Indicating Financial Distress Using Probability Forecasts: An Application to the UK Unsecured Credit Market

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Abstract

This paper develops an integrated model of household portfolio and expenditure decisions and the macroeconomic context in which these decisions are taken. Economic theory motivates the model's long-run equilibrium relationships. These relationships are embedded within a vector-autoregressive model that can accommodate complex dynamics but has a coherent long-run structure. We define the events associated with financial distress and describe forecasting methods that can be applied to the model to predict the likely occurence of these events as an indicator of distress. The analysis is illustrated using unsecured credit market data for the UK.

Keywords: Unsecured Credit, Household Portfolio and Expenditure Decisions, Macroeconometric Model of UK, Probability Forecasts, Financial Distress.
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1 Introduction

Three trends can be identified in household consumption and debt patterns for both northern Europe and the United States in recent years. First, there has been a lower saving rate compared with previous decades as households have typically consumed a greater share of their earned incomes. Also there has been higher indebtedness, in absolute and per capita terms, as much of this consumption has been funded by running up consumer credit. Third, there has been a change in the composition of debt towards short-term unsecured (revolving) credit such as credit card debt that has been borrowed at variable rates of interest. Thus, in the US, which tends to lead European trends, the share of credit card to total debt is now approaching 50%, and in the UK the share is 30% and growing.

There is some controversy over whether these developments are sustainable or whether the financial sector is likely to experience increases in the incidence of defaults on outstanding debt, bad loan write-offs and other symptoms arising from financial distress in the household sector. Agencies, including credit providers and central banks (with their dual responsibility for price and financial stability), are 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 case; and Durkin, 2000, Maki, 2000, 2001, and Barnes and Young, 2003, for the US), there is relatively little advice on how to use macroeconomic data when gauging the likelihood of emerging distress. Central banks still rely on traditional methods of detecting financial distress by keeping their fingers on the pulse of the financial system through open channels of communication with financial institutions, and through the monitoring of particular financial indicators, such as the interest burden on existing short-term debt. However, low interest rates in northern European economies and the US have encouraged the rapid growth in unsecured credit in recent years, resulting in a marked increase in the burden of debt (as documented in Maki, 2000). On this basis, the traditional methods suggest that a credit crisis should already have happened. Since there has not been an occurrence to date, this demonstrates the need for a more accurate means of assessing financial distress.

The reliance on traditional measures might be explained by the difficulties in measuring and conveying the likelihood of emerging distress using macroeconomic data. The *first* difficulty arises because financial distress relates to economic conditions in a variety of markets, and forecasts will require the development of a general macroeconometric model accommodating some detailed modelling of households' financial decisions. The size and lack of transparency of most macroeconometric models makes it difficult to relate the model forecasts to the underlying economic theory, and renders infeasible simulation exercises that might be used to investigate uncertainty. A *second* difficulty arises in specifying and measuring particular macroeconomic events that are associated with financial distress. The interest

[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).

burden measure is an intuitively reasonable measure and is relatively straightforward to forecast (being based on a (log-) linear function of outstanding credit, interest rates, and disposable income). But, as noted above, this measure has not provided much insight into household behaviour in recent years and illustrates that a reliable indicator of financial distress needs to be clearly grounded in theory so that it can reflect adequately the behavioural decisions that underlie its movements. A *third* difficulty is in accommodating the variety of circumstances that might be associated with distress. Distress will be associated with combinations of household decisions and macroeconomic conditions that affect households, involving output growth and unemployment, for example, as well as difficulties in meeting interest payments. A useful macroeconomic indicator of distress might need to be able to describe in a simple way the likelihood of a potentially complex conjunction of events associated with distress. And a *fourth* difficulty is that of conveying the uncertainties associated with any macroeconomic forecasts in a simple way and one that is useful to decision makers concerned not just with the most likely outturns of particular macroeconomic variables, as described by their point forecasts, but by the whole range of potential future outcomes and the risks that are associated with them.

This paper describes a technical apparatus that can provide explicit forecasts of the probability of financial distress using macroeconomic data, addressing each of the difficulties outlined above. We describe a number of long-run relationships that economic theory provides between the key household finance and other macroeconomic variables and note how these can be embedded within an otherwise unrestricted time series model of the data. A simple, compact "long-run structural" macroeconometric model is obtained that is sufficiently flexible to explain the complex dynamic interactions between the key variables but that is also based on (and accommodates) economic theory. This provides the model with transparent long-run properties and also motivates consideration of specific events and indicators of financial distress that have clear structural/behavioural interpretations. Most importantly, the model is small enough to be able to use simulation methods to investigate the uncertainties associated with forecasts of the key variables and to be able to provide explicit forecasts of the probability of specified events taking place. Probability forecasts can relate to the occurrence of single events based on a single variable or based on some linear combination of variables, or they can describe the likely occurrence of joint events. Hence, they are able both to 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 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 based on macroeconomic data in precisely the form that can be used by agencies in decision-making.

The remainder of the paper is organised as follows. The next section considers the economic framework while Section 3 sets out the form of the corresponding econometric model that can be used to generate probability forecasts. We then illustrate the modelling strategy and its use in forecasting financial distress using UK data, describing the model estimation and associated probability forecasts in Section 4. Section 5 concludes.

2 The Economic Framework

The economic framework underlying the investigation of financial distress has two components. The first is a 'core' macroeconomic framework concerned with the domestic variables essential to a basic understanding of any macroeconomy (output, inflation, the exchange rate, the domestic and foreign price levels, the nominal interest rate and real money balances) and associated foreign variables (foreign output, foreign interest rate and oil prices). These provide the context within which the choices and decisions of the household sector are made. This second component of the model we label a 'satellite' to the macroeconomic 'core'. In what follows, we describe the economic underpinnings of the 'core' and the 'satellite' models before turning to their econometric specification and use in probability forecasting in Section 3. Our description of the core model is relatively brief since it is discussed in detail in Garratt et al. (2003a). It is important to describe both components of the model here, however, to emphasise the integratedness of the model of the household sector and the rest of the macroeconomy. Previous modelling of these aspects of economic behaviour has often been fragmented, but here we bring them together so that we can produce event probability forecasts that relate to the variety of circumstances that might be associated with distress.[2]

2.1 The 'core' macroeconomic framework

Our core model of the macroeconomy is based on an explicit statement of the long-run relationships that exist between the variables of the core obtained from macroeconomic theory. These relationships are based on stock-flow and accounting identities, arbitrage conditions, and long-run solvency requirements that ensure stationary asset-income ratios. Despite the variety of approaches taken to macroeonomic modelling, and the existence of many models of the macroeconomy, it can be argued that there is a reasonable degree of consensus on these long-run relationships,[3] so that the long-run features of our core are similar to those of Obstfeld and Rogoff's (1996) textbook small open economy models, for example. These long-run relationships are approximated by log-linear equations, with disturbances that characterise the transitory (although potentially prolonged) deviations of the system from these long-run relations.

Specifically, and with details provided in Garratt et al. (2003a), three arbitrage conditions are accommodated within the core, specifying that purchasing power parity (PPP), uncovered interest parity (UIP) and Fisher inflation parity (FIP) hold in the steady state. These provide three equations that relate the behaviour of prices (P_t) and interest rates (R_t) in a small open economy to their starred 'foreign' equivalents and the exchange rate (E_t) :

$$P_{t+1} = E_{t+1} P^*_{t+1} \exp(\eta_{ppp,t+1}), \tag{2.1}$$

[2]In looking at the credit market, it is not unusal to find that consumption decisions are separated from money holding and borrowing decisions. However, recent attempts to model the consumption, asset allocation and credit process together have proved successful. Evidence is given in Muellbauer and Murphy (1989), Bacchetta and Gerlach (1997), Thomas, (1997a,b), Ludvigson (1999) and Chrystal and Mizen (2005).

[3]See, for example, the comparison of large-scale macroeconometric models, 'structural VAR models' and Dynamic Stochastic General Equilibrium models provided in Garratt et al. (2001).

$$(1 + R_t) = (1 + R_t^*) \left(\frac{E_{t+1}^e}{E_{t+1}} \right) \left(1 + \frac{\Delta E_{t+1}}{E_t} \right) \exp(\eta_{uip,t+1}), \tag{2.2}$$

$$(1 + R_t) = (1 + \rho_{t+1}) \left(\frac{P_{t+1}^e}{P_{t+1}} \right) \left(1 + \frac{\Delta P_{t+1}}{P_t} \right) \exp(\eta_{fip,t+1}), \tag{2.3}$$

where the real rate of return on physical assets over the period t to $t+1$ is denoted by ρ_{t+1} and the superscript e denotes an expectation. The terms $\eta_{ppp,t+1}$, $\eta_{uip,t+1}$ and $\eta_{fip,t+1}$represent interpretable (structural) disturbances from the parity conditions. Economic theory invariably provides a less-than-complete description of the dynamic processes influencing these disturbances, although the underlying stochastic process will be stationary given that these are disequilibrium terms. Substituting the terms $\frac{E_{t+1}^e}{E_{t+1}}$ and $\frac{P_{t+1}^e}{P_{t+1}}$ with expressions $\exp(\eta_{E,t+1}^e)$ and $\exp(\eta_{P,t+1}^e)$, respectively, to represent expectational errors, (2.1)-(2.3) provide three (log-linear) relations between measurable variables and amalgam (reduced form) long-run stationary errors (see (3.11)-(3.15) below).

