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Household Credit and Probability Forecasts of Financial Distress in the United Kingdom

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by

Abstract

The growth of unsecured household credit relative to income has been marked in recent years and many observers have questioned whether it is sustainable. This paper develops a theory-based empirical model of equilibrium household consumption and credit. The equilibrium relationships are embedded within a vector-autoregressive model that can accommodate complex dynamics with a coherent long-run structure. We define the events associated with financial distress and describe probability forecasting methods that can be applied to the model to predict the likely occurence of distress events. The analysis is illustrated using unsecured credit market data for the UK.

Keywords: Financial Distress, Probability Forecasts, Household Spending and Credit

JEL Classification: E44, E50.

1 Introduction

Unsecured borrowing has grown considerably in relation to incomes in the industrialised countries over the last decade: US total household debt to income was 142% of disposable income in 2003, comparable with other countries such as the UK (138%), Japan (121%) and Australia (141%), although Germany (102%) borrowed slightly less and the Netherlands (185%) slightly more. For the US and the UK, this represented a near tripling of total debt to income since 1990. In many countries, there is some controversy over whether a growing level of borrowing to personal income is sustainable, particularly if interest rates on borrowing should increase. In most industrialised countries, interest rates have fallen steadily with inflation over the last decade and a half, and therefore the burden of the outstanding debt has grown less dramatically than the debt to income ratio. In the UK the debt servicing burden December 1990 was 25.8% of disposable income, but had fallen to 15.9% by December 1997 and 13.8% in Dec 2005. But there is much less certainty about the path of inflation and interest rates looking forward, and the debt burden will increase should interest rates rise. Beyond some point, the extent of the burden could prompt a correction to household debt holdings as it did in the late 1990s. Under these circumstances, the implications for the financial sector are a likely increase in the incidence of defaults on outstanding debt, bankruptcies, bad loan write-offs or individual voluntary agreements (IVAs) with the lender over scheduled part-payment of the outstanding balance.

Agencies, including credit providers and central banks (with their dual responsibility for price and financial stability), are therefore keen to understand and anticipate the macroeconomic circumstances under which financial distress occurs.[1] However, despite the large and sophisticated literature that exists on the determinants of financial stability or distress at the household level using micro-level data (see Benito, Whitley and Young, 2001, and Cox, Whitley and Brierley, 2002, for the UK; and Durkin, 2000, Maki, 2000,

[1] A substantial literature exists on the consequences for banks should more borrowers default in adverse circumstances, and much of the thinking behind the new Capital Accord proposed by the Bank for International Settlements (Basel II) seeks to implement best practice by introducing macroeconomic considerations into credit risk models (c.f. Borio, Furfine and Lowe, 2001; Lowe, 2002).

2001, and Barnes and Young, 2003, for the US), there is relatively little advice on how to use macroeconomic time-series or household sector data to forecast the likelihood of emerging 'distress'. There is in fact no accepted definition of a 'distress' event that might be the trigger for a correction. Therefore this paper addresses two issues: first, it considers the conceptual matter of how to define financial 'distress' events and second, it addresses the practical question of how to predict financial distress by quantifying the likelihood of their occurrence.

Our objective is to use an empirical household choice model with a workable definition of financial distress that can be used to measure the likelihood of individual households facing severe adverse events. Adverse events are drastic enough to force trajectories for consumption, money balances and, particularly, borrowing to deviate substantially from their desired paths c.f. Padoa-Schioppa (2002) and Foot (2003)[2]. While households may deal with small deviations by varying consumption, money balances or borrowing at the margin, we anticipate that arrears, default and ultimately bankruptcy will occur in the event of large shocks. These outcomes might appear in the data with a (considerable) lag, but a model that predicts the likelihood of events that give rise to these outcomes will provide early warning of difficulties further down the line.

This paper describes a technical apparatus that can provide explicit forecasts of the likely occurrence of distress events. We describe long-run relationships for consumption and credit equilibrium embedded within an otherwise unrestricted time series model of the data. We use this model to provide combined forecasts of the outcomes of household decisions over consumption and credit. We define 'distress' in terms of events involving disequilibrium credit holdings, income growth or other factors and then generate forecasts of the probability that the events take place. Use of probability forecasts means we can summarise the likelihood of the occurrence of conjunctions of events of interest and to describe automatically the uncertainties surrounding the forecast outcomes. We argue that

[2]The importance of adverse events has been noted by Wadhwani (2002) and Nickell (2003) in the context of consumer borrowing; and the minutes of the Bank of England's Monetary Policy Committee (MPC) meeting in June 2002 explicitly considered the "risk that indebted households might have to adjust their balance sheets and consequently reduce their consumption sharply in the event of an adverse shock" (MPC Minutes, June 2002, p.4).

probability forecasts, obtained on the basis of a long-run structural model and focusing on joint events concerned with excess holdings of credit and the likelihood of recession, can provide measures of the likelihood of emerging distress to aid decision-making.

The remainder of the paper is organised as follows. The next section offers a brief summary of the background to consumption and credit studies, Section 3 sets out the form of the econometric model that can be used to generate probability forecasts. We then illustrate the modelling strategy by forecasting financial distress using UK data in Section 4. Section 5 concludes.

2 Household Consumption, Credit and Distress

The standard approach to the intertemporal household decision problem has focused on consumption (C_t) out of income (Y_t) and accumulated wealth (W_t), and has been based on results derived by Samuelson (1969) and Merton (1969) that maximises the intertemporal utility function $U = \sum_{i=0}^{N} \beta^i u(C_{t+i})$ subject to an intertemporal budget constraint $\sum_{i=0}^{N} A_{t+i+1} = \sum_{i=0}^{N} A_{t+i}(1 + R_{t+i}) + (Y_{t+i} - C_{t+i})$. The solution ensures that the marginal value of wealth equals the marginal utility of consumption, and an Euler equation links the marginal utility of consumption today with the marginal utility of consumption in the future (c.f. Attanasio, 1999). Assumptions about the specific form of the utility function yield precise consumption functions, as illustrated by Merton (1971), Hall (1978), Hansen and Singleton (1983) using variants of the HARA class of utility functions and, if the consumption function is quadratic then the consumption is a linear function of accumulated wealth and current income i.e. $C_{t+i} = \sum_{i=0}^{N} A_{t+i}(1 + R_{t+i}) + Y_{t+i}$. However, the assumptions required to impose a quadratic utility function are demanding since they imply increasing risk aversion, and other assumptions generally adopted with quadratic utility functions, such as certainty equivalence and the view that income is diversifiable.

