics relating to the variables in $\boldsymbol{X}$ are shown. All monetary variables are deflated to 1991 prices.

To summarize, our rich panel dataset therefore enables us to contribute to the existing literature on social interaction and stock market participation in a number of ways. First, we explore whether the positive association between social interaction and stock market participation prevails within a joint framework which allows for other facets of the household financial portfolio. Second, we explore the effects of social interaction on the holding of a range of financial assets as well on the holding of different types of debt. Thus, in contrast to the existing literature, we ascertain whether social interaction has wider implications for household finances. Third, we extend the existing literature by exploring the effects of social interaction on the amount of household assets and liabilities held rather than restricting the analysis to the holding of a particular type of asset, which has been the focus of much of the existing literature. The joint modeling approach developed in this paper enables us to allow for the interdependence that potentially exists across different parts of the household financial portfolio. Finally, the incorporation of time varying coefficients for the effects of social interaction introduces an additional layer of accuracy in determining the influence of social interaction on household finances.

[10]These controls are not included when we model the value of housing and mortgage debt.

[11]GCSE level qualifications are taken after 11 years of formal compulsory schooling and approximate to the U.S. honors 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 U.K.

[12]Furthermore, following Christelis *et al.* (2010), who argue that cognitive skill is associated with stock market participation, computer usage may also act as a proxy for cognitive skill.

4. Results

4.1. *The Twelve Equation Model: The Types of Debt and Financial Assets Held*

In the case of modeling the holding of different types of debt and financial assets, that is, estimating equation (2), in terms of overall model performance, the calculated log Bayes factor is 16, giving decisive 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, that is, the estimated variance–covariance matrix, these are generally statistically significant, indicating the presence of unobserved household heterogeneity (see Table A3 in the Appendix). The covariance terms between each type of financial asset generally reveal positive interdependence. Interestingly, there is also positive interdependence found between each type of financial asset and credit card debt, overdrafts, and personal loans. These findings indicate interdependence across the different parts of the estimated model and, hence, endorse our joint modeling approach since a univariate approach would overlook such interdependence. Moreover, not taking interdependence into account would result in less efficient parameter estimates from a statistical perspective. Statistically significant correlations in the error terms suggest that there are unobserved factors which influence the probability of jointly holding different types unsecured debt and financial assets. Whilst a positive correlation between various debt and asset categories is perhaps not surprising, there are some instances where a positive correlation exists between debt and financial assets, for example credit card debt and share ownership. This implies that, even after conditioning on observable covariates, households hold portfolios comprising both assets and liabilities.

Table 1a presents the results of estimating equation (2) relating to the determinants of the probability of holding particular types of debt and financial assets where the reported coefficients are the Bayesian posterior mean estimates (BPMEs) of β_k and α_{kt}. For brevity, we do not present the 95 percent credible interval for each parameter estimate. These are, however, available on request. Initially, we focus on the covariates in $\boldsymbol{X}$ and the estimates of β_k. Clearly, for debt and financial assets, there is some evidence of gender effects. For example, considering the effect of gender on the probability of having credit card debt, the "Odds Ratio" (OR) is given by $\exp\left(\hat{\beta}_k\right) = \exp(0.3087)$ and is equal to 1.36. Hence, the relative probability of male headed households having credit card debt, in comparison to that of females, is 36 percent. Conversely, male headed households are less likely to have a personal loan. Interestingly, where statistically significant, male headed households have a lower probability of holding financial investments. For example, in terms of the likelihood of holding stocks and shares, $\mathrm{OR} = \exp\left(\hat{\beta}_k\right) = \exp(-0.5586) = 0.57$.

Households with a married head of household are generally less likely to hold unsecured debt and, conversely, have a higher probability of holding financial assets. In general, there is no effect of ethnicity on the probability of holding debt or financial assets, which contrasts with the U.S. findings of Hong *et al.* (2004). We have also interacted gender and ethnicity to ascertain whether there is an additional effect. In each of the 12 outcomes, the interaction term is statistically