A fourth long-run (log-linear) relationship for inclusion in the core model relates to domestic and foreign outputs. Output in this model is determined by a neoclassical growth model, as described in Binder and Pesaran (1999), for example, where the logarithm of the real per capita output level is a function of the capital stock per effective labour unit (adjusting for labour-augmenting technological inputs). Denoting real per capita aggregate output by Y_t, a constant returns to scale production function is given by $Y_t = F(K_t, A_t N_t) = A_t N_t F(\frac{K_t}{A_t N_t}, 1) = A_t N_t f(\kappa_t)$ where labour, N_t, and capital stock, K_t and A_t represents an index of labour-augmenting technological progress and $\frac{K_t}{A_t N_t} = \kappa_t$ is the capital stock per effective labour unit. Assuming the aggregate saving rate is monotonic in κ_t, the neoclassical growth model shows that κ_t converges to a time-invariant steady state value. The evolution of output over time is therefore determined primarily by technological progress A_t in the long-run, although transitory business cycle and unemployment fluctuations may cause output to deviate from this long-run level. (These deviations might be denoted by η_{nt}, say). Further, assuming that per capita output at home and abroad is driven by the same technology, subject to transitory periods of catch-up during which technological advances spread across national borders (measured by η_{at}), we have, in logarithms:

$$y_t - y_t^* = \ln(\gamma) + \ln\{f(\kappa_t)/f^*(\kappa_t^*)\} + \eta_{at} + (\eta_{nt} - \eta_{nt}^*), \tag{2.4}$$

where foreign variables are starred. This provides a long-run (log-linear) relationship between domestic and foreign outputs.

Finally in the core model, the financial system operates with the provision of liquidity by the central bank. The demand for high powered money is defined by:

$$\frac{H_{t+1}}{Y_t} = F_h(Y_t, R_t, t) \exp(\eta_{hl,t+1}), \quad F_{hl1} \geq 0, \ F_{hl2} \leq 0, \tag{2.5}$$

reflecting the fact that the banking system demands more liquidity as output increases and less as the interest rate under the control of the monetary authorities increases. The real interest rate is defined as a stationary variable. The precise functional form of this expression is unclear but, assuming that a log-linear approximation is appropriate, (2.5) provides a fifth long-run relationship within the core macroeconomic model.

The economic framework outlined above describes the macroeconomic context determining magnitudes of variables that are exogenous to the household sector, such as inflation and the interest rate. The next section describes the satellite model explaining household portfolio and expenditure decisions explicitly.

2.2 Household portfolios and expenditure

The household sector concerns portfolio management and consumer expenditure defining the equilibrium consumption, borrowing and money balances of households. We assume that the sector can be understood by considering decisions of a representative household and that the household makes decisions over real consumption expenditure, C_t, and portfolio decisions that involve deposits (real money balances), M_t and household borrowing (real bank lending), L_t. A household can consume more than current income and money balances by borrowing at a given real interest rate R^l_t.

The household gains utility from real consumption and money balances and maximises an intertemporal utility function $U = \sum_{i=0}^{\infty} \beta^i u(C_{t+i}, M_{t+i})$, where $0 < \beta < 1$ is a discount rate, subject to the budget constraint

$$C_{t+i} + M_{t+i} + (1 + R^l_{t+i-1})L_{t+i-1} = \widetilde{Y}_{t+i} + M_{t+i} + L_{t+i}, \tag{2.6}$$

where all variables except the interest rate are in real terms. In the first period there is no initial borrowing, hence $L_{t-1} = 0$. The budget constraint indicates that total consumption of goods, $P_{t+1}C_{t+i}$, accumulation of nominal money balances $P_{t+1}(M_{t+i} - M_{t+i-1})$ and the payment of the principal and interest on existing nominal debts $(1 + R^l_{t+i-1})P_{t+1}L_{t+i-1}$ must be financed from earned income, $P_{t+i}\widetilde{Y}_{t+1}$ or additional borrowing, $P_{t+1}L_{t+i}$.

The household maximises the Bellman equation $V(C_{t+i}, M_{t+i}) = u(C_{t+i}, M_{t+i}) + \beta V(C_{t+i+1}, M_{t+i+1})$ to give the resulting first order conditions that define the optimal levels of deposit holding, borrowing and, from the budget constraints, consumption expenditure in each period, driven by income and interest rates. In practice, adjustment costs, short-lived liquidity constraints and inertias may cause the household to deviate from the desired levels for (possibly prolonged) periods. Further, there might be aggregation issues that mean that the relationships derived for the representative household do not hold precisely at the aggregate level. But, ultimately, these first order conditions provide reasonable descriptions of the long-run relationships that hold in the household sector. More specifically, we might write

$$M_t = g_m(\widetilde{Y}_t, R^l_t).\exp(\eta_{mt}) \quad g_{m1} > 0, g_{m2} < 0, \tag{2.7}$$

$$L_t = g_l(\widetilde{Y}_t R^l_t).\exp(\eta_{lt}) \quad g_{l1} > 0, g_{l2} < 0, \tag{2.8}$$

$$C_t = g_c(\widetilde{Y}_t R^l_t).\exp(\eta_{ct}) \quad g_{c1} > 0, g_{c2} < 0, \tag{2.9}$$

where, η_{mt}, η_{lt}, and η_{ct} represent disequilibria from the desired equilibrium magnitudes. These three equations are standard equilibria for money, borrowing and consumer expenditure decisions in the long run, and have been the subject of independent investigation in Chrystal and Mizen (2005). Whereas the majority of the previous literature has separated the consumption decision from money holding and borrowing decisions, and the demand for money has been explored without reference to behaviour of household consumption expenditure or credit conditions, we tie all three decisions together[4].

Household decisions over consumer expenditure, borrowing and money holding are determined in part by the interest rates set by financial intermediaries. Financial intermediaries' rates respond in turn to official rates adjusted by some markup process following Heffernan, (1997, 2002) and Hofmann and Mizen (2003), with full pass through in the long run. The intermediaries mark up the interest rate for loans to reflect their risk exposure in the credit market, and the differential represents the return that a profit making institution can earn on the marginal unit:

$$\ln(1 + R_t^l) = \{\ln(1 + R_t) + \ln(1 + d_L)\}. \exp(\eta_{Rt}), \quad d_l > 0. \tag{2.10}$$

This provides the reasoning behind our second main block of equations reflecting the behaviour of households and banks.

2.3 Financial distress

We turn now to the meaning of 'financial distress'. Clearly, the focus of this paper is on the indicators of financial distress obtainable on the basis of macroeconomic data of the core model and the household sector described in the paragraphs above, and not magnitudes that might be of interest to particular agencies (the number of loan defaults, or the level of credit card arrears, say, or microlevel data). Nevertheless, financial distress has to be first described at the level of the individual household.

We consider an individual household faces distress when its trajectories for consumption, borrowing and money balances are disrupted by adverse economic events that cause them to deviate from their desired paths (effectively relating to the values of η_{mt}, η_{lt}, and η_{ct} in (2.7)-(2.9) above)[5]. The extent of the distress will vary depending on the extent to which realisations differ from the desired levels[6]. Households may deal with deviations by increasing repayments, but in the event that they cannot do this there will be an accumulation of arrears, default and ultimately bankruptcy. These outcomes might appear in the data with a (considerable) lag.

[4]Some important exceptions exist including Bacchetta and Gerlach (1997), which finds a significant predictive content in consumer credit growth for consumer expenditure growth in five OECD countries, and Ludvigson (1999), who focuses on the US credit-consumption growth relationship. This is consistent with credit constrained consumption (Japelli and Pagano, 1989) and supports our systems approach adopted here.

[5]This approach has been supported by others for example Padoa-Schioppa (2002) and Foot (2003).

[6]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).

What then constitutes an adverse event and what determines its impact on the household? Given (2.7)-(2.9), the obvious candidates for adverse events include a fall in income (through lower wages or unemployment), or an increase in the cost of debt servicing (due to interest rate increases). Such events, in the presence of any adjustment costs or inertia, would cause consumer expenditure, borrowing and liquidity to deviate from their optimal trajectories at least temporarily. Further, the impact of these events is likely to depend on the balance sheet position of the household; the impact will be more adverse if, for example, there is an imbalance between the value of assets and liabilities, or a high ratio of borrowing to income, or a high proportion of income devoted to debt servicing. The extent of the distress is therefore likely to be related to an imbalance between assets and liabilities or between income streams and servicing costs.

These observations have implications for measures of financial distress based on aggregate data. Measures of disequilibrium in the credit market, given by the analogue of η_{lt} in the aggregate relationship (2.9), will indicate 'excess holdings of credit' (i.e. holdings of credit held over and above their desired level) at the macroeconomic level. But the level of excess holdings will not provide a straightforward, monotonically increasing measure of distress. For an individual household, there are likely to be thresholds beyond which the household will accumulate arrears or default, while at the aggregate level the importance of larger excess holdings of credit will depend on the proportion of households in close proximity to their thresholds.[7] This suggests that any indicator of distress should look at circumstances in which excess holdings cross a range of threshold values, with the expectation of a non-linear response, and not simply observe the aggregate value of credit market disequilibrium. Further, we would expect macroeconomic conditions to have an impact on the response of households to excess credit because imbalances between income streams and servicing costs are more likely to exist during periods of low growth or recession. We therefore require an indicator that can take account of the level of excess credit holdings and macroeconomic circumstances such as the likelihood of a recession.