With these difficulties in mind, some authors have adopted a precautionary saving model, c.f. Carroll (1997), which implies consumption will generally be less than expected under certainty equivalence due to the desire to save as a precaution against variable income. Others have introduced credit constraints allowing present consumption out of future income through borrowing on credit markets; c.f. Deaton (1991). Where credit is constrained, it has a similar effect to precautionary saving since, if households expect to be constrained by fixed limits on borrowing, they will save to avoid needing a loan they would not obtain if they were to apply for it (Attanasio, 1999). Ludvigson (1999) builds on Deaton (1991) and Carroll (1997) but allows access to credit to vary stochastically with current income, which is consistent with the lending practice of banks. His purpose is to establish whether movements in consumption growth are associated with predictable movements in credit. This highlights an important issue: namely, whether credit and money respond *passively* to the desired consumption path or are themselves influential over the path of expenditure. Consumption has traditionally been regarded as the primary variable, with money and credit taking a relatively passive role to allow consumption path to be smoothed through time. However, Chrystal and Mizen (2005) [hereafter CM] argue that monetarist and credit channels of transmission imply that money and credit will not necessarily be passive and may have an important bearing on consumption paths. They model consumption, money and borrowing decisions simultaneously which in reduced form implies each endogenous variable is a function of a small set of exogenous driving variables such as income, wealth, interest spreads and inflation.

Other empirical studies have followed a similar pattern but have modelled pairs (consumption and money balances or credit) by substituting out one of the endogenous variables in the long-run equations for the remaining two. Fisher and Vega (1993) and Thomas (1997a) consider the relationship between household consumption expenditure and money balances in the UK, finding that the two decisions are intertwined. Bacchetta and Gerlach (1997) and Ludvigson (1999) find significant predictive content in consumer credit growth for consumer expenditure growth in five OECD countries and the US credit-consumption growth relationship, respectively. In the modelling exercise in this paper, we consider consumption and credit explicitly, with money in the background. We do not depart from the argument in CM that consumer expenditure, money holding and credit decisions are all closely related intertemporal household decisions, but we focus on the reduced form relationship between consumption, credit and exogenous driving variables in a dynamic system. The theoretical literature on consumption and credit informs us about the variables that should be included in each of the consumer expenditure, money and credit equations (e.g. the relevant scale variables and interest rate spreads), and therefore the types of restrictions we might impose to identify the system. Coefficients in the reduced forms estimated in this paper will be amalgamations of theory-driven restrictions to coefficients (such as unit coefficients on income for example) and freely estimated parameters in each of the structural equations.

2.1 Modelling household decisions in a dynamic context

Our empirical analysis of household decisions over consumption, credit and money holdings follows the long-run structural modelling approach elaborated in Garratt et al. (2006). Here, the complex dynamics in the underlying household portfolio and expenditure decisions are captured within a VAR framework. But the VAR model also accommodates any long-run relationships suggested by economic theory (and allows the validity of these to be tested). A VAR model of this sort provides a straightforward means of investigating the sources of financial distress and, through the calculation of probability forecasts, provides a vehicle for generating indicators of potential financial distress over the medium- and long-term. This approach builds on previous work at the Bank of England by Fisher and Vega (1993), Thomas (1997a), Brigden and Mizen (2004) and CM.

The discussion above notes that, while some authors have suggested that consumption evolves independently of credit and money holdings, others have argued that consumption is influenced by these factors even in the long run. Since credit holdings and money holdings are themselves driven to a large extent by the transactions motive arising from consumption decisions, the latter view suggests that long-run consumption levels, credit and money holdings are explained in an entirely simultaneous system driven by income, wealth, and the costs of holding money and credit. In these circumstances, any restrictions suggested by economic theory have to relate to system-wide properties. So, for example, studies of consumption are often interested in the extent of income/wealth homogeneity (motivated by interest in the permanent income hypothesis). In the market for credit, on the other hand, income and wealth stimulate borrowing on the demand side, and justify provision of credit from financial institutions on the supply-side, supported by indicators of ability to pay (income multiples) and collateral assets (wealth). The relationship between credit holdings and income and wealth may or may not be homogenous in income and wealth therefore. Moreover, if credit holdings are not homogenous in income/wealth, then there would be no homogeneity in the system either given the simultaneity of the system.

Allowing for simultaneity across all household decisions motivates long-run relations of the form

$$\begin{aligned} c_t &= \beta_{10} + \beta_{11}y_t + \beta_{12}a_t + \beta_{13}\pi_t + \beta_{14}(r_t^l - r_t) + \xi_{1,t+1} && (2.1) \\ l_t &= \beta_{20} + \beta_{21}y_t + \beta_{22}a_t + \beta_{23}\pi_t + \beta_{24}(r_t^l - r_t) + \xi_{2,t+1} && (2.2) \end{aligned}$$

where c_t and l_t represent household real consumer expenditure and borrowing, y_t is real disposable income, a_t is net wealth, π_t is inflation, and $(r_t^l - r_t)$ is the spread of the credit rate of interest around the policy determined rate, r_t, and where $\xi_{1,t+1}$ and $\xi_{2,t+1}$ represent mean-zero and stationary deviations from the long-run equilibria. Generally, these equations should be interpreted as reduced forms that have been derived by substituting out consumption and money in the lending equation and lending and money in the consumption equation. Coefficient values and restrictions in any one equation cannot necessarily be interpreted as statements about household consumption or lending equations and the $\xi_{i,t+1}$ represent amalgamations of deviations from the behavioural consumption, money and credit equilibrium relations. If, on the other hand, we adopt the Samuelson-Merton approach to consumption, then the first equation would be structural in the sense that it explains consumer expenditure as a function of income, wealth and interest rates, independent of money and credit in the long run, and the coefficients in the equation have a more behavioural interpretation. Later in the paper, we consider different sets of restrictions on (2.1)-(2.2) that reflect these alternative views on the long run relations. This introduces an element of model uncertainty into the analysis, but the techniques used for calculating probability forecasts can readily accommodate this extra sophistication in generating the indicators of distress.

The long-run structural modelling approach notes that equations (2.1)-(2.2) can be written more compactly as measurable deviations from the long-run relationships:

$$\boldsymbol{\xi}_t = \boldsymbol{\beta}'\mathbf{z}_{t-1} - \boldsymbol{\beta}_0, \qquad (2.3)$$

where $\boldsymbol{\beta}_0 = (\beta_{10}, \beta_{20})'$, $\boldsymbol{\xi}_t = (\xi_{1t}, \xi_{2t})'$,

$$\mathbf{z}_t' = (\mathbf{y}_t', \mathbf{x}_t'), \ \mathbf{y}_t' = (c_t, l_t, y_t), \quad \mathbf{x}_t' = \left(a_t, \pi_t, r_t^l - r_t\right), \tag{2.4}$$

and

$$\boldsymbol{\beta}' = \begin{pmatrix} 1 & 0 & -\beta_{11} & -\beta_{12} & -\beta_{13} & -\beta_{14} \\ 0 & 1 & -\beta_{21} & -\beta_{22} & -\beta_{23} & -\beta_{24} \end{pmatrix}. \tag{2.5}$$

The variables are split between the $\mathbf{y}_t$ which we treat as endogenously determined, in the sense that deviations from the long-run equilibria of (2.1)-(2.2) impact on these variables, and the 'long-run forcing' variables, $\mathbf{x}_t$, which we assume evolve independently of these deviations. Our inclusion of output among the endogenous variables is in recognition of the important part played by consumption spending in the business cycle.