TABLE 1a

Type of Debt and Assets and Social Interaction

	Hire Purchase	Credit Card	Personal Loan	Overdraft	Individual Loan	Other Debt	Shares	National Savings	Premium Bonds	Unit Trust	Personal Equity Plan	Other Investment
Intercept	–5.1410*	–3.8890*	–3.5960*	–4.5380*	–4.6290*	–1.0770*	–5.1790*	–6.1430*	–4.4230*	–6.5200*	–6.4400*	–4.5280*
Male	–0.2971	0.3087*	–0.2726*	–0.3794	–0.2170	0.8011*	–0.5586*	–0.1626	–0.3677*	–1.1510*	–0.3807	–0.4116
Married	–0.0996	–0.3798*	–0.4278*	–0.4848	–1.2090*	0.0642	0.3843*	1.1900*	0.3601*	–0.2015	0.7840*	0.5131*
White	0.2334	–0.0039	–0.1235	–0.3952	–0.2943	–0.2902	0.1238	0.3887	0.5875*	0.0882	0.1042	–0.1970
Age 18–24	0.1242	0.4611	0.9221*	1.8760*	1.3690*	0.1298	–0.5761	0.6134	–0.9099*	–1.6360*	–1.5390*	–0.3717
Age 25–34	0.4327	0.6053*	0.9154*	0.6751	0.9032	0.1949	–0.2662	–0.0246	–0.7807*	–0.7553	–0.3116	–0.0419
Age 35–44	0.4172	0.4647*	0.4503*	–0.0905	0.2583	–0.0275	0.0017	0.2918	–0.5548*	–0.6921	0.2166	–0.0992
Age 45–54	–0.1319	0.4211*	0.2895	–0.2707	0.3520	–0.1803	–0.2373	0.7074	–0.0748	–0.0769	–0.0421	0.2342
GCSEs	0.2823	0.1842	0.1887	0.2676	0.9784	1.9450*	0.6986*	0.1926	0.2126	1.3310*	0.6366	–0.1256
A Levels	–0.2052	0.6449*	0.2153	1.1010	0.9867	0.8751*	0.7421*	0.9231	0.5023	1.8140*	0.4245	0.4631
Teaching/nursing	0.2104	0.7473*	0.1982	1.4860*	1.1260*	1.3500*	0.2832	0.2996	–0.1095	0.8777*	0.2465	0.2034
Other education	–0.1521	0.0720	0.1028	–1.7470*	–0.8969	2.3930*	–0.6957	–2.5800*	–0.9210*	–1.0310	–0.6593	–0.2517
Degree	–0.2433	0.3755	0.0224	2.2260*	1.4990*	0.6540*	1.1170*	0.9916*	0.4353	1.9840*	0.9601*	0.5295
Rent	0.2486	–0.1624	–0.4116	–0.6776	–0.1934	–0.1316	0.0630	0.1138	0.1368	–0.7829	0.5338	0.2919
Mortgage	0.1029	0.2439	–0.2527	–0.4472	–0.1469	–1.3270*	1.0170*	0.2855	0.6439*	1.6310*	1.0320*	0.6987*
Owned outright	–0.3180	–0.3541	–0.8596	–1.1360*	–0.3138	–1.9610*	1.3550*	1.8830*	0.8817*	2.3990*	1.8460*	1.6780*
Health	0.2801	0.1644	–0.2398	–0.0577	–0.8115*	–0.1574	–0.0026	0.4035	–0.0008	0.2563	0.7954*	–0.0877
Log labor income	0.0773	0.0130	0.0816	–0.1199	–0.1053	–0.3162*	0.2722*	0.1441	0.1908*	0.2267*	0.2083*	0.2170*
Log other income	0.0860	0.1570*	0.1232*	0.0803	–0.0051	0.1899*	0.0901*	–0.0208	0.0608	0.0311	0.0789	0.0307
Number of adults	–0.0120	–0.0244	0.0112	0.2347*	0.0594	–0.0119	–0.1174	–0.5706*	–0.0745	–0.3625*	–0.2206*	–0.3924*
Number of children	0.1427	0.1727*	0.0162	0.0949	0.4172*	0.1217	–0.1590	0.0312	–0.0771	–0.4024*	–0.2908*	–0.0682
Employee	0.5528	0.2323	0.6403*	0.5007	0.6717	–0.9228*	–0.9348*	–1.1170*	–0.6614*	–0.9048	–0.6442	–1.0700*
Self employed	0.7313*	0.2443	0.3717	0.6157	0.3852	–1.5920*	–0.7442*	–0.5471	–0.5704	–0.6761	–0.3179	–0.8848*
Unemployed	0.3243	0.6597	1.0090*	1.2630*	0.3465	–0.5737	–0.1730	–0.8825	0.4388	–1.4940	–0.0438	0.2921
Computer in home	–0.2025	–0.2524*	–0.3367*	0.4393	0.2716	0.0549	0.0633	0.1783	0.0306	0.3187	0.2157	–0.5203*
Computer brought last year	–0.0701	0.1067	–0.1891	0.3556	0.2064	–0.5223*	0.0732	–0.2456	–0.0348	0.2419	–0.0772	0.0620
Read newspaper	0.0038	–0.0670	–0.2331*	–0.1388	–0.0964	–0.1792	–0.0143	–0.3134	–0.0041	0.0826	–0.0630	0.1165
Number of clubs [$t-1$]	0.1761*	0.0387*	0.1070*	0.0290*	0.1128*	0.0267*	0.1877*	0.1616*	0.0770*	0.1183*	0.0715*	0.2716*
Number of clubs [$t-2$]	0.2197*	0.0905*	0.1578*	0.2324*	0.2274*	0.1044*	0.2608*	0.2128*	0.1598*	0.2327*	0.3504*	0.2965*
Number of clubs [$t-3$]	0.2720*	0.1216*	0.1938*	0.3075*	0.3721*	0.2848*	0.2914*	0.2787*	0.2494*	0.3020*	0.4213*	0.3345*