This amounts to an argument that it is conjunctions of events that cause distress, and distress only happens when these combinations of occurrences occur together.[8] These con-

[7] Cox, Whitley and Brierley (2002) indicate from an analysis of the British Household Panel Survey data 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).

[8] The complexity of the interrelatedness of excess credit holdings and output growth is illustrated in the following regression explaining the (logarithm of the) value of credit card accounts in arrears, a_t, in the UK 1990q2-2001q1, estimated using OLS:

$$a_t = \underset{(5.81)}{.0115} + \underset{(13.18)}{.6946} a_{t-1} + \underset{(4.11)}{.0140} \xi_{8t} - \underset{(2.40)}{.0158} \Delta y_t^{MA} - \underset{(2.28)}{.0123} \left(\xi_{8t} * I(\Delta y_t^{MA} < 0)\right) + \widehat{\varepsilon}_t,$$

$$R^2 = 0.9734, \quad \widehat{\sigma}^2 = 0.0014, \quad SC(4) = 4.998, \quad FF(1) = 6.414, \quad N(2) = 0.069, \quad H(1) = 2.51$$

where ξ_{8t} is a measure of excess credit holdings (described in detail in Section 3 below), Δy_t^{MA} is a four-quarter moving average of output growth, $I(.)$ is an indicator function taking the value of one when a recession occurs and zero otherwise, t-ratios are in parentheses and SC, FF, N and H are chi-squared statistics for serial correlation, functional form, normality and heteroskedasticity respectively. The results show that both excess holdings and output growth are important explanatory variables for this particular measure of financial distress, and that the interaction between the business cycle and excess holdings is also significant.

junctions give rise to financial corrections to previously adopted decision paths that prove to be infeasible under the new circumstances. To predict when distress occurs and corrections to consumption, borrowing and liquidity are required, we need to forecast a complex set of joint events rather than simple events, and prediction of these events will require probability event forecasts not simple point forecasts. Our core-satellite model can be used for this purpose, and can answer questions like 'what is the probability that excess credit holdings will rise by x percentage points in the next year *and* income growth will fall below the threshold level, y ?' as a critical joint event.[9] The forecast value of this probability shows directly the likelihood of the occurrence of the conjunction of events related to financial distress and automatically conveys the uncertainties surrounding the forecast outcomes. Presentation of the forecasts for various values of x and y provides information on emerging distress in a form that can be used by agencies in decision-making.

3 The Econometric Formulation of the Model

In this section, we describe the modelling strategy that will provide a long-run structural vector-autoregressive (VAR) model of household decision-making and its macroeconomic context. The modelling strategy is described in detail in Garratt et al. (2003a) and provides a practical approach to incorporating the long-run structural relationships that are suggested by economic theory in a general VAR framework. The model that is obtained has the advantage of VAR models in being able to capture complicated dynamic processes like those underlying household portfolio and expenditure decisions. But it also has the advantage of being able to accommodate (and test the validity of) the long-run relationships that exist between the variables as suggested by economic theory. Further, it 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.

3.1 Modelling household decisions and the macroeconomic context

The modelling strategy begins with an explicit description of the measurable deviations from the long-run relationships suggested by economic theory in terms of the variables of interest. Hence, for the model of the core macroeconomic variables, we employ a log-linear

[9] The components of the model can be used for forecasting for inflation targeting central banks (see Pesaran et al., 2003) and the analysis of household sector consumer expenditure and financing decisions (see Chrystal and Mizen, 2005) separately, but here we use them together to give forewarning of financial distress using event probability forecasts.

approximation of the five long-run equilibrium relationships discussed in Section 2.1 to write:

$$p_t - p_t^* - e_t = a_{10} + a_{11}t + \xi_{1,t+1}, \tag{3.11}$$
$$r_t - r_t^* = a_{20} + \xi_{2,t+1}, \tag{3.12}$$
$$y_t - y_t^* = a_{30} + \xi_{3,t+1}, \tag{3.13}$$
$$h_t - y_t = a_{40} + a_{41}t + a_{42}r_t + a_{43}y_t + \xi_{4,t+1}, \tag{3.14}$$
$$r_t - \Delta p_t = a_{50} + \xi_{5,t+1}, \tag{3.15}$$

where $p_t = \ln(P_t)$, $p_t^* = \ln(P_t^*)$, $e_t = \ln(E_t)$, $y_t = \ln(Y_t)$, $y_t^* = \ln(Y_t^*)$, $R_t = \ln(1+i_t)$, $R_t^* = \ln(1+i_t^*)$, and $h_t - y_t = \ln(H_{t+1}/Y_t)$. The (long-run) reduced form disturbances $\xi_{i,t+1}, i = 1, 2, ..., 5$, are combinations of a number of long-run structural shocks and, although we know these to be stationary, they have no obvious economic interpretation. We have allowed for intercept and trend terms (when appropriate) in order to ensure that (long-run) reduced form disturbances, $\xi_{i,t+1}$ have zero means. These five long-run relations can be written more compactly as

$$\boldsymbol{\xi}_{at} = \boldsymbol{\beta}_a' \mathbf{z}_{t-1} - \mathbf{a}_0 - \mathbf{a}_1(t-1), \tag{3.16}$$

where

$$\mathbf{z}_t = (p_t^o, e_t, r_t^*, r_t, \Delta p_t, y_t, p_t - p_t^*, h_t - y_t, y_t^*)' . \tag{3.17}$$

$$\mathbf{a}_0 = (a_{01}, a_{02}, a_{03,}a_{04}, a_{05})', \ \mathbf{a}_1 = (a_{11}, 0, 0, a_{14}, 0),$$
$$\boldsymbol{\xi}_{at} = (\xi_{1t}, \xi_{2t}, \xi_{3t}, \xi_{4t}, \xi_{5t})',$$

and

$$\boldsymbol{\beta}_a' = \begin{pmatrix} 0 & -1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & -1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & -1 \\ 0 & 0 & 0 & -a_{42} & 0 & -a_{43} & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 & -1 & 0 & 0 & 0 & 0 \end{pmatrix}. \tag{3.18}$$

Turning to the long-run relationships suggested by the theory relating to household portfolio and expenditure decisions, as described in Section 2.2, we can write

$$c_t = b_{10} + b_{11}t + \widetilde{y}_t + b_{12}r_t + \xi_{6,t+1}$$
$$m_t = b_{20} + b_{21}t + \widetilde{y}_t + b_{22}r_t + \xi_{7,t+1} \tag{3.19}$$
$$l_t = b_{30} + b_{31}t + \widetilde{y}_t + b_{32}r_t^l + \xi_{8,t+1} \tag{3.20}$$
$$r_t^l = b_{40} + b_{41}t + r_t + \xi_{9,t+1} \tag{3.21}$$

or, more compactly,

$$\boldsymbol{\xi}_{bt} = \boldsymbol{\beta}_b'(\mathbf{w}_{t-1}, r_{t-1}) - \mathbf{b}_0 - \mathbf{b}_1(t-1), \tag{3.22}$$

where

$$\mathbf{w}_t = \left(c_t - \widetilde{y}_t, m_t - \widetilde{y}_t, l_t - \widetilde{y}_t, r_t^l\right)'. \tag{3.23}$$

$$\mathbf{b}_0 = (b_{01}, b_{02}, b_{03,}b_{04})',\ \mathbf{b}_1 = (b_{11}, b_{21}, b_{31}, b_{41}),$$

$$\boldsymbol{\xi}_{bt} = (\xi_{6t}, \xi_{7t}, \xi_{8t}, \xi_{9t})',$$

and

$$\boldsymbol{\beta}_b' = \begin{pmatrix} 1 & 0 & 0 & 0 & -b_{12} \\ 0 & 1 & 0 & 0 & -b_{22} \\ 0 & 0 & 1 & -b_{32} & 0 \\ 0 & 0 & 0 & 1 & -1 \end{pmatrix}. \tag{3.24}$$

Assuming that the variables in $\mathbf{z}_t$ and $\mathbf{w}_t$ are difference-stationary, the standard VAR approach to modelling the short-run dynamics of the variables is to assume that changes in these variables, $(\Delta\mathbf{z}_t,\ \Delta\mathbf{w}_t)$, can be well-approximated by a linear function of a finite number of past changes in their difference; i.e. a linear function of $(\Delta\mathbf{z}_{t-s},\ \Delta\mathbf{w}_{t-s})$, with $s = 1, 2, ..., p$. In contrast, the long-run structural VAR modelling strategy also embodies the disturbances $\boldsymbol{\xi}_t = (\boldsymbol{\xi}_{at}',\ \boldsymbol{\xi}_{bt}')'$ in the standard VAR model of $(\Delta\mathbf{z}_t,\ \Delta\mathbf{w}_t)$:

$$\begin{pmatrix} \Delta\mathbf{z}_t \\ \Delta\mathbf{w}_t \end{pmatrix} = \mathbf{c}_0 - \boldsymbol{\alpha}\boldsymbol{\xi}_{t-1} + \sum_{s=1}^{p-1} \Psi_s \begin{pmatrix} \Delta\mathbf{z}_{t-s} \\ \Delta\mathbf{w}_{t-s} \end{pmatrix} + \mathbf{u}_t. \tag{3.25}$$