The variables in $\mathbf{z}_t$ are difference-stationary so the standard VAR approach to modelling the short-run dynamics of the variables is to assume that changes in these variables, $\Delta\mathbf{z}_t$, can be well-approximated by a linear function of a finite number of past changes in their difference; i.e. a linear function of $\Delta\mathbf{z}_{t-i}$, with $i = 1, 2, ..., p$. In contrast, the long-run structural VAR modelling strategy also embodies the disturbances $\boldsymbol{\xi}_t$ in the standard VAR model of $\Delta\mathbf{z}_t$:

$$\Delta\mathbf{z}_t = \mathbf{c}_0 - \boldsymbol{\alpha}\boldsymbol{\xi}_{t-1} + \sum_{i=1}^{p-1} \Psi_i \Delta\mathbf{z}_{t-i} + \mathbf{u}_t. \tag{2.6}$$

Given the definition of the long-run disturbances in (2.1)-(2.2), the model in (2.6) can be rewritten

$$\Delta\mathbf{z}_t = \mathbf{d}_0 - \boldsymbol{\alpha}\boldsymbol{\beta}'\mathbf{z}_{t-1} + \sum_{i=1}^{p-1} \Psi_i \Delta\mathbf{z}_{t-i} + \mathbf{u}_t \tag{2.7}$$

which is the standard reduced form vector error correction model, with $\mathbf{d}_0$ and $\boldsymbol{\beta}$ simple functions of the $\mathbf{c}_0$, $\boldsymbol{\alpha}$, $\mathbf{b}_0$, and $\boldsymbol{\beta}$. The long-run modelling strategy has the dual advantage of being able to capture both complex dynamic relationships that exist between variables in the short-run and economically meaningful long-run relationships i.e. consumer expenditure, money and credit equilibria.

2.2 Measuring financial distress

An important task of this paper is to consider whether there are 'distress' events defined at the macroeconomic level that correspond to financial distress at the household level. The discussion above focused on the determinants of the long-run levels of household consumption and credit holdings and clearly these determinants will be important in defining household distress events too. We consider that households make financial decisions based on their expectations of income, wealth, interest rates over their lifetimes. In the presence of transactions costs in obtaining credit, households will choose a preferred trajectory for credit holdings that will gradually bring credit holdings into line with a target level based on the expected future values of these determinants. Financial distress in the household occurs when the actual trajectory for credit holdings deviates substantially from the desired path.

Deviations of credit from the preferred trajectory could arise from idiosyncratic household-specific factors or unexpected changes in any of the underlying determinants (e.g. an unexpected fall in income through loss of employment, or an increase in the cost of debt servicing due to an unexpected rise in interest rates). We might assume that a household can accommodate small deviations of credit holdings from its preferred trajectory, but that there is an upper bound for excess credit (i.e. holdings of credit in excess of the preferred level) above which the household will default on payments, incur bankruptcy or exhibit one of the many other signs of financial distress observable with a lag. In these circumstances, the likelihood of a household suffering financial distress is directly related to the level of excess credit holdings since an idiosyncratic shock or forecast error is more likely to cause excess credit to rise above the upper bound when excess holdings are high and close to the upper bound. But the relationship is non-linear, reflecting the density functions of the underlying shocks and forecast errors,[3] and will vary over time as the uncertainty associated with the forecasts of the determinants varies.

At the macroeconomic level, the level of aggregate excess credit will be associated with a cross-section of credit holdings within households each matched against a cross-section

[3]For example, if the excess holdings are denoted x, the upper bound is c and the shocks, ε, are $N(0,\sigma^2)$, then $\Pr(x+\varepsilon > c) = 1 - \Phi(\frac{c-x}{\sigma})$, (where $x < c$) and $\frac{\partial \Pr}{\partial x} = \frac{1}{\sigma}\phi(\frac{c-x}{\sigma}) > 0$ which rises as $x \to c$.

of threshold values.[4] The relationship between household distress and aggregate excess credit depends on these cross-sectional distributions, but it seems reasonable to assume that the positive non-linear relationship between distress and excess credit carries over to the macroeconomic level. This suggests that a useful indicator of distress at the forecast horizon $T+h$ will be provided by estimates of the probability that the aggregate excess credit measure exceeds a specified critical value; i.e. $\Pr(\xi_{2,T+h} > c)$ where $\xi_{2,T+h}$ are the disequilibrium terms in (2.2).[5] This indicator directly reflects the degree of household credit imbalance and will be superior to simple point forecasts of the future levels of excess credit (as measured by estimates of $\xi_{2,t+h}$) because the point forecasts will not be able to capture the nonlinearities highlighted above, nor will they be able to reflect the impact of the time variation in the uncertainty associated with the forecasts of the underlying variables.

It is worth noting that, while the indicator $\Pr(\xi_{2,T+h} > c)$ provides a sensible aggregate analogue to the concept of distress at the household level, it is possible that other macroeconomic events would capture different aspects of financial distress experienced in different households. For example, a slowdown in economic growth might bring a wage moderation and some reduction in hours worked, resulting in lower incomes across the economy. This would raise the probability of distress in all households although the effect would be evenly spread and could be relatively small. In contrast, a more severe recession (involving a *fall* in output as opposed to a slowdown in the rate of increase, say) might result in larger wage cuts and job losses in particular sectors. Here the effect of the lower incomes would be accurately reflected by the rise in excess credit holdings, but, if it is true that the effects of a recession are concentrated on particular households

[4]From an analysis of the British Household Panel Survey data, Cox, Whitley and Brierley (2002) indicate that there is considerable heterogeneity within the household sector in the response of debt-to-income ratios to finanical conditions (indicated by the households' position in the distribution of income and wealth in this case).

[5]Note that the measure, ξ_{2t}, is based on the stock of credit to income and the movement in the cost of borrowing. It therefore provides a direct measure of households' financial exposure in time t that reflects not just time-t decisions but also the time-t consequences of household decisions and credit market inertias prior to time t.

through unexpected unemployment, then the consequent increase in financial distress in those households would not be adequately captured by the excess credit holding measure alone.

The example above suggests that it is the conjunction of macroeconomic events that might be associated with distress, and this insight is readily captured by the use of probability forecasts to indicate distress because it is straightforward to estimate the forecasts of the probability of *joint* events. Hence, in the example above, financial distress might be more accurately reflected by estimates of the probability that excess credit exceeds a critical value and output falls; i.e. $\Pr\{(\xi_{2,T+h} > c) \cap (\Delta y_t < 0)\}$. Alternatively, distress might arise when excess credit exceeds its threshold OR recession occurs $\Pr\{(\xi_{2,T+h} > c) \cup (\Delta y_t < 0)\}$. There are a number of possibilities that involve alternative events including other variables and the techniques can be readily adapted to accommodate more complicated joint events. Our own view is that forecasts of the probability of the occurrence of excess credit holdings and recession is a useful indicator to demonstrate the prediction of financial distress in households in the UK in the 1990s (when the UK last experienced financial distress on a large scale) and the present.

2.3 Forecasting financial distress

Having discussed the usefulness of joint events that we will focus on as indicators of financial distress, it is a relatively straightforward matter to generate forecasts of the probability of these events occurring using the vector error correction model described in (2.7) through stochastic simulation techniques[6]. These techniques can allow for many possible re-runs of the future to allow for stochastic variation in the data, the possibility that parameters vary around their estimated values, and that more than one model be considered as a description of the relationship between the variables in the system. We refer to these as stochastic, parameter and model uncertainty.