Notes: *denotes statistical significance at the 5% level. The estimated model also includes regional controls. Parameters reported are Bayesian posterior mean estimates (BPMEs).

insignificant. For certain types of debt and financial assets, there is evidence of life cycle effects. For example, relative to households with a head aged 55 and over, those aged 18 to 24 have a higher probability of having a personal loan, an overdraft, or loan from a private individual. Such findings suggest that relatively young individuals are more likely to feel the pressure of adverse financial or macroeconomic shocks and may be more likely to make use of informal credit channels. In addition, households with a head in this age category have a lower probability of holding premium bonds, unit trusts, or a personal equity plan.

Compared to those households where the head has no education, the reference category, educational attainment is positively associated with stock market participation. For example, those households with a head with a degree have a higher probability of owning stocks and/or shares, which is consistent with the findings of Hong *et al.* (2004) for the U.S., and Guiso *et al.* (2008), who analyze Dutch and Italian survey data. In addition, households with a head whose highest educational attainment is a degree are more likely to hold national savings, unit trusts, and personal equity plans.

The influence of income has distinct effects on the probability of holding the different types of debt and financial assets. In particular, other household income is positively associated with holding credit card debt and having a personal loan. This may be a cause for concern given that non-labor income includes benefit income, the recipients of which are likely to be lower income households. However, in general, household labor income has no influence on holding debt. Whilst, in contrast, household labor income is generally positively related to holding each type of financial asset, there are no effects from other household income. In terms of the other covariates, outright home ownership generally increases the probability of holding each type of financial asset, which may reflect a wealth effect.

Turning to the influence of social interaction, we have compared the model estimated in equation (2), which includes dynamics, to a more restrictive static model, where, in terms of equation (3), $\alpha_{kt} = \alpha_k$. The null hypothesis that the static specification is preferred to a dynamic one is rejected decisively given that the log Bayes factor is 6, thereby endorsing our dynamic modeling approach. With respect to the hypothesis that the effect of social interaction varies across the 12 components of the household balance sheet, it is apparent that social interaction is positively associated with the six types of debt and the six types of financial assets. So, in terms of direction, the effect of social interaction does not vary across the types of debt and assets analyzed. We now turn to examine the magnitude of the effects.

In order to ascertain the economic magnitude of the effects of social interaction on the probability of holding a particular category of debt or asset, in Table 1b we show how the reported probabilities change for a one standard deviation increase in social interaction, denoted by σ_{SI} (reported in Table A2 in the Appendix). This is calculated as follows: $\{\exp(\hat{\alpha}_{kt}) \cdot \sigma_{SI}\}$. The exposure effect of social interaction is positive at each point in time. There are some differences, however, in terms of the magnitude of the estimated effects. For example, in the case of debt, the estimated effect of social interaction at $t - 3$ is particularly pronounced for overdrafts and loans from private individuals, where a one standard deviation increase in social interaction increases the probability of holding the two types of debt by approximately 28 and 36 percentage