Given the definition of the long-run disturbances in (3.11)-(3.15) and in (3.19)-(3.21), the model in (3.25) can be rewritten

$$\begin{pmatrix} \Delta\mathbf{z}_t \\ \Delta\mathbf{w}_t \end{pmatrix} = \mathbf{d}_0 + \mathbf{d}_1 t - \boldsymbol{\alpha}\boldsymbol{\beta}' \begin{pmatrix} \mathbf{z}_{t-1} \\ \mathbf{w}_{t-1} \end{pmatrix} + \sum_{s=1}^{p-1} \Psi_s \begin{pmatrix} \Delta\mathbf{z}_{t-s} \\ \Delta\mathbf{w}_{t-s} \end{pmatrix} + \mathbf{u}_t \tag{3.26}$$

which is the standard reduced form vector error correction model, with $\mathbf{d}_0$, $\mathbf{d}_1$ and $\boldsymbol{\beta}$ simple functions of the $\mathbf{c}_0$, $\boldsymbol{\alpha}$, $\mathbf{a}_0$, $\mathbf{a}_1$, $\mathbf{b}_0$, $\mathbf{b}_1$, $\boldsymbol{\beta}_a$ and $\boldsymbol{\beta}_b$.[10] From the outset, this model embodies the predictions of economic theory, as it relates to the long-run, by imposing the restrictions suggested by theory on the $\boldsymbol{\beta}$ matrix.[11]

[10] Note that, so long as the long-run relations underlying $\boldsymbol{\xi}_{t-1}$ are accommodated within the model, this reduced form VECM is consistent with any number of structural models in which the contemporaneous (and other short-run dynamic) relations between variables are specified. For example, it is consistent with a model in which the central bank operates with an explicitly defined loss function:

$$L = \frac{1}{2}\sum_{i=0}^{\infty} \delta^i \left[\ln(1 + \frac{\Delta P_{t+i+1}}{P_t})^2 + \lambda \ln(Y_{t+i})^2\right]$$

where δ is the discount term and λ defines the relative weight between inflation and output, so that the central bank's reaction function relates the interest rate to inflation and output, with the Taylor rule as a special case (c.f. Taylor, 1993, Clarida *et al.*, 1998, Gerlach and Smets, 1999, Nelson, 2000).

[11] When economic theory provides sufficient restrictions on the $\boldsymbol{\beta}$ matrix, the model can be estimated imposing just exact-identifying restrictions and then imposing all the restrictions suggested by the theory. The test of the validity of any over-identifying restrictions provides a test of the validity of the underlying theory of the long-run.

The long-run structural 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. Estimation of VAR models becomes impractical in the presence of many variables as the number of parameters that are estimated becomes very large, therefore, our system needs to be small enough to estimate all the parameters given the sample size. Even if they exist, longer time series cannot always resolve the problem as this introduces the possibility of structural instability. This is certainly a problem in the modelling exercise outlined above, where the nine variables in the macroeconomic model are already close to the practical limit of estimation, and where the household sector introduces a further four additional variables.

One approach to dealing with the problem is to link the two models with a block recursive structure, which will considerably reduce the number of parameters to be estimated. This approach can be sensibly applied in this context by arguing that the variables of the household sector are influenced by those of the macroeconomic model, but do not exert a corresponding influence on the macroeconomic model. Hence, the household portfolio and expenditure decisions are made taking into account the macroeconomic context, but these household allocation decisions do not impact on the evolution of the national macroeconomic aggregates.[12] Here, then, the set of sectoral variables in $\mathbf{w}_t$ are influenced by those in $\mathbf{z}_t$, but not vice-versa, so that the structural model underlying the (reduced form) model of (3.26) takes the form

$$\begin{pmatrix} \Theta_z & \mathbf{0} \\ \Theta_0 & \Theta_w \end{pmatrix} \begin{pmatrix} \mathbf{z}_t \\ \mathbf{w}_t \end{pmatrix} = \mathbf{f}_0 + \mathbf{f}_1 t + \sum_{s=1}^{p} \begin{pmatrix} \Theta_{11s} & \mathbf{0} \\ \Theta_{21s} & \Theta_{22s} \end{pmatrix} \begin{pmatrix} \mathbf{z}_{t-s} \\ \mathbf{w}_{t-s} \end{pmatrix} + \begin{pmatrix} \mathbf{v}_{zt} \\ \mathbf{v}_{wt} \end{pmatrix} \tag{3.27}$$

for the various parameter matrices (Θ's and $\mathbf{f}$'s), and with structural errors ($\mathbf{v}_{zt}$, $\mathbf{v}_{wt}$). In these circumstances, the structure of the model is block triangular and there is a causal structure from $\mathbf{z}_t$ to $\mathbf{w}_t$. If we assume that the elements of the $\mathbf{v}_{zt}$ and $\mathbf{v}_{wt}$ are uncorrelated, then the system is block recursive. This structure has the advantage that the analysis of the variables in $\mathbf{z}_t$ can be carried out without reference to those in $\mathbf{w}_t$. Further the variables in $\mathbf{w}_t$ can be considered in a stand-alone model of the household sector taking the values of $\mathbf{z}_t$ (and in particular the value of r_t) as given, as is the case in Chrystal and Mizen (2005).

3.2 Measuring financial distress

The model described above provides an extremely useful vehicle with which to provide quantitative assessments of financial distress. In particular, the error correction term associated with disequilibrium in the credit market, ξ_{8t}, subject to the caveats in Section 2.3, provides a measure of excess credit.[13] Since this will not be related to distress in a simple way, we introduce thresholds to capture nonlinearities; i.e we consider events $A : \{\xi_{8t} > c_1\}$, for

[12] Of course, the macroeconomic variables in $\mathbf{z}_t$ can themselves be distinguished according to whether they are endogenously determined within the macoeconomic model or determined exogenously. In the core model, the price of oil is taken as exogenously determined, for example.

[13] Note that the measure, ξ_{8t}, is based on a stock position 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.

various values of c_1. Further, to take into account the impact on distress of debt servicing in relation to income, we also consider the occurrence of events $B : \{\Delta y_t^{MA} < c_2\}$ where Δy_t^{MA} is a (four-quarter) moving average of current and recent growth and c_2 is a threshold (with recession defined where $c_2 = 0$, say). Both of these elements play an important part in defining and quantifying financial distress. The discussion of Section 2.3 suggests that in defining an indicator of financial distress, we might consider the occurrence of the joint event $A \cup B$ (i.e. households are financially exposed *or* there is recession/low growth) and of event $A \cap B$ (i.e. households are financially exposed *and* recession/low growth occurs).

Having identified the 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 (3.26) through stochastic simulation techniques. The VAR model underlying the vector error correction model is given by

$$\begin{pmatrix} \mathbf{z}_t \\ \mathbf{w}_t \end{pmatrix} = \sum_{i=1}^{p} \Phi_i \begin{pmatrix} \mathbf{z}_{t-i} \\ \mathbf{w}_{t-i} \end{pmatrix} + \mathbf{d}_0 + \mathbf{d}_1 t + \mathbf{u}_t,\ t = 1, 2, ..., T, \tag{3.28}$$

where $\Phi_1 = \mathbf{I} - \boldsymbol{\alpha}\boldsymbol{\beta}' + \Psi_1$, $\Phi_i = \Psi_i - \Psi_{i-1}$, $i = 2, ..., p-1$, $\Phi_p = -\Psi_{p-1}$ and $\mathbf{u}_t$ is assumed to be a serially uncorrelated *iid* vector of shocks with zero means and a positive definite covariance matrix, Σ. Focusing on the case where there is no parameter uncertainty, we can assume the estimators of Φ_i, $i = 1, \ldots, p$, $\mathbf{d}_0$, $\mathbf{d}_1$ and Σ are given and denoted by $\hat{\Phi}_i$, $i = 1, \ldots, p$, $\widehat{\mathbf{d}}_0$, $\widehat{\mathbf{d}}_1$ and $\hat{\Sigma}$, respectively. Then the point estimates of the h-step ahead forecasts of $\mathbf{z}_{T+h}$ and $\mathbf{w}_{T+h}$, conditional on Ω_T, denoted by $\hat{\mathbf{z}}_{T+h}$ and $\widehat{\mathbf{w}}_{T+h}$ respectively, can be obtained recursively by

$$\begin{pmatrix} \widehat{\mathbf{z}}_{T+h} \\ \widehat{\mathbf{w}}_{T+h} \end{pmatrix} = \sum_{i=1}^{p} \hat{\Phi}_i \begin{pmatrix} \widehat{\mathbf{z}}_{T+h-i} \\ \widehat{\mathbf{w}}_{T+h-i} \end{pmatrix} + \widehat{\mathbf{d}}_0 + \widehat{\mathbf{d}}_1 (t+h),\ h = 1, 2, \ldots, \tag{3.29}$$

where the initial values, $\mathbf{z}_T, \mathbf{z}_{T-1}, \ldots, \mathbf{z}_{T-p+1}$, $\mathbf{w}_T, \mathbf{w}_{T-1}, \ldots, \mathbf{w}_{T-p+1}$, are given. To obtain probability forecasts by stochastic simulation, we simulate the values of $(\mathbf{z}_{T+h}, \mathbf{w}_{T+h})'$ by

$$\begin{pmatrix} \widehat{\mathbf{z}}^{(r)}_{T+h} \\ \widehat{\mathbf{w}}^{(r)}_{T+h} \end{pmatrix} = \sum_{i=1}^{p} \hat{\Phi}_i \begin{pmatrix} \widehat{\mathbf{z}}^{(r)}_{T+h-i} \\ \widehat{\mathbf{w}}^{(r)}_{T+h-i} \end{pmatrix} + \widehat{\mathbf{d}}_0 + \widehat{\mathbf{d}}_1 (t+h) + \mathbf{u}^{(r)}_{T+h},\ h = 1, 2, \ldots;\ r = 1, 2, ..., R, \tag{3.30}$$

where superscript '(r)' refers to the r^{th} replication of the simulation algorithm, and $\mathbf{z}_s^{(r)} = \mathbf{z}_s$, $\mathbf{w}_s^{(r)} = \mathbf{w}_s$ for all in-sample values $s = T,\ T-1, \ldots$ and for all r. To keep matters simple in this paper, the $\mathbf{u}^{(r)}_{T+h}$'s will be drawn by parametric methods (although a variety of non–parametric methods can also be applied). The probability that the event $\varphi(\mathbf{z}_{T+1}, \ldots, \mathbf{z}_{T+h}, \mathbf{w}_{T+1}, ..., \mathbf{w}_{T+h})$ takes place, where the event is defined with respect to the variables in $\mathbf{z}_t$ or $\mathbf{w}_t$ over some forecast horizon $T+1, T+2, ..., T+h$, is then computed as

$$\pi(\varphi) = \frac{1}{R} \sum_{r=1}^{R} I\left(\varphi(\mathbf{z}^{(r)}_{T+1}, \ldots, \mathbf{z}^{(r)}_{T+h}, \mathbf{w}^{(r)}_{T+1}, ..., \mathbf{w}^{(r)}_{T+h})\right),$$