Consider the case where we abstract from parameter uncertainty for the time being and focus on a given model, denoted M_q. One can use the estimated version of the model, based on the observed data $\mathbf{Z}_T = (\mathbf{z}_1, \mathbf{z}_2, ..., \mathbf{z}_T)'$, to generate S replications of the future

[6]See Garrett *et al.* (2003, 2006 ch7) for details.

vintages of data, denoted $\widehat{\mathbf{Z}}^{(s)}_{T+1,T+H} = (\widehat{\mathbf{z}}^{(s)}_{T+1}, \widehat{\mathbf{z}}^{(s)}_{T+2}, ..., \widehat{\mathbf{z}}^{(s)}_{T+H})'$ for $s = 1, ..., S$. The simulated replications are obtained using random draws from the estimated distribution of the innovations on the assumption that the model continues to hold over the forecast horizon $T+1, ..., T+H$. These S simulated future vectors of variables provide the estimated density function of $\mathbf{Z}_{T+2,T+H}$ that is conditional on the observations available at the end of period T and model M_q denoted $\Pr(\mathbf{Z}_{T+1,T+H} \mid \mathbf{Z}_T,\ M_q)$. A relative frequency measure of the number of times an event occurs in these simulations provides a forecast of the probability that the event will take place. Hence, if we denote the event by $\varphi(\mathbf{z}_{T+1}, \ldots, \mathbf{z}_{T+h})$, given that the event is defined with respect to the variables in $\mathbf{z}_t$ over the forecast horizon $T+1, T+2, ..., T+H$, then the forecast probability of the event is computed as

$$\pi(\varphi,\ \mathbf{Z}_T,\ M_q) = \frac{1}{S}\sum_{s=1}^{S} I\left(\varphi(\mathbf{z}^{(s)}_{T+1}, \ldots, \mathbf{z}^{(s)}_{T+h})\right),$$

where $I(.)$ is an indicator function which takes the value of unity if the event occurs and zero otherwise.

Extending the simulation exercise to accommodate parameter uncertainty for the given model simply involves an additional iteration of the simulation procedure in which replications of the historical data and of the model parameters are also produced. This provides an estimate of the density function of $\mathbf{Z}_{T+1,T+H}$ and the associated event probabilities accommodating both stochastic and parameter uncertainty.

A further step allows accommodation of uncertainties arising from model choice. This is achieved adapting the approach of Draper (1995) and Hoeting *et al.* (1999) in which, assuming that there are Q different models, denoted M_q, $q = 1, ..., Q$, it is noted that the pdf of $\mathbf{Z}_{t+2,t+H}$ conditional on $\mathbf{Z}_{t+1}$ and accommodating model uncertainty is provided by the "Bayesian model averaging" formula,

$$\Pr(\mathbf{Z}_{T+1,t+H} \mid \mathbf{Z}_T) = \sum_{q=1}^{Q} \Pr(M_q \mid \mathbf{Z}_T) \Pr(\mathbf{Z}_{T+1,t+H} \mid \mathbf{Z}_T, M_q). \tag{2.8}$$

The $\Pr(\mathbf{Z}_{t+2,t+H} \mid \mathbf{Z}_{t+1},\ M_q)$ are given directly by the simulation exercises described above for each model while Draper (1995) suggests the use of the familiar Schwarz Bayesian information criterion to obtain weights attached to each model M_q given by

$$\Pr(M_q \mid \mathbf{Z}_T) = \frac{\exp(SBC^*_{q,T})}{\sum_{j=1}^{Q} \exp(SBC^*_{j,T})} \tag{2.9}$$

where $SBC^*_{q,T} = SBC_{q,T} - \max_j(SBC_{j,T})$, $SBC_{q,T} = LL_{q,T} - \left(\frac{k_q}{2}\right)\ln(T)$ is the Schwarz Bayesian information criterion, and $LL_{q,T}$ is the maximized value of the log-likelihood function for model M_q based on data available at time T. Hence, using the simulation techniques outlined above for each of the possible models available, this model averaging formula provides a straightforward means of obtaining the density $\mathbf{Z}_{T+1,t+H}$ taking into account all forms of uncertainty. Further, the application of the same averaging formula to the forecast event probabilities also provides probability forecasts that accommodate model uncertainty as well as the other forms of uncertainty.

3 Analysing Financial Distress in the UK

In this section, we undertake an analysis of the UK household financial sector using quarterly data over the period 1981q1-2004q4 to investigate the usefulness of the modelling framework described above and to consider the role of probability forecasts as indicators of financial distress. Our approach to modelling household decisions follows the Bank of England tradition from recent years; c.f. Fisher and Vega (1993), Thomas (1997a,b), Brigden and Mizen (1999) and CM. Real household consumer expenditure, real total consumer credit, and real disposable income levels are treated as endogenous variables in the model, and we assume that real wealth, inflation and the spread of the credit card rate over the 3-month Treasury bill rate are determined exogenously in the long-run.[7]

The first step in the analysis is to gauge the time series properties of the data. ADF tests applied to each of the series determine the order of integration as shown in Table 1, and these tests indicate that we can treat all the variables under consideration as $I(1)$. To choose the lag length in the VAR analysis, we estimate unrestricted VAR systems in differences of order $p = 1, .., 4$, while also including up to two lags of the exogenous variables. The (adjusted) likelihood ratio test statistics obtained when testing the contribution of the additional lags took the values 11.16 when testing the insignificance of the fourth lagged difference, and 17.69 when testing the insignificance of the third lagged difference. Each of these is compared to χ^2_9, indicating that a cointegrating VAR includ-

[7]In this study, we use the same variables detailed in the CM Data Appendix updated to 2004 using data sources from Bank of England and ONS.

ing up to four lags of the levels is appropriate for subsequent analysis. Significant outliers in the residuals from the underlying regressions (i.e. those that exceed three standard deviations) are removed with dummy variables to ensure that they do not have an undue impact on the econometric specification or forecasts.[8]

The next step is to conduct tests to establish the number of long-run relationships that exist between the series using the Johansen procedure and to test any over-identifying restrictions suggested by economic theory. We estimate a cointegrating VAR system with unrestricted intercepts and test for cointegrating rank. The results are shown in Table 2 and, while there are some conflicting signals from the various trace statistics, maximal eigenvalue statistics and selection criteria, the statistics provide some evidence for the presence of two cointegrating relationships. We proceed on this basis on the grounds that such a system has a natural economic interpretation. Estimating the system subject to four ($=2^2$) exactly-identifying restrictions provides a maximised log-likelihood of 1051.4. The imposition of additional over-identifying restrictions reflecting assumptions about the role of income and wealth in the consumption and credit equations provides three alternative models, the validity of which can be tested using likelihood ratio tests. Our first model M_1, restricts the coefficient on y_t to unity in the credit equation (2.2); this allows us to make direct comparisons between the credit equilibrium and the credit-income ratio, which has been a source of much speculation concerning the sustainability of borrowing in relation to income. In model M_2, we impose long-run income and wealth homogeneity in the consumption and credit equations so that the sum of the coefficients on income and wealth is equal to unity in both equations (2.1)-(2.2). Lastly, in model M_3, we continue to impose the income and wealth homogeneity in the consumption equation but return to a unit coefficient restriction on income in the credit equation.