TABLE 1b

Effect of a 1 Standard Deviation Increase in Social Interaction

	Hire Purchase	Credit Card	Personal Loan	Overdraft	Individual Loan	Other Debt	Shares	National Savings	Premium Bonds	Unit Trust	Personal Equity	Other Invest
Number of clubs [$t-1$]	11.81%	2.55%	4.33%	3.49%	4.94%	3.71%	13.11%	10.19%	1.25%	5.53%	0.70%	23.01%
Number of clubs [$t-2$]	16.78%	2.63%	9.77%	18.28%	17.68%	4.06%	21.69%	15.98%	10.01%	18.31%	33.09%	26.10%
Number of clubs [$t-3$]	23.06%	5.87%	13.80%	27.50%	36.01%	24.64%	25.47%	23.88%	20.31%	26.81%	42.87%	30.99%

points, respectively.[13] The latter suggests that social networks may play a crucial role in the provision of informal financial support, signaling the importance of financial support from family or friends if faced with financial difficulties. In contrast, relatively small exposure effects are found in the case of credit card debt, which may reflect the widespread use of this particular channel of credit. Interestingly, social interaction at $t - 3$ has relatively large effects on the holding of personal equity plans, unit trusts, and other investments, suggesting that the effect of social interaction is not just limited to share ownership. The positive effect of social interaction on share ownership, which is consistent with the findings in the existing literature (see, e.g., Hong *et al.*, 2004; Christelis *et al.*, 2010), is thus found to be robust within a joint modeling framework, which allows for the holding of debt as well as other types of financial assets. Although there are differences found with respect to the size of the estimated social interaction effects, there does not appear to be a clear pattern in the relative magnitudes relating, for example, to the degree of complexity associated with the various financial instruments.[14,15]

In order to explore how robust our findings are to an alternative proxy of social interaction, we construct a measure based on the average number of clubs that adult individuals in the household are actively members of. Table 2a reports the BPMEs for average active club membership in the household, where again it is apparent that all the BPMEs are statistically significant. In Table 2b we present the effect of a one standard deviation increase in the alternative measure of social interaction. The standard deviation is considerably lower than that of the standard deviation of the social interaction of the head of household at 0.8104 as are the BPMEs shown in Table 2a in comparison to those of Table 1a. Consequently, the effect of a one standard deviation increase in the average number of clubs of which adults in the household are members of is generally smaller in magnitude compared to that reported in Table 1b.

4.2. *The Four Equation Model: The Amount of Debt and Financial Assets Held*

Next we jointly model the log amounts of unsecured debt, secured debt, financial assets, and property value; see equations (4) to (6). With respect to overall model performance, the calculated log Bayes factor is 14, which once again gives decisive support for rejecting the null hypothesis that the slope parameters are jointly equal to zero. The estimated variance–covariance matrix, shown in Table A4

[13]The figure for individual loans, for example, is calculated as follows: $\{\exp(\hat{\alpha}_{kt}) \cdot \sigma_{SI}\} = \{\exp(0.3721) \cdot 0.9375\} = 1.36$, that is, 36 percentage points.

[14]For robustness analysis, we have also explored the sensitivity of our findings to instrumenting the measure of social interaction. Given that the selection of instruments is always subject to debate, we have explored two different instruments. First, in order to allow for neighborhood effects, we have used the average rate of social interaction in the local authority district that the household resides in. Second, following Agarwal *et al.* (2011), who argue that mobility weakens investment in social capital as well as social connections, we use a measure of the head of household's geographical mobility, the number of years they have resided in their current home. The results based on instrumenting social interaction are consistent with our previous findings and are available on request.

[15]As discussed in King and Leape (1998), wealth is an important determinant of household portfolio decisions. Hence, we explore the robustness of the empirical results presented in Table 1 to including net wealth in the set of control variables. Our findings, which are available on request, are robust to the inclusion of this additional explanatory variable.

TABLE 2a

Type of Debt and Assets and Social Interaction; Alternative Measure

	Hire Purchase	Credit Card	Personal Loan	Overdraft	Individual Loan	Other Debt	Shares	National Savings	Premium Bonds	Unit Trust	Personal Equity	Other Invest
Mean clubs in household [$t-1$]	0.0829*	0.0395*	0.0535*	0.0318*	0.1005*	0.0320*	0.0562*	0.0771*	0.0545*	0.0867*	0.0610*	0.1143*
Mean clubs in household [$t-2$]	0.1403*	0.1180*	0.1291*	0.2499*	0.1668*	0.0991*	0.1026*	0.1245*	0.0940*	0.2978*	0.1854*	0.1460*
Mean clubs in household [$t-3$]	0.1904*	0.1461*	0.1657*	0.3419*	0.2954*	0.3676*	0.1269*	0.1739*	0.1489*	0.3879*	0.2499*	0.2009*

Notes: *denotes statistical significance at the 5% level. Controls as in Table 1a. Parameters reported are Bayesian posterior mean estimates (BPMEs).