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

4 Analysing Financial Distress in the UK

To investigate the usefulness of the modelling framework described above, and to consider the role of probability forecasts as indicators of financial distress, we describe an analysis of the UK macroeconomy and the household financial sector using quarterly data over the period 1985q1-2001q1. A list of the variables and their description is provided in Table 1. The data employed in modelling of the UK economy is identical to Garratt et al. (2003b) while the data used in modelling the UK household financial sector matches that used in Chrystal and Mizen (2005). In both cases, a detailed description of the data construction is provided in the earlier papers. Consumption (C_t) is simply real consumer expenditure by households, Money (M_t) are real M4 holdings which incorporates chequing accounts and savings accounts in banks and building societies, and real unsecured credit (L_t) is measured by total lending to individuals minus loans secured upon housing. Consumption, money and credit are all expressed relative to real net labour income ($\widetilde{Y}_t$) which provides the relevant measure of households' incomes, and are displayed in Figures 1-3. Figures 4-5 show the interest rate on unsecured (credit card) debt (r_t^l) relative to the Treasury bill rate, r_t, expressed in levels and as a differential, $(r_t^l - r_t)$, in percentage points.

4.1 Empirical results

The empirical analysis of this paper is undertaken using the block-recursive structure described in (3.27). This means that the core macroeconomic model can be estimated without reference to the household sector, and that the household sector in turn can be considered in a stand-alone model taking the values of the variables in the macroeconomic model (and in particular the value of r_t) as exogenously-determined. Given that the estimation and testing of the UK macroeconomic model is described in some detail in Garratt et al. (2003a), we provide only a brief summary of the results for the macroeconomic model and concentrate on the model of the household sector.

The first step in the analysis is to ascertain the order of integration of the series. The results of Table 2 indicate that $(c_t - \widetilde{y}_t)$, $(m_t - \widetilde{y}_t)$, $(l_t - \widetilde{y}_t)$, and r_t^l are all $I(1)$ variables, as the null of a unit root is not rejected when applied to levels but is rejected, and in most cases convincingly so, when applied to differenced data.[14] Similar results are reported in Garratt et al.(2003a) to establish the difference stationarity of the variables of the core model of the macroeconomy.

Next, we turn to the choice of lag length in the VAR. In Garratt et al. (2003a), it was determined that a VAR of order 2 was sufficient to adequately capture the short-run dynamics of the data. Focusing on the variables involved in the household sector (namely, $(c_t - \widetilde{y}_t)$, $(m_t - \widetilde{y}_t)$, $(l_t - \widetilde{y}_t)$, r_t^l and r_t), we estimated unrestricted VAR systems, including seasonal dummies, of order $p = 1$, 2, 3, and 4. The (adjusted) likelihood ratio test statistics obtained when testing the contribution of the additional lags took the values 1170.9 (to test the joint insignificance of the the first lags), 35.57 (to test the insignificance of the second lags), 41.82 (to test the joint insignificance of the the third lags), and 29.52 (to test the joint

[14]The reported results relate to Dickey-Fuller regressions in which an intercept and upto four lags terms are included. Qualitatively similar results are obtained if a time trend is included also.

insignificance of the the fourth lags). Each of these is compared to χ^2_{25}, indicating that a VAR of order 3 is appropriate in the subsequent analysis.

The third 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. For the variables of the core macroeconomic model, the analysis of Garratt et al. (2003b) confirms that there are five cointegrating relationships among the nine macroeconomic variables considered, using data over the period 1985q1-2001q1, and that the over-identifying restrictions implicit in the cointegrating matrix $\boldsymbol{\beta}'_a$ in (3.18) could not be rejected. Hence the economic theory briefly elaborated in Section 2 relating to the long-run relationships in the macroeconomic model are consistent with the data.

Turning to the model of the household sector, we estimate a cointegrating VAR system for the five variables $(c_t - \widetilde{y}_t)$, $(m_t - \widetilde{y}_t)$, $(l_t - \widetilde{y}_t)$, r^l_t and r_t, treating r_t as an exogenous I(1) variable determined outside this system (in the macroeconomic model). We chose to estimate the cointegrating system with unrestricted intercepts and restricted time trends to allow for the possibility of trended behaviour in the long-run relations (as suggested by economic theory), but to exclude the possibility of explosively-trended behaviour in levels. We also include seasonal dummies to capture remaining seasonality in the data. We proceed with the analysis under the assumption that there are four cointegrating relations in the sectoral household data, as suggested by the economic theory of Section 2.2.[15] Estimating the system subject to sixteen ($=4^2$) exactly-identifying restrictions, to reflect the presence of four cointegrating relations, provides a maximised log-likelihood of 649.41. The imposition of the additional over-identifying restriction implied by (3.24) reduces the likelihood value to 648.98, while the imposition of a further two restrictions on the trend coefficients in the cointegrating relations provides the estimated vector error correction model described in Table 3 and the associated likelihood value of 648.91. The likelihood ratio test of the three over-identifying restrictions is 0.9949, therefore, which is compared to χ^2_3 and provides no evidence with which to reject the theory-based restrictions of the previous section.

The error correction model of the household sector reported in Table 4 has good statistical properties and a sensible economic interpretation. The error correction term $\xi_{6,t}$ relates to the equilibrium consumption-to-income ratio, the level of which responds (weakly but in the correct direction) to the level of the market rate of interest following an intertemporal substitution argument. The second term $\xi_{7,t,}$ relates to the equilibrium level of liquid balances in relation to income, which also responds to the market rate of interest (although also weakly). The third term $\xi_{8,t}$, which represents the long-run equilibrium position of unsecured lending-to-income, is important for our purpose since it is to be used to measure borrowing relative to the sustainable level supported by current economic conditions (i.e. excess hold-

[15] Table 3 provides the test for cointegrating rank based on the maximal eigenvalue statistic and the trace statistic. The maximal eigenvalue statistics indicate the possibility of two or three cointegrating vectors among the five series (depending on the critical values used), while the trace statistic more clearly suggests three vectors. The relatively flat log-likelihoods that deliver these results are demonstrated in the final panel of Table 3. This also shows that the corresponding model selection criteria suggest that the imposition of four cointegrating relationships is also acceptable. Given the lack of consensus in these results (largely due to the known frailty of the tests in small samples), we choose four relationships since this ties in with our economic priors and is subsequently shown not to be at variance with an acceptable econonometric model.

ings). This measure is more sensitive to the rate of interest on credit cards (the unsecured lending rate) with an estimated elasticity of -0.0175 than other error correction terms. There is also a significant upward trend, capturing the growth in unsecured borrowing to income over our sample, amounting to approximately one percent per quarter.

The final term $\xi_{9,t}$ in this system is an interest rate pass-through equation with one-for-one adjustment in the long run from the market rate to the credit card rate. There is also a significant downward trend in the equation which we interpret as capturing the effect of greater competition between suppliers of unsecured credit. A coefficient of 0.145 on the trend implies that there has been a fall of 0.145 of a percentage point (on average) on credit card rates in relation to the monetary policy rate in each quarter, which amounts to a fall of about nine percentage points over the entire length of our sample. This is consistent with the evidence that interest rates on credit cards have been set in a progressively more competitive environment over the sample.

The error correction regressions of Table 4 provide evidence to support the approach taken in the paper to model household decision making. There are strong interdependencies in the determination of the consumption-income, money-income and credit-income ratios and of the interest rate differential, with disequilibria in these magnitudes contributing significantly across the four separate regressions. The Table also demonstrates that there are various dynamic feedbacks between the variables in each equation, and this will generate complex short-run dynamics in the system as a whole. The regression results of the Table are good, with a relatively high degree of explanatory power in each case and with diagnostic statistics which are satisfactory.[16]

The discussion of Section 3.2 suggested the use of the error correction term from the long-run relationship describing the equilibrium credit-income ratio as an indicator of financial exposure. The third equation of the model of the household sector in Table 4 defines the disequilibrium term by

$$\xi_{8,t+1} = (l_t - \widetilde{y}_t) + 0.01746 r_t^l - 0.01211t,$$

which falls over time to reflect changes in taste towards credit card debt but rising as credit card rates rise. The (de-meaned) in-sample values of this disequilibrium term are plotted in Figure 6 and the associated histogram of values plotted in Figure 7. The histogram illustrates a bi-modal distribution with a standard deviation of 0.21 and values ranging from -0.26 to 0.36. The evolution over time of the disequilibrium term shows the series to be relatively high at the start of the sample period, rising to its highest values in 1989/1990 and peaking in 1989q3[17]. A relatively monotonic reduction in the series then occurred through the early nineties to 1994, after which there was a moderate increase to 2001. The time profile of

[16]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 VAR based on information criteria. The normality test statistic in the interest rate equation is also high, in common with other studies, and this reflects the presence of a number of outliers in the early years of the sample when official rates were more volatile and administered rates of interest on credit cards did not follow official rates exactly.