Table 3 provides the estimated cointegrating relations obtained under these different assumptions. In each case, the over-identifying restrictions are readily accepted, especially when considered against the bootstrapped critical values calculated to accommodate any small-sample effects in the analysis. The coefficients on income and wealth in the consumption equation of model M_1 are, at 0.87 and 0.074, in line with previous estimates

[8] This relates to the observations in 1993q1 and 1995q1.

reported in the literature cited above and close to unity in sum even in this unrestricted model.[9] The unity restriction on income in the credit equation appears compatible with the data but the model implies there is a strong additional influence from wealth on the credit-income ratio. Inflation has a strong positive impact on consumption and a weaker (and statistically insignificant) effect on credit holdings, while the credit spread has its anticipated negative impact on credit holdings in the long run and a similarly-signed effect on consumption. One interpretation of the lack of homogeneity on income and wealth coefficients in the credit equation is that it reflects the readiness of lenders to assess creditworthiness on the basis of more than current income. Higher net wealth levels have a positive impact on credit rating exercises and these allow revaluations of *gross wealth,* e.g. financial assets and property, to influence lending constraints.

Given that the unrestricted estimates are close to unity, it is not surprising to find that the restriction that the income and wealth coefficients sum to unity in the credit equation of model M_2 are also accepted by the data. This means that borrowing is tied to the sum of current income and wealth levels, but the finding that the wealth coefficient is larger than the income coefficient is counter-intuitive and the effect of inflation on credit appears large in this model. Model M_3 combines the best features of models M_1 and M_2 by imposing the relatively uncontentious unit effect of income and wealth in the consumption equation and the unit income effect in the credit equation. We recognise that there is some ambiguity on the best choice of model and we will take model uncertainty into account when evaluating financial distress probabilities later in the paper.

The error correction models underlying the long-run relations of Table 3 have good statistical properties and show that the modelling framework is capable of capturing the complicated dynamic interactions between household consumption, credit holdings and disposable income. The overall explanatory power of the regressions is high, at 55%, 80% and 57% in Model M_3 according to R^2, for example, and the diagnostic statistics are satisfactory.[10] The regressions are heavily parameterised, but significant feedbacks

[9] The LR test statistic of the unity restriction imposed in the consumption equation moving from model M_1 to model M_3 takes the value of just 0.6, cf. $\chi^2(1)$.

[10] There remains some evidence of serial correlation in the residuals of the consumption-income equation, but to overcome this problem with the inclusion of further lags would overrule the choice of the order of the

are observed between the growth in consumption, credit and disposable income. The dynamics of the system are complex, and are best evaluated by inspection of the associated persistence profiles reported in Figure 1.[11] These show that the system is stable but that equilibrium is restored only slowly, with the 'half-life' of a shock to the consumption and credit equilibrium of the order of 4.5 quarters and 9.6 quarters respectively. If distress is related to credit market disequilibrium then the consequence of persistence in the disequilibria will imply any distress observed today will be the result of macroeconomic conditions over the previous 2-4 years.

Figure 2 plots the value of ξ_{lt} for $t = 1981q1 - 2004q4$ obtained from models $M_1 - M_3$. The values from M_2 are rather more volatile than those from M_1 and M_3 (which are relatively similar, as might be expected from the estimates of the cointegrating relations). But the time profiles of all three measures appear to capture well the widespread financial distress experienced in the UK in the late 1980's and early 1990's (as evidenced by outstanding debt figures, bankruptcies and other household-level indicators of distress). The figure also indicates that households were not particularly exposed to the dangers of excess credit at the end of the sample by historical standards, and with the value of $\xi_{2,t}$ taking positive but moderate values, were not as financially exposed in 2004q4 as they were in the 1980s and 1990s.

3.1 Probability forecasts of distress events in the UK

In this section, we illustrate the ability of event probability forecasts to indicate the likelihood of financial distress by considering two separate episodes for the UK. The first episode relates to the end of our sample period in 2004 when the key characteristics of the economy were low inflation, low interest rates and strong economic growth. Unsecured

VAR based on information criteria. Tests of functional form, normality of residuals and heteroskedasticity are all safely less than relevent critical values.

[11]While impulse response functions show the time profile of the effect of a typical shock to a single variable, persistence profiles illustrate the response of the linear combination of variables that define the equilibrium relations. If the system is stable, the effect of the shock to this combination is zero at the infinite horizon by construction and, normalising the impact of the shock to be 1 standard deviation, the half-life is the time taken for the profile to fall below 0.5.

debt to income levels had risen to unprecedented levels during this period, prompting worries about the sustainability of the high level of borrowing although, in terms of default rates, arrears and other household-level indicators of distress, these anxieties have not translated into serious problems to date compared to the experiences of the late eighties/early nineties. The second episode we consider is from this earlier period, considering data ending in 1990q4. Deregulation of the financial system had made access to unsecured borrowing easier at that time than at any time since the second world war and borrowing had risen to unprecedented levels. Despite the fact that rates on unsecured credit were some 5-10 percentage points higher than at the end of the sample, there was not the same concern about the sustainability of the high level of borrowing at the time since much of the borrowing was justified by high asset values as housing and equity markets boomed. Subsequent data from arrears and default rates indicates that optimism was misplaced, and as equity and property markets moved from boom to bust there was considerable financial distress during this period. The remainder of the section uses the probability forecast method to quantify the likelihood of a distress event for each period.

Table 4 describes forecast probabilities that the level of excess credit holdings is greater than a variety of threshold values defined as multiples of the standard deviation of $\xi_{2,t}$ over the eight quarter periods beginning 2005q1 and 1990q4. The forecast probabilities are based on simulations taking into account stochastic uncertainty, and are based on model M_3 using the data set available at the time (i.e. up to 2004q4 and 1990q4 respectively). As is clear, the forecast probabilities of distress provided for the period 2005q1 onwards are all much lower than those for the period 1990q4 onwards, reflecting the impression provided by the household-level indicators that distress was considerably higher in the earlier period. Concentrating on the 2-standard deviation threshold, we find the probability of distress almost equal to zero in 2005q1-2006q4 while it runs at 10-30% through most of 1991q1-1992q4. Similarly, at the 1-standard deviation threshold, the probabilities of excess credit holdings are in the region 5-12% through 2005q2-2006q4 but are between 66-82% in 1991q1-1992q4.[12]

[12]These figures reflect a lower point forecast for the disequilibrium credit holdings over the most recent period (which lie in the range [.001, .009], compared to [.081, .121] for the earlier period), but the