TABLE 2b

Effect of a 1 Standard Deviation Increase in Social Interaction; Alternative Measure

	Hire Purchase	Credit Card	Personal Loan	Overdraft	Individual Loan	Other Debt	Shares	National Savings	Premium Bonds	Unit Trust	Personal Equity	Other Invest
Mean clubs in household [$t-1$]	1.97%	6.22%	4.36%	4.04%	8.88%	16.33%	8.00%	3.57%	5.95%	9.15%	4.04%	0.93%
Mean clubs in household [$t-2$]	6.76%	8.82%	7.80%	14.07%	4.26%	10.52%	10.21%	8.22%	10.98%	11.63%	2.46%	6.23%
Mean clubs in household [$t-3$]	11.96%	15.70%	14.51%	16.35%	10.40%	17.04%	14.28%	12.47%	14.43%	16.63%	13.87%	9.15%

in the Appendix, which reflects the correlations in the unobservable effects across the equations, reveals that the estimated variance parameters are all positive and statistically significant. Positive interdependence is also found in the unobservable effects between all types of debt and both parts of the model, that is, binary and continuous outcomes. This means that, even after controlling for observable characteristics, households are likely to hold (and in higher amounts) unsecured and secured debt simultaneously. This is consistent with the findings of Brown and Taylor (2008), who examine the level of overall debt and financial assets in the U.K., U.S., and Germany. Similarly, there is some evidence of positive interdependence in the errors terms between secured debt, home ownership, and property value. Indeed, perhaps not surprisingly the largest covariance found is between the error terms of the amount of mortgage debt and the probability of home ownership.

Table 3a presents the parameter estimates of β_k and α_{kt}, which show the effects of the covariates $\boldsymbol{X}$ and social interaction SI, respectively, on the probability that each outcome occurs and the level—that is, amount—of the continuous outcome, conditional on holding a positive amount. Whilst in Tables 1 and 2 the different types of debt reported relate to unsecured debt and the different types of financial assets relate to non-housing financial assets, the four-equation model also incorporates the level of secured—that is, mortgage—debt and the estimated house value, given their importance in the household balance sheet. Initially, we comment briefly on the covariates in $\boldsymbol{X}$.

With respect to gender and ethnicity, having a male head of household and/or a white head of household are both associated with a higher likelihood of owning a home and having a higher property value, conditional on ownership, whilst conversely white household heads are found to have lower levels of secured debt. We have also included an interaction term between gender and ethnicity which is found to be statistically insignificant. Households with married heads not only have a higher probability of having mortgage debt, which may reflect the fact that secured loans are the joint liability of both spouses, but they also have a larger amount of mortgage debt. For both unsecured and secured debt, there is evidence of life cycle effects on the likelihood of holding the respective types of debt, culminating at the age range of 25 to 34. This is also the age group where the amount of unsecured and secured debt is at its highest level. The effects of age on both the probability of owning a home and the value of the property are monotonic and largest for those households where the head is approaching retirement.

In comparison to having a head with no education, having a degree decreases (increases) both the likelihood of holding and the amount of unsecured (secured) debt held. Conversely, having a degree relative to a head of household with no qualifications is positively associated with both the probability of holding and with accumulating greater amounts of both financial assets and property value. With regards to housing tenure, the only significant effect stems from outright home ownership—that is, without a mortgage—which is associated with a higher probability of possessing non-housing financial assets and, conditional on owning property, having a larger estimated house value. Interestingly, the head of household's employment status has no influence on either type of debt, financial assets, or house value. The only consistent income effect stems from other household income which increases both the probability of holding and the amount