[17]In fact the data on unsecured credit 2-6 months in arrears (as a percentage of active accounts) provided by the Association for Payment Clearing Services (APACS) shows that arrears peaked in 1991q1. The implications of distress clearly accumulate so it is unsurprising that the arrears should peak some time after

the measure reflects 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 so on). It also indicates that households were not financially exposed at the end of the sample, with the value of $\xi_{8,t+1}$ actually lying (well) below zero. Inspection of this Figure indicates that, in aggregate, households were not holding excess credit at this time so that there would be little financial stress arising from this source.

4.2 Probability forecasts of distress events in the UK

In this section, we evaluate the ability of a probability event forecast model to indicate the likelihood of financial distress in two separate periods for the UK. The first of our periods, beginning at the end of our sample period in 2001, relates to the recent episode of low inflation, low interest rates and strong economic growth. Unsecured debt to income levels have risen to unprecedented levels during this period, prompting worries about the sustainability of the high level of borrowing although no such distress has emerged to date. The second period we consider is an episode from a decade earlier when Treasury Bill rates were roughly double those of the first period and rates on unsecured credit were some 5-10 percentage points higher. Borrowing was also high but there was not the same concern about the sustainability of this level of borrowing despite the fact that deregulation of the financial system had made access to unsecured borrowing easier than at any time since the second world war. Subsequent data from arrears and default rates indicates that there was financial distress during this period.

We can use the model described in Table 4, along with the corresponding macroeconomic model of the UK described in Garratt et al. (2003b), to generate point forecasts and probability forecasts of the economic variables over the eight quarter forecast horizon 2001q2-2003q1. Equivalent forecasts can be obtained over the earlier period 1990q2-1992q1 using a model of exactly the same form as that in Table 4 (including the same long-run relationships), but estimated over the period 1979q1-1990q1. These are the forecasts that would have been obtained (in real time) in a period when we know, in retrospect, that there was widespread financial distress.[18] Before describing the probability forecasts of financial distress in the UK for these two periods, it is worth commenting on the point forecasts. While these point forecasts cannot convey the uncertainties surrounding the events underlying financial distress (either singly or jointly), they are indicative of the state of the macroeconomy and household sector, and they are presented in Tables 5a and 5b.

In the most recent episode, starting 2001q2, market interest rates are forecast to remain relatively low and constant over the forecast period, falling in the range 5.46%-5.74%, and credit card rates of interest stay fairly constant at about 19-20%. Forecast values of output growth Δy_t^{MA} fall from an annual rate of 1.84% to below sample average rates of growth but then recover to 2.02% at the end of the forecast period. The credit-income ratio in logarithms

the peak in distress indicated by the disequilibrium measure. Whitley, Windram and Cox (2004) study the relationship between arrears, debt-to-income and interest rates, providing a plausible dynamic econometric model.

[18]The sample period was chosen to be of approximately similar duration to that of the modelling exercise of Table 4 but to avoid the high inflation years of the mid-seventies.

rises from -0.36 in 1999q1 to -0.22 in 2003q1 by the end of the forecast period, indicating a credit-income ratio moving from 70% to 80%. With these moderate changes taking place between 2001q2 and 2003q1, it is unsurprising that the point forecast of ξ_{8t} itself changes only moderately over the two year forecast horizon, being predicted to fall from -0.19 in 2001q1 to -0.23 a year later and -0.25 in 2003q1. This indicates that, in terms of financial distress, there was little cause for concern over this period. In contrast, Table 5b provides the equivalent table for forecasts that would have been obtained over the period 1990q2-1992q1. In 1990q1, Treasury Bill rates in the UK were 13.61% and would have been forecast (at the time) to remain at similar levels over the 8-period horizon. This pattern would have been mirrored in the very high credit card rates forecasted for the period. Growth prospects over this earlier period were comparable, if a little lower, to those predicted for 2001 onwards, but the credit-income ratio would have been predicted to rise (although it's forecast remained lower than was actually obtained in 2001q1). Taken together, these forecasts would have generated predicted values for ξ_{8t} that fall over the period of the forecast horizon, but stay at very high levels by historical standards.[19]

The point forecasts described above are important in identifying trends in the series, and the disequilibrium measure gives some indication of indebtedness and potential distress but as we have argued in earlier sections they cannot capture the nonlinearities adequately. The likelihood of financial distress is best conveyed by calculating the forecast probabilities of *joint events* involving, for example, the disequilibrium term ξ_{8t} and output growth Δy_t^{MA}. Table 6 provides these indicators. Table 6a focuses on the forecasts for 2001q2-2003q1 and describes the probability forecasts for the joint event $A \cup B$, ; i.e. that there are excess credit holdings *or* recession/low growth. The first three columns use $c_2 = 0$, and are concerned with the likely occurrence of recession ($\Delta y_t^{MA} < 0$) while the fourth-sixth columns use $c_2 = 0.01$ and relate to the occurrence of low growth ($\Delta y_t^{MA} < 1\%$). We consider three values for c_1 (=0.20, 0.30 or 0.40) which represent 'high', 'very high' and 'unprecedentedly high' levels of excess credit holdings when compared to the experiences given in Figure 6. The forecast probabilities of the Table reflect the finding that the point forecasts of excess holdings remain very low throughout the forecast horizon so that the likelihood of their exceeding the chosen critical thresholds is virtually zero.[20] The probabilities provided in the Table 6 therefore reflect solely the likelihood of recession or low growth. The likelihood of recession rises from zero to 0.19 over 2001 and falls back to 0.14 by 2003q1, while the likelihood of low growth rises from 0.21 to 0.43 and then falls back to 0.29 in 2003q1. Since financial distress occurs when *either* excess holdings are high *or* recession/low growth occurs, it is not surprising to find that these figures indicate that the likelihood of distress was relatively small (but not zero due to the uncertainty over growth prospects) over the period.

A very different picture emerges in Tables 6b and 6c which report the forecast probabilities of $A \cup B$ and $A \cap B$ over the period 1990q2-1992q1. In Table 6b, the first and

[19] The precise timing of the occurence of 'financial distress' depends on the particular measure used. Data on unsecured credit 2-6 months in arrears (as a percentage of active accounts) provided by the Association for Payment Clearing Services (APACS) shows that this measure peaked in 1991q1, almost exactly two years after the peak in our disequilibium measure. Since arrears data record the accumulated effects of financial distress they are therefore not particularly useful indicators of distress looking forward, although they can confirm the existence of financial distress after the event.

[20] The probability of $A \cap B$ is also zero throughout, therefore.

fourth columns of the Table are consistently one, reflecting the finding that the probability of excess holdings being 'high' ($c_1 = 0.20$) is one. More variability is observed in columns 2 and 5 relating to 'very high' excess holdings but these too are large throughout the forecast horizon. More moderate figures are found in columns 3 and 6 reflecting the finding that, although excess holdings were generally unlikely to achieve the 'unprecedentedly high levels' of $c_1 = 0.40$, the possibility of recession/low growth was relatively high at that time. This is confirmed in the figures of Table 6c concerned with events where excess holdings are high/very high/unprecedentedly high *and* recession/low growth is experienced. The probability of the very unpleasant conjunction of events in columns 1 and 2 (4 and 5) are strikingly high for this forecast exercise, and only fall to zero in column 3 (6) because unprecedentedly high excess holdings were deemed unlikely. The extreme conjunction of events in this final Table would certainly be associated with financial distress in many households so that the probabilities reflect well what we know actually took place in the UK over this period. In fact, the highest probabilities in Table 6c combining excess credit above a given threshold and a recession are to be found in the period when arrears were at their highest levels. Clearly the process of fine tuning the thresholds with data from previous periods of distress would aid the calibration of the model, but the point is made that the approach gives a clearer guide to distress than previous methods.

In contrast to the complex process of assessing the information in many single variable forecasts, this method provides a straightforward statement of the likelihood of an event - comprising many elements relating to the household and the macroeconomy - in a single probability forecast. The advantages of this method over conventional forecasts of economic variables or disequilibrium indicators are evident, and aids communication of the likelihood of financial distress in the future. The process can take into account the nonlinearities inherent in measuring financial distress and can provide forecasts of future conditions before the realities of distress become apparent in arrears or default data.

5 Concluding comments

Despite the clearly discernible trends in macroeconomic variables that show consumer credit financed expenditure rising to unprecedented levels in several of the major economies, assessments of the sustainability of current levels of household debt have not taken into account macro data. Measurement 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. Most macroeconomic analysis of consumer indebtedness has used forecasts derived from dynamic linear relationships without the benefit of a sound theoretical base. The reasons for this are that there are genuine difficulties in measuring and conveying the likelihood of financial distress in a more sophisticated way and in relating this to macroeconomic data.