Table 5 presents comparable statistics to Table 4 but taking into account parameter and model uncertainty. The first columns reproduce the figures of the previous table reporting the likelihood that the disequilibrium credit holdings exceed 1-standard deviation taking into account stochastic uncertainty only. The second columns report the same event probability but accommodating the effects of parameter uncertainty as well as stochastic uncertainty, based on Model M_3. These figures are broadly similar to those of the first columns, with the probabilities typically lying within 10% of the figures based on stochastic uncertainty alone. The third columns provides the same event probability forecast (i.e. the probability that forecast values of $\xi_{2,t}$ exceed 1-standard deviation), but based on Model M_2 and taking into account stochastic uncertainty only. These probabilities continue to reflect the much larger likelihood of distress in 1990q1-1992q4 than 2005q1-2006q4, but are rather larger than the corresponding figures based on model M_3, showing that the uncertainty on the distress measure arising from the choice of model is considerably larger than uncertainty arising from the parameter estimation for any given model. Finally, in the fourth columns of Table 5, we report the same event probability, but this time taking into account the uncertainty arising from our choice between the three models of Table 3. Given the weighting formula of (2.9) and the likelihood values reported in Table 3, the weights assigned to models M_1, M_2 and M_3 are 0.4742, 0.1745 and 0.3513 respectively, so these figures are influenced, but are not dominated, by the larger probabilities suggested by Model M_2. These figures therefore accommodate the primary sources of uncertainty surrounding the distress probabilities, associated with the stochastic variation and model uncertainty, and reflect the view that the probabilities of distress were less than 14% for the most recent period, compared to 74-79% over 1991q1-1996q4.

Table 6 presents probability forecasts that indicate the level of financial distress that might be experienced as the economy slows down, either taken alone or in conjunction with excess credit holdings. So, the first columns of the table reports the forecast probability of a recession occurring in each of our two periods, where a recession is defined simply as negative output growth. These figures show that output growth prospects were much

probability forecasts also convey the uncertainties surrounding the forecasts and therefore present a more easily interpretable measure of the likelihood of distress than the simple point forecasts.

healthier during the more recent period with the probability of negative growth between 7-29% over 2005q1-2006q4 compared to 22-52% in 1991q1-1992q4. The relatively poor growth prospects in 1990 will have exacerbated the effects of the excess credit holdings on households' financial distress experienced at the time. The joint probabilities reported in the second columns of the table therefore represent a concise means of aggregating these influences in a single indicator of financial distress, showing the likelihood of the joint event that disequilibrium credit holdings exceed 1-standard deviation *and* that output growth is negative based on Model M_3 and, for purposes of comparison with the previous tables, accommodating stochastic uncertainty only. The final columns show the same joint probability, but this time taking into account model uncertainty. Once again, comparison of the figures obtained over the two periods shows that there are low levels of distress forecast for the period 2004q1-2006q4, with probabilities in the range 0-5%, compared to the distress levels forecast for 1991q1-1992q4, with probabilities in the range 16-37%.

4 Conclusions

Unsecured debt levels of households in the industrialised countries have followed clearly discernible trends relative to income, rising to unprecedented levels in recent years. Research into the sustainability of current levels of household debt has relied upon relatively simple forecasting methods using economic time series that are not always available ahead of time to provide adequate forewarning of future distress. Measurement of the scale of default risk and bankruptcy has been based largely on microeconomic data at the level of the household, and the challenge of including macroeconomic developments in the assessment of these risks have been undertaken only to a limited extent. While central banks and financial institutions are eager to understand and monitor the impact of macroeconomic developments on consumer debt levels for the purpose of assessing financial stability, the tools to predict how they will affect distress are in their infancy.

This paper offers a new technology using probability forecasts allowing the quantification of predefined distress events to be evaluated giving forewarning of distress. These methods are able to capture any nonlinearities in the relationships between time series variables and distress and can assess complex combinations of events. Our application illustrates how this approach can offer insights in the UK unsecured credit market over the previous two decades - showing that the probability forecasting method can identify periods when financial distress was experienced from those when it was not. While the processes laid out here can be refined and the range of applications extended this technology allows financial institutions to determine the likelihood of distress and the associated uncertainty surrounding the forecast.

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Table 1 : **Augmented Dickey-Fuller Unit Root Tests Applied to Household Sector Variables; 1981q1- 2004q4**

(i) For the First Differences					
Variable	ADF(0)	ADF(1)	ADF(2)	ADF(3)	ADF(4)
Δc_t	-9.28*	-4.79*	-4.56*	-3.99*	-3.15
Δl_t	-4.46*	-2.83	-2.05	-1.89	-2.22
Δy_t	-15.29*	-7.79*	-5.54*	-5.13*	-4.07*
Δw_t	-8.55*	-9.27*	-5.63*	-4.88*	-4.18*
$\Delta \pi$	-8.40*	-5.96*	-4.47*	-5.46*	-4.44*
$\Delta(r_t^l - r_t)$	-10.32*	-8.55*	-7.99*	–6.82*	-7.03*

(ii) For the Levels					
Variable	ADF(0)	ADF(1)	ADF(2)	ADF(3)	ADF(4)
c_t	-1.17	-1.36	-2.08	-2.09	-2.37
l_t	-2.03	-2.22	-2.65	-3.37	-3.75*
y_t	-3.11	-2.31	-2.46	-2.57	-2.51
w_t	-1.59	-1.87	-1.19	-1.49	-1.48
π_t	-3.31	-3.39	-3.17	-3.27	-2.85
$(r_t^l - r_t)$	-3.30	-3.27	-2.79	-2.56	-2.12

Notes: When applied to the first differences, augmented Dickey-Fuller (1979, ADF) test statistics are computed using ADF regressions with an intercept and s lagged first-differences of dependent variable while, when applied to the levels, ADF statistics are computed using ADF regressions with an intercept, a trend and s lagged first-differences of dependent variable. The relevant lower 5 per cent critical values for the ADF tests are -2.89 and -3.46 respectively and * indicates significance at the 5 per cent level.

Table 2 : **Cointegration Rank Statistics for the Household Sector**

$$c_t,\ l_t,\ y_t,\ w_t,\ \pi_t,\ (r_t^l - r_t)$$

(a) Trace Statistic

H_0	H_1	Test Statistic	95% Critical Values	90% Critical Values
$r = 0$	$r = 1$	64.30	53.41	49.56
$r \leq 1$	$r = 2$	31.12	33.35	30.37
$r \leq 2$	$r = 3$	12.26	16.90	14.76

(b) Maximum Eigenvalue Statistic

H_0	H_1	Test Statistic	95% Critical Values	90% Critical Values
$r = 0$	$r = 1$	33.18	30.74	28.11
$r \leq 1$	$r = 2$	18.86	24.22	21.67
$r \leq 2$	$r = 3$	12.26	16.90	14.76

(c) Model Selection Criteria

Rank	Max Log Likelihood	AIC	SBC	HQC
$r = 0$	1025.3	941.3	833.6	897.8
$r = 1$	1041.9	949.9	832.0	902.3
$r = 2$	1051.4	953.4	827.7	902.6
$r = 3$	1057.5	955.5	824.7	902.6

Notes: The underlying VAR model is of order 4 and contains unrestricted intercepts and restricted trend coefficients, with y_t, w_t, π_t, and $(r_t^l - r_t)$ treated as exogenous $I(1)$ variable. The statistics refer to Johansen's log-likelihood-based trace and maximal eigenvalue statistics and are computed using 96 observations for the period 1981q1-2004q4. AIC, SBC and HQC in Table 2(c) refer to Akaike Information, Schwarz Bayesian and Hannan-Quinn Criteria.