TABLE 3a

Two Part Model: Log Amount of Debt, Assets, and Social Interaction

	Unsecured Debt		Secured Debt		Financial Assets		House Value	
	prob ($Y > 0$)	log (Y)|$Y > 0$	prob ($Y > 0$)	log (Y)|$Y > 0$	prob ($Y > 0$)	log (Y)|$Y > 0$	prob ($Y > 0$)	log (Y)|$Y > 0$
Male	0.1087	0.2031	–0.0636	–0.1443	0.0260	–0.1488	0.4214*	0.6287*
Married	–0.3058*	–0.5040*	1.0950*	1.4410*	0.5955*	1.1360*	1.2900*	2.3440*
White	0.1255	0.1898	–0.5697*	–1.0950*	0.0064	0.0701	0.4590*	0.4933*
Age 18–24	0.6513*	0.6703	1.2270*	2.6250*	–0.3177	–0.4960	–0.8985*	–1.9810*
Age 25–34	0.9516*	1.4310*	1.4890*	3.5920*	–0.3859*	–0.6390*	–0.7528*	–1.4630*
Age 35–44	0.4337*	0.6249*	1.3580*	3.2230*	0.0349	–0.0167	–0.4273*	–0.7878*
Age 45–54	0.1610	0.1379	0.8533*	1.9780*	0.0417	0.0185	–0.0958	–0.2689
GCSEs	–0.2215	–0.4101*	–0.1089	–0.2584	0.1351	0.3852	–0.0457	0.0629
A Levels	–0.0329	–0.0189	0.0629	0.1772	0.1428	0.2572	0.3941*	0.5073
Teaching/nursing	0.1689	0.2982	–0.1043	–0.1950	0.1119	0.2296	–0.1260	–0.1273
Other education	0.3485*	0.5680*	–0.0220	0.0903	0.0103	–0.3327	–0.4487*	–0.5166
Degree	–0.3837*	–0.3842*	0.5328*	1.0520*	0.5606*	1.4570*	0.3528*	0.6921*
Rent	–0.1042	–0.0986	–	–	–0.0195	–0.1722	–	–
Mortgage	–0.0172	0.1205	–	–	–0.2173	0.0710	–	–
Owned outright	–0.2863	–0.4929	–	–	0.0929*	0.1105*	–	–
Health	–0.0578	–0.1786	0.1847	0.4532*	0.0426	0.1097	0.2966*	0.6196*
Log labor income	–0.0426	–0.0407	–0.0160	–0.0191	0.1509*	0.2814*	–0.0200	0.0128
Log other income	0.1492*	0.2529*	0.1502*	0.3503*	0.0217	0.0166	0.1134*	0.1584*
Number of adults	–0.0702	–0.0986	–0.0536	–0.1432	–0.2207*	–0.3441*	0.1107*	0.1900*
Number of children	0.1083*	0.1205	0.0199	0.0713	–0.2198*	–0.4159*	–0.0575	–0.0674
Employee	0.0083	0.0202	–0.0728	–0.2126	–0.1136	–0.2643	0.0626	0.0303
Self employed	0.0144	–0.0395	–0.0886	–0.1701	–0.0748	0.1319	–0.2709	–0.4290
Unemployed	–0.4737*	–0.6534	0.1114	0.2318	0.2164	0.4437	0.4467	0.6516
Computer in home	0.0961	0.3165*	0.7427*	1.7510*	0.5473*	0.8008*	0.5186*	1.1810*
Computer brought last year	–0.0501	–0.0197	–0.1108	–0.2810	0.0792	0.0470	0.0540	0.0608
Read a national newspaper	0.0866	0.1727	0.1023	0.2249	0.0418	–0.0225	0.1197	0.2005
Number of clubs [t – 1]	0.2089*	0.0734*	0.0610*	0.0674*	0.1318*	0.1903*	0.1040*	0.0672*
Number of clubs [t – 2]	0.1230*	0.2431*	0.1030*	0.3469*	0.7326*	0.2525*	0.0858*	0.1268*
Number of clubs [t – 3]	0.1720*	0.3382*	0.2340*	0.7286*	0.4200*	0.4240*	0.1358*	0.2598*

Notes: Y denotes the amount of debt or value of assets of a household. *denotes statistical significance at the 5% level. The estimated model also includes regional controls. Parameters reported are Bayesian posterior mean estimates (BPMEs).

held of both types of debt. Both the probability of owning non-housing financial assets and the amount of such assets held are positively related to labor income. For example, a 1 percent increase in labor income is associated with a 16 percent higher probability of owning non-housing assets. This is calculated as follows: OR = exp(0.1509) = 1.16, that is, 16 percent (given that the continuous outcome is logged). The effects of the covariates on the amount of liabilities and assets held are generally consistent with that of the existing literature (see, e.g., Cox and Jappelli, 1993; Gropp *et al.*, 1997; Brown and Taylor, 2008).