This paper offers a technology that is established on a theoretical base, that has nonlinearities in the relationships between macroeconomic and household level variables, which can assess the probability that complex joint events will occur in the future that are likely to trigger financial distress. Our application illustrates how this approach can offer insights in the UK unsecured credit market - showing that the probability forecasting method can identify periods when financial distress was experienced from those when it was not, relating these experiences to both macroeconomic and household data. We expect that the processes laid out here can be refined and that the range of applications is much wider than the prediction of financial distress in credit markets, but our paper offers a first step towards a new modelling approach to help understand and predict household financial distress using macroeconomic data.

Table 1: **List of Variables and their Descriptions**

c_t : natural logarithm of the UK real consumer expenditure by household.

m_t : natural logarithm of the UK real M4 balances held by households.

l_t : natural logarithm of the UK real unsecured M4 lending to households by banks and building societies.

$\widetilde{y}_t$: natural logarithm of the UK real net labour income.

r^l_t : is the annual interest rate on credit card balances.

y_t : natural logarithm of the UK real per capita GDP at market prices (1995 = 100).

p_t : natural logarithm of the UK Producer Price Index (1995 = 100).

$\widetilde{p}_t$: natural logarithm of the UK Retail Price Index, All Items (1995 = 100).

r_t : is computed as $r_t = \ln(1+R_t/100)$, where R_t is the 90 day Treasury Bill average discount rate per annum.

h_t : natural logarithm of UK real per capita M0 money stock (1995 = 100).

e_t : natural logarithm of the nominal Sterling effective exchange rate (1995 = 100).

y^*_t : natural logarithm of the foreign (OECD) real per capita GDP at market prices (1995 = 100).

p^*_t : natural logarithm of the foreign (OECD Producer Price Index) (1995 = 100).

r^*_t : is computed as $r^*_t = \ln(1+R^*_t/100)$, where R^*_t is the weighted average of 90 day interest rates per annum in the United States, Germany, Japan and France.

p^o_t : natural logarithm of oil prices, measured as the Average Price of Crude Oil.

t : time trend, taking the values $1, 2, 3, \ldots$, in $1985q1, 1985q2, 1985q3, \ldots$, respectively.

Notes: For the data sources of the variables of the household sector, see the Data Appendix in Chrystal and Mizen (2005). For the data sources of the variables of the core macroeconomic model, and a detailed description of the construction of foreign prices and interest rates, see the Data Appendix in Garratt *et al.* (2000).

Table 2 : **Augmented Dickey-Fuller Unit Root Test Applied to Variables in the Household Sector; 1985q1- 2001q1**

(i) For the First Differences					
Variable	ADF(0)	ADF(1)	ADF(2)	ADF(3)	ADF(4)
$\Delta(c_t - \widetilde{y}_t)$	-9.39	-5.41[a]	-5.02	-3.49	-2.90
$\Delta(m_t - \widetilde{y}_t)$	-8.02[a]	-4.84	-3.92	-3.04	-2.41
$\Delta(l_t - \widetilde{y}_t)$	-4.71	-2.70	-2.09[a]	-1.86	-1.70
Δr_t^l	-6.53	-5.46	-3.85	-3.66	-3.63[a]

(ii) For the Levels					
Variable	ADF(0)	ADF(1)	ADF(2)	ADF(3)	ADF(4)
$(c_t - \widetilde{y}_t)$	-2.16[a]	-1.94	-2.17	-1.98	-2.32
$(m_t - \widetilde{y}_t)$	-2.84[a]	-2.87	-2.71	-2.66	-2.53
$(l_t - \widetilde{y}_t)$	-0.71	-1.10	-1.53	-1.77[a]	-1.86
r_t^l	-0.85	-1.31	-1.17	-1.53	-1.42[a]

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 and s lagged first-differences of dependent variable. The relevant lower 5 per cent critical values for the ADF tests is -2.91. The symbol "a" denotes the order of augmentation in the Dickey-Fuller regressions chosen using the Akaike Information Criterion, with a maximum lag order of four.

Table 3: **Cointegration Rank Statistics for the Household Sector**

$$(c_t - \widetilde{y}_t), (m_t - \widetilde{y}_t), (l_t - \widetilde{y}_t), r_t^l, r_t$$

(a) Trace Statistic

H_0	H_1	Test Statistic	95% Critical Values	90% Critical Values
$r = 0$	$r = 1$	83.55.	72.10	68.04
$r \leq 1$	$r = 2$	49.34	49.36	46.00
$r \leq 2$	$r = 3$	28.86	30.77	27.96
$r \leq 3$	$r = 4$	9.44	15.44	13.31

(b) Maximum Eigenvalue Statistic

H_0	H_1	Test Statistic	95% Critical Values	90% Critical Values
$r = 0$	$r = 1$	34.22	34.70	32.12
$r \leq 1$	$r = 2$	20.47	28.72	26.10
$r \leq 2$	$r = 3$	19.43	22.16	19.79
$r \leq 3$	$r = 4$	9.44	15.44	13.31

(c) Model Selection Criteria

Rank	Max Log Likelihood	AIC	SBC	HQC
$r = 0$	607.63	547.63	482.40	521.90
$r = 1$	624.75	555.75	480.73	526.15
$r = 2$	634.98	558.98	476.36	526.38
$r = 3$	644.70	563.70	475.63	528.95
$r = 4$	649.41	565.41	474.09	529.38

Notes: The underlying VAR model is of order 3 and contains unrestricted intercepts and restricted trend coefficients, with 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 65 observations for the period 1985q1-2001q1. The asymptotic critical values are taken from Pesaran, Shin and Smith (2000). AIC, SBC and HQC in Table 3(c) refer to Akaike Information, Schwarz Bayesian and Hannan-Quinn Criteria.

Table 4: **Reduced Form Error Correction Specification for the Household Sector**

Equation	$\Delta(c_t - \widetilde{y}_t)$	$\Delta(m_t - \widetilde{y}_t)$	$\Delta(l_t - \widetilde{y}_t)$	Δr^l_t
$\widehat{\xi}_{6,t}$	.302* (.174)	−.377† (.177)	.922† (.234)	−14.237 (12.242)
$\widehat{\xi}_{7,t}$	−.238† (.089)	−.170† (.091)	−.446† (.120)	12.700† (6.275)
$\widehat{\xi}_{8,t}$	−.041 (.031)	−.053* (.031)	−.156† (.042)	−1.340 (2.185)
$\widehat{\xi}_{9,t}$	.003* (.002)	.001 (.002)	.003 (.002)	−.436† (.125)
$\Delta(c_{t-1} - \widetilde{y}_{t-1})$	−.439* (.244)	−.195 (.248)	−.402 (.328)	17.612 (17.131)
$\Delta(c_{t-2} - \widetilde{y}_{t-2})$	.195 (.216)	.411* (.220)	.553* (.292)	−32.707† (15.208)
$\Delta(m_{t-1} - \widetilde{y}_{t-1})$	.199 (.253)	−.223 (.258)	−.357 (.341)	−25.953 (17.810)
$\Delta(m_{t-2} - \widetilde{y}_{t-2})$	−.249 (.244)	−.298 (.248)	−.451 (.328)	28.209 (17.122)
$\Delta(l_{t-1} - \widetilde{y}_{t-1})$	−0.011 (.163)	.156 (.166)	.183 (.220)	−.794 (.11.455)
$\Delta(l_{t-2} - \widetilde{y}_{t-2})$	−.219 (.149)	−.314† (.152)	−.230 (.201)	9.772 (10.501)
Δr^l_{t-1}	−.001 (.002)	.001 (.002)	−.002 (.002)	.249† (.123)
Δr^l_{t-2}	−.002 (.002)	−.001 (.002)	−.001 (.002)	−.097 (.113)
Δr_t	.001 (.002)	.001 (.002)	.004 (.002)	.102 (.021)
Δr_{t-1}	.001 (.002)	−.000 (.002)	−.002 (.003)	.291* (.164)
Δr_{t-2}	.002 (.002)	.001 (.002)	.001 (.003)	−.012 (.154)
$\overline{R}^2$	.311	.301	.591	.513
$\hat{\sigma}$	.010	.010	.013	.682
$\chi^2_{SC}[4]$	10.01†	8.99*	5.69	4.56
$\chi^2_{FF}[1]$	0.01	0.05	0.90	2.66
$\chi^2_{N}[2]$	1.07	0.82	0.40	41.93†
$\chi^2_{H}[1]$	0.10	0.49	0.25	1.94

Notes: The four error correction terms are given by

$$\begin{aligned}
\widehat{\xi}_{6,t+1} &= (c_t - \widetilde{y}_t) + \underset{(0.0089)}{0.01176} r_t, \\
\widehat{\xi}_{7,t+1} &= (m_t - \widetilde{y}_t) + \underset{(0.0110)}{0.00465} r_t, \\
\widehat{\xi}_{8,t+1} &= (l_t - \widetilde{y}_t) + \underset{(0.0373)}{0.01746} r^l_t - \underset{(0.0063)}{0.01211} t, \\
\widehat{\xi}_{9,t+1} &= r_t - r^l_t + \underset{(0.0477)}{0.14545} t.
\end{aligned}$$

The regressions also contain an intercept and seasonal dummies. Standard errors are given in parenthesis. "∗" indicates significance at the 10% level, and "†" indicates significance at the 5% level. The diagnostics are chi-squared statistics for serial correlation (SC), functional form (FF), normality (N) and heteroscedasticity (H).