Table 3: **Estimates of Cointegration Relations subject to Over-Identifying Restrictions**

Model M_1

$$c_t = 0.3681 + \underset{(0.1343)}{0.87032} y_t + \underset{(0.0515)}{0.07384} w_t + \underset{(0.0034)}{0.008271} \pi_t - \underset{(0.0037)}{0.002351} (r_t^l - r_t) + \widehat{\xi}_{ct},$$

$$l_t = -7.9536 + \underset{(-)}{1.0000} y_t + \underset{(0.0600)}{0.51488} w_t - \underset{(0.0122)}{0.005716} \pi_t - \underset{(0.0123)}{0.013451} (r_t^l - r_t) + \widehat{\xi}_{lt},$$

$$LLF = 1050.0; \qquad \chi^2_{LR}[1] = 2.74; \qquad CV(90\%, 95\%) = \begin{cases} 2.71,\ 3.84\ \text{(Asy)} \\ 8.39,\ 6.05\ \text{(Boot)} \end{cases}$$

Model M_2

$$c_t = -0.1772 + \underset{(0.0198)}{0.95807} y_t + \underset{(0.0198)}{0.04193} w_t + \underset{(0.0021)}{0.010310} \pi_t - \underset{(0.0028)}{0.004194} (r_t^l - r_t) + \widehat{\xi}_{ct},$$

$$l_t = -2.6449 + \underset{(0.1216)}{0.25529} y_t + \underset{(0.1216)}{0.74471} w_t - \underset{(0.0133)}{0.031346} \pi_t - \underset{(0.0171)}{0.000333} (r_t^l - r_t) + \widehat{\xi}_{lt},$$

$$LLF = 1049.0; \qquad \chi^2_{LR}[2] = 4.84; \qquad CV(90\%, 95\%) = \begin{cases} 4.61,\ 5.99\ \text{(Asy)} \\ 14.20,\ 11.27\ \text{(Boot)} \end{cases}.$$

Model M_3

$$c_t = -0.1829 + \underset{(0.0183)}{0.95670} y_t + \underset{(0.0183)}{0.04330} w_t + \underset{(0.0020)}{0.010257} \pi_t - \underset{(0.0028)}{0.004108} (r_t^l - r_t) + \widehat{\xi}_{ct},$$

$$l_t = -8.2505 + \underset{(-)}{1.0000} y_t + \underset{(0.0550)}{0.53300} w_t - \underset{(0.0113)}{0.003143} \pi_t - \underset{(0.0121)}{0.012209} (r_t^l - r_t) + \widehat{\xi}_{lt},$$

$$LLF = 1049.7; \qquad \chi^2_{LR}[2] = 3.25; \qquad CV(90\%, 95\%) = \begin{cases} 4.61,\ 5.99\ \text{(Asy)} \\ 15.03,\ 11.44\ \text{(Boot)} \end{cases}.$$

Notes: Results are based on a cointegrating VAR estimated with unrestricted intercepts and no trends. Models $M_1 - M_3$ are estimated assuming the existence of two cointegrating relations and subject to over-identifying restrictions. LLF is the value of the maximised log-likelihood; χ^2_{LR} is the test-of the overidentifying restrictions; CV(90%,95%) are the critical values with 'Asy' denoting the relevant asymptotic values and and 'Boot' the corresponding critical values obtained through a bootstrap replication of the system to take into account small sample properties of the test (see Garratt et al, 2006).

Table 4 : **Probability Forecasts involving Credit Disequilibria,** $\xi_{l,t}$

$\Pr\left\{\xi_{l,T+h} > c\right\}$, Model M_3, **2005q1-2006q4**

Forecast Horizon	$c = 0.5 \times sd$ $= 0.025$	$c = 1 \times sd$ $= 0.070$	$c = 1.5 \times sd$ $= 0.105$	$c = 2 \times sd$ $= 0.140$
2005q1	0.096	0.004	0.001	0.000
2005q2	0.246	0.054	0.007	0.000
2005q3	0.323	0.102	0.020	0.003
2005q4	0.274	0.087	0.016	0.002
2006q1	0.259	0.087	0.019	0.002
2006q2	0.294	0.108	0.029	0.005
2006q3	0.305	0.121	0.036	0.008
2006q4	0.299	0.125	0.037	0.007

$\Pr\left\{\xi_{l,T+h} > c\right\}$, Model M_3, **1991q1-1992q4**

Forecast Horizon	$c = 0.5 \times sd$ $= 0.025$	$c = 1 \times sd$ $= 0.070$	$c = 1.5 \times sd$ $= 0.105$	$c = 2 \times sd$ $= 0.140$
1991q1	0.962	0.656	0.174	0.012
1991q2	0.900	0.633	0.268	0.059
1991q3	0.914	0.699	0.368	0.122
1991q4	0.906	0.703	0.401	0.147
1992q1	0.908	0.726	0.431	0.178
1992q2	0.923	0.756	0.506	0.244
1992q3	0.940	0.810	0.584	0.314
1992q4	0.944	0.822	0.611	0.361

Notes: Forecasts are based on the model M_3, estimated using data 1981q1-2004q4, as reported in Table 3, supplemented with a 4th-order VAR in differences for the exogenous variables. The probability forecasts are based on simulations taking into account stochastic uncertainty only.

Table 5 : **Probability Forecasts involving Credit Disequilibria,** $\xi_{l,t}$

$\Pr\{\xi_{l,T+h} > (1 \times sd)\}$, **2005q1-2006q4**

Forecast Horizon	Model M_3 (Stoch. only)	Model M_3 (Stoch.+Parm.)	Model M_2 (Stoch.only)	Weighted Model (Stoch.+Model)
2005q1	0.004	0.005	0.003	0.005
2005q2	0.054	0.057	0.066	0.061
2005q3	0.102	0.100	0.128	0.110
2005q4	0.087	0.090	0.117	0.097
2006q1	0.087	0.093	0.127	0.099
2006q2	0.108	0.118	0.155	0.123
2006q3	0.121	0.134	0.175	0.138
2006q4	0.125	0.138	0.176	0.142

$\Pr\{\xi_{l,T+h} >(1 \times sd)\}$, **1991q1-1992q4**

Forecast Horizon	Model M_3 (Stoch. only)	Model M_3 (Stoch.+Parm.)	Model M_2 (Stoch. only)	Weighted Model (Stoch.+Model)
1991q1	0.656	0.677	0.999	0.761
1991q2	0.633	0.640	0.982	0.725
1991q3	0.699	0.690	0.958	0.762
1991q4	0.703	0.675	0.913	0.749
1992q1	0.726	0.664	0.853	0.748
1992q2	0.756	0.680	0.798	0.758
1992q3	0.810	0.710	0.764	0.788
1992q4	0.822	0.714	0.717	0.783

Notes: Forecasts are based on the weighted model, estimated using data 1981q1-2004q4, supplemented with a 4th-order VAR in differences for the exogenous variables. The probability forecasts are based on simulations taking into account stochastic uncertainty only (columns 1 and 3), stochastic and parameter uncertainty (column 2), or stochastic and model uncertainty (column 4).