We now focus on the key parameters of interest associated with social interaction, namely α_{kt}. As with modeling the binary outcomes, we have compared the model estimated in equations (4) to (6), which includes dynamics to a more restrictive static model, where in terms of equation (3), $\alpha_{kt} = \alpha_k$. Again, the null hypothesis that the static specification is preferred to a dynamic one is rejected decisively given the log Bayes factor of 8. Social interaction is associated with a higher probability of each outcome occurring, which is consistent with the results of Table 1a. For example, a one standard deviation increase in social interaction increases the probability of holding unsecured debt by: OR = {exp(0.1720) · 0.9375} = 1.11, that is, around 11 percentage points.

Social interaction is also found to be positively related to holding higher amounts of both unsecured and secured debt, as well as financial assets and housing assets. For example, a one standard deviation increase in social interaction increases the level of unsecured debt by: OR = {exp(0.3382) · 0.9375} = 1.31, approximately 31 percentage points. Thus, our findings support the hypothesis that social interaction influences the amount of debt and assets held. In terms of differences in the effects of social interaction across the four continuous measures, it is apparent that, in contrast to the relatively small effect on the value of housing assets, social interaction at $t-3$ has a particularly pronounced effect on the value of secured debt.

In Table 3b we show the results of replicating the two-part modeling analysis of debt and assets for the alternative measure of social interaction based on the average number of clubs of which adults in the household are active members. Consistent

TABLE 3b

Two Part Model: Log Amount of Debt, Assets, and Social Interaction; Alternative Measure

	Unsecured Debt		Secured Debt		Financial Assets		House Value	
	prob $(Y>0)$	$\log(Y)\vert Y>0$	prob $(Y>0)$	$\log(Y)\vert Y>0$	prob $(Y>0)$	$\log(Y)\vert Y>0$	prob $(Y>0)$	$\log(Y)\vert Y>0$
Mean clubs in household [$t-1$]	0.2467*	0.0577*	0.2441*	0.0908*	0.0634*	0.3400*	0.4700*	0.2412*
Mean clubs in household [$t-2$]	0.2446*	0.3579*	0.3085*	0.3469*	0.0366*	0.2449*	0.3444*	0.2982*
Mean clubs in household [$t-3$]	0.2504*	0.2363*	0.3444*	0.4700*	0.2000*	0.4211*	0.9601*	0.3361*

Notes: Y denotes the amount of debt or value of assets of a household. *denotes statistical significance at the 5% level. Controls as in Table 3a. Parameters reported are Bayesian posterior mean estimates (BPMEs).

with the results shown in Table 3a, social interaction is found to have positive effects on the probability of holding and the amount of both types of liabilities and both types of assets held. In terms of the monetary amounts held in debt and financial assets, the effect of social interaction is positive at each point in time.

5. Conclusion

We have developed a joint modeling framework, which has allowed us to explore the relationship between social interaction and debt and asset holding at the household level. This framework has enabled us to conduct comprehensive empirical analysis of the relationship between social interaction and household finances, thereby furthering our understanding of the implications of social interaction for financial and economic outcomes. Furthermore, the joint modeling approach developed in this paper has allowed for the interdependence that potentially exists across the different parts of the household financial portfolio. Additionally, the incorporation of time varying coefficients for the effects of social interaction has introduced an extra layer of accuracy in determining the influence of social interaction on household finances.

Our findings suggest that social interaction has positive influences on both sides of the household balance sheet, indicating that the effect of social interaction is not just restricted to the particular case of share ownership. Throughout the findings, there is evidence that the influence of social interaction on both debt and assets, in terms of the holding of such financial instruments *per se* as well as the amounts held, is determined by a dynamic process. In terms of the relative magnitude of the effects, we find a relatively large effect in the case of loans from private individuals, highlighting the potentially important role played by informal credit channels in mitigating financial problems. Our findings thus indicate that social interaction plays an important role in many aspects of household finances and, hopefully, will serve to simulate further research in this area.

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher’s web-site:

Table A1: SUMMARY STATISTICS—DEPENDENT VARIABLES
Table A2: SUMMARY STATISTICS—CONTROL VARIABLES
Table A3: VARIANCE-COVARIANCE MATRIX TYPES OF DEBT AND ASSETS
Table A4: VARIANCE-COVARIANCE MATRIX TWO-PART MODEL