Table 6 : **Probability Forecasts involving Recession and/or Credit Disequilibria**

2005q1-2006q4

Forecast Horizon	Model M_3 $\Pr\{\Delta y_{T+h} < 0\}$	Model M_3 $\Pr\{\xi_{l,T+h} > (1 \times sd) \cap (\Delta y_{T+h} < 0)\}$	Weighted Model $\Pr\{\xi_{l,T+h} > (1 \times sd) \cap (\Delta y_{T+h} < 0)\}$
2005q1	0.069	0.001	0.001
2005q2	0.254	0.023	0.025
2005q3	0.232	0.037	0.039
2005q4	0.266	0.032	0.036
2006q1	0.231	0.031	0.035
2006q2	0.260	0.038	0.044
2006q3	0.288	0.047	0.054
2006q4	0.263	0.044	0.047

1991q1-1992q4

Forecast Horizon	Model M_3 $\Pr\{\Delta y_{T+h} < 0\}$	Model M_3 $\Pr\{\xi_{l,T+h} > (1 \times sd) \cap (\Delta y_{T+h} < 0)\}$	Weighted Model $\Pr\{\xi_{l,T+h} > (1 \times sd) \cap (\Delta y_{T+h} < 0)\}$
1991q1	0.219	0.167	0.158
1991q2	0.353	0.258	0.279
1991q3	0.497	0.378	0.277
1991q4	0.510	0.388	0.369
1992q1	0.459	0.362	0.355
1992q2	0.426	0.350	0.340
1992q3	0.397	0.342	0.329
1992q4	0.370	0.352	0.306

Notes: Forecasts are based on the weighted model, estimated using data 1981q1-2004q4, supplemented with a 4th-order VAR in differences for the exogenous variables. Recession is defined to occur when $\{\Delta y_{T+h} < 0\}$.

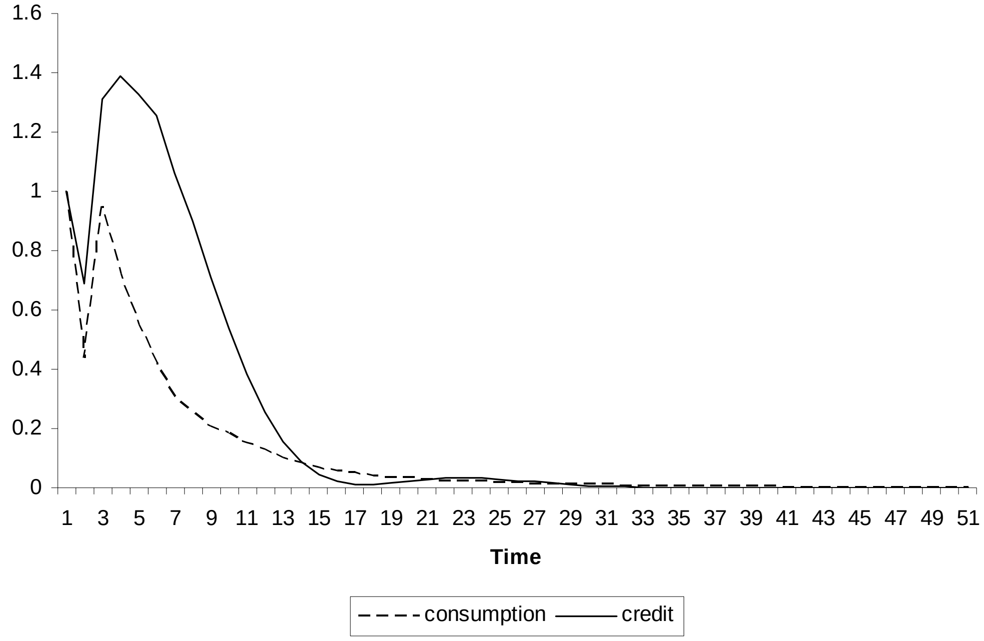

Figure 1: Persistence Profiles of the Effect of a Sytem-Wide Shock to CV's

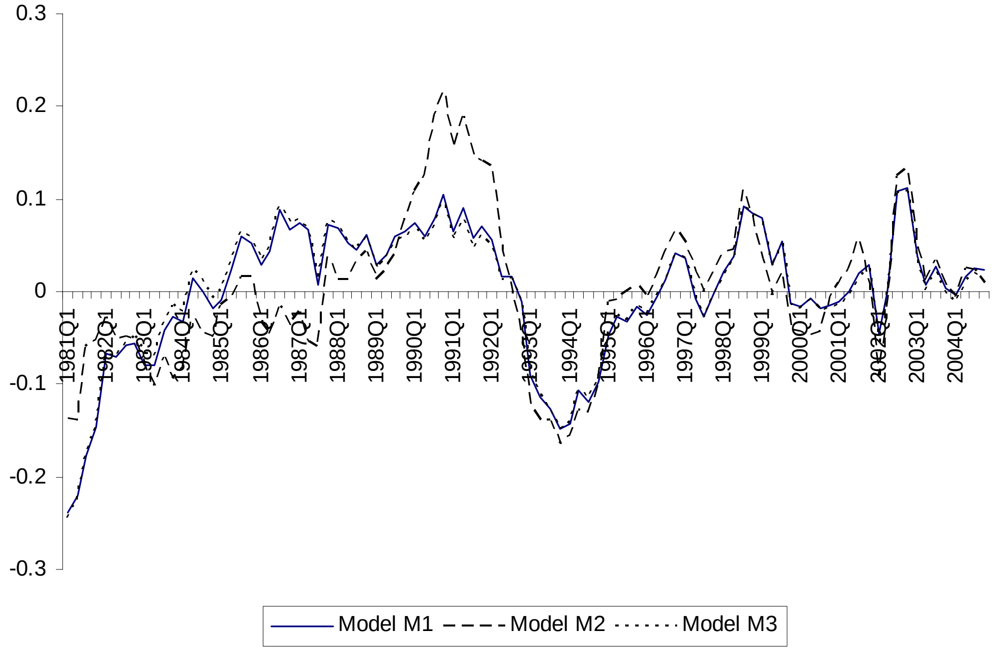

Figure 2: Disequilibrium Credit Holdings Based on Models $M_1 - M_3$

Working Paper List 2006

Number	Author	Title
06/04	Paul Mizen & Serafeim Tsoukas	Evidence on the External Finance Premium from the US and Emerging Asian Corporate Bond Markets
06/03	Woojin Chung, Richard Disney, Carl Emmerson & Matthew Wakefield	Public Policy and Retirement Saving Incentives in the U.K.
06/02	Sarah Bridges & Richard Disney	Debt and Depression
06/01	Sarah Bridges, Richard Disney & John Gathergood	Housing Wealth and Household Indebtedness: Is There a 'Household Financial Accelerator'?

Working Paper List 2005

Number	Author	Title
05/02	Simona Mateut and Alessandra Guariglia	Credit channel, trade credit channel, and inventory investment: evidence from a panel of UK firms
05/01	Simona Mateut, Spiros Bougheas and Paul Mizen	Trade Credit, Bank Lending and Monetary Policy Transmission