Table 5a : **Point Forecasts of Market and Credit Card Rates, Output Growth, Credit-Income Ratio, and Credit-Income Disequilibria, 2001q2-2003q1**

(Quarter on quarter changes)

Forecast Horizon	r_t	Δy_t^{MA}	r_t^l	$(l_t - \widetilde{y}_t)$	$\widehat{\xi}_{8,t}$
2001q2	5.53	1.84	19.63	-0.27	-0.21
2001q3	5.74	1.30	20.59	-0.27	-0.20
2001q4	5.69	1.28	20.21	-0.27	-0.22
2002q1	5.58	1.27	19.54	-0.28	-0.23
2002q2	5.51	1.42	19.49	-0.25	-0.24
2002q3	5.47	1.65	19.57	-0.24	-0.24
2002q4	5.46	1.89	19.38	-0.24	-0.25
2003q1	5.46	2.02	19.04	-0.22	-0.25

Table 5b : **Point Forecasts of Market and Credit Card Rates, Output Growth, Credit-Income Ratio, and Credit-Income Disequilibria, 1990q2-1992q1**

(Quarter on quarter changes)

Forecast Horizon	r_t	Δy_t^{MA}	r_t^l	$(l_t - \widetilde{y}_t)$	$\widehat{\xi}_{8,t}$
1990q2	12.03	1.02	29.83	-0.45	0.33
1990q3	11.21	1.16	28.52	-0.42	0.32
1990q4	10.76	1.36	26.35	-0.40	0.30
1991q1	10.54	0.95	24.94	-0.36	0.30
1991q2	10.50	1.29	24.60	-0.33	0.31
1991q3	10.52	1.39	24.15	-0.30	0.31
1991q4	10.58	1.56	24.00	-0.29	0.31
1992q1	10.65	1.74	23.95	-0.28	0.31

Notes: Forecasts are based on models of the form reported in Table 4, combined with the macroeconomic model described in Garratt et al. (2003a). The term Δy_t^{MA} relates to the four-quarter moving average of output growth while $\widehat{\xi}_{8,t+1}$ is defined in the notes to Table 4.

Table 6a : **Probability Forecasts involving Credit-Income Disequilibria, Recession and Slow Growth, 2001q2-2003q1**

Forecast Horizon	$\Pr(A \cup B)$ $c_1 = 0.20$ $c_2 = 0.00$	$\Pr(A \cup B)$ $c_1 = 0.30$ $c_2 = 0.00$	$\Pr(A \cup B)$ $c_1 = 0.40$ $c_2 = 0.00$	$\Pr(A \cup B)$ $c_1 = 0.20$ $c_2 = 0.01$	$\Pr(A \cup B)$ $c_1 = 0.30$ $c_2 = 0.01$	$\Pr(A \cup B)$ $c_1 = 0.40$ $c_2 = 0.01$
2001q2	0.00	0.00	0.00	0.21	0.21	0.21
2001q3	0.04	0.04	0.04	0.33	0.33	0.33
2001q4	0.09	0.09	0.09	0.38	0.38	0.38
2002q1	0.19	0.19	0.19	0.43	0.43	0.43
2002q2	0.16	0.16	0.16	0.36	0.36	0.36
2002q3	0.16	0.16	0.16	0.32	0.32	0.32
2002q4	0.14	0.14	0.14	0.30	0.30	0.30
2003q1	0.14	0.14	0.14	0.29	0.29	0.29

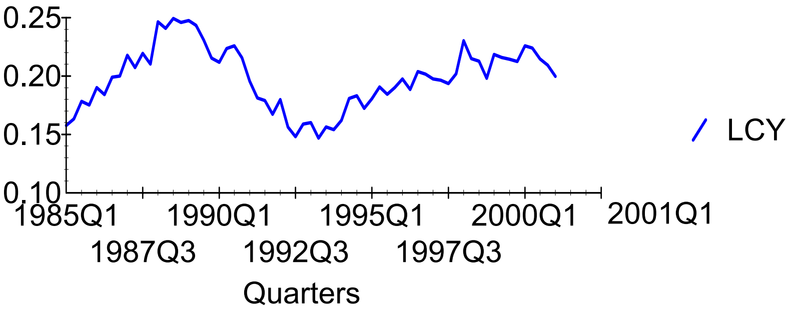
Table 6b : **Probability Forecasts involving Credit-Income Disequilibria, Recession and Slow Growth, 1990q2-1992q1**

Forecast Horizon	$\Pr(A \cup B)$ $c_1 = 0.20$ $c_2 = 0.00$	$\Pr(A \cup B)$ $c_1 = 0.30$ $c_2 = 0.00$	$\Pr(A \cup B)$ $c_1 = 0.40$ $c_2 = 0.00$	$\Pr(A \cup B)$ $c_1 = 0.20$ $c_2 = 0.01$	$\Pr(A \cup B)$ $c_1 = 0.30$ $c_2 = 0.01$	$\Pr(A \cup B)$ $c_1 = 0.40$ $c_2 = 0.01$
1990q2	1.00	0.94	0.14	1.00	0.97	0.49
1990q3	1.00	0.89	0.17	1.00	0.92	0.45
1990q4	1.00	0.52	0.15	1.00	0.66	0.40
1991q1	1.00	0.65	0.28	1.00	0.74	0.46
1991q2	1.00	0.77	0.31	1.00	0.82	0.46
1991q3	1.00	0.80	0.31	1.00	0.84	0.44
1991q4	1.00	0.75	0.29	1.00	0.80	0.42
1992q1	1.00	0.79	0.28	1.00	0.83	0.40

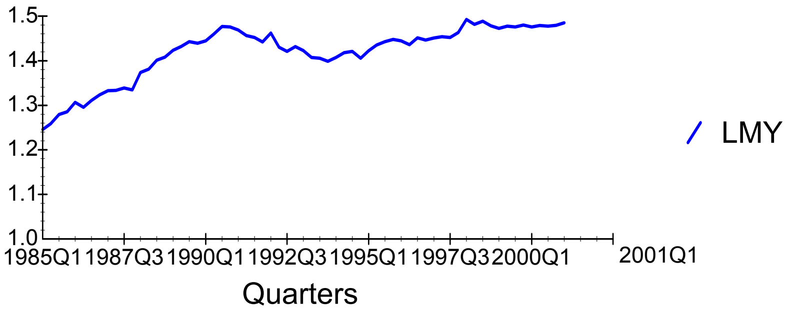
Table 6c : **Probability Forecasts involving Credit-Income Disequilibria Recession and Slow Growth, 1990q2-1992q1**

Forecast Horizon	$\Pr(A \cap B)$ $c_1 = 0.20$ $c_2 = 0.00$	$\Pr(A \cap B)$ $c_1 = 0.30$ $c_2 = 0.00$	$\Pr(A \cap B)$ $c_1 = 0.40$ $c_2 = 0.00$	$\Pr(A \cap B)$ $c_1 = 0.20$ $c_2 = 0.01$	$\Pr(A \cap B)$ $c_1 = 0.30$ $c_2 = 0.01$	$\Pr(A \cap B)$ $c_1 = 0.40$ $c_2 = 0.01$
1990q2	0.14	0.13	0.00	0.49	0.45	0.00
1990q3	0.17	0.14	0.00	0.45	0.39	0.00
1990q4	0.15	0.07	0.00	0.40	0.18	0.00
1991q1	0.28	0.13	0.00	0.46	0.22	0.01
1991q2	0.30	0.18	0.00	0.45	0.27	0.00
1991q3	0.30	0.18	0.00	0.43	0.27	0.00
1991q4	0.29	0.15	0.00	0.41	0.23	0.00
1992q1	0.27	0.16	0.01	0.40	0.24	0.01

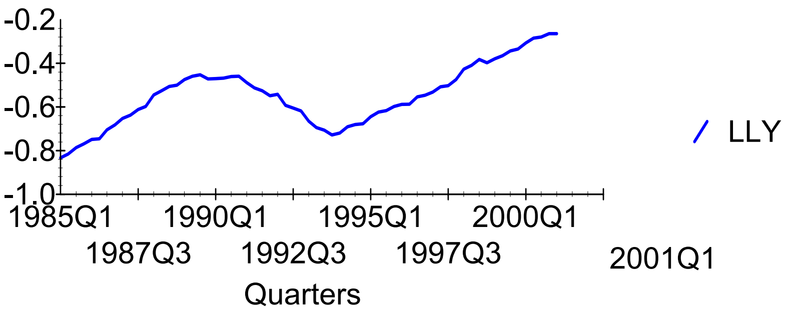
Notes: The probability estimates relate to the quarter-on-quarter forecasts of the credit-income disequilibria and the four-quarter moving average of output growth (denoted Δy_t^{MA}). Recession is defined to occur when the latter falls below zero and slow growth is where it falls below 1%. Event A=$\{\widehat{\xi}_{8,t} > c_1\}$ and B=$\{\widehat{\xi}_{8,t} > c_2\}$. A∪B means 'disequilibrium exceeds a critical value **OR** recession/slow growth occurs' and A∩B means 'disequilibrium exceeds a critical value **AND** recession/slow growth occurs'. The probability estimates for 2001q1-2003q1 are computed using the model reported in Table 4, combined with the macroeconomic model described in Garratt et al. (2003a), and take account of future uncertainty. A corresponding model, estimated using data 1979q1-1990q1, is used for the probability estimates for 1990q2-1992q1. The computations are carried out using 1,000 replications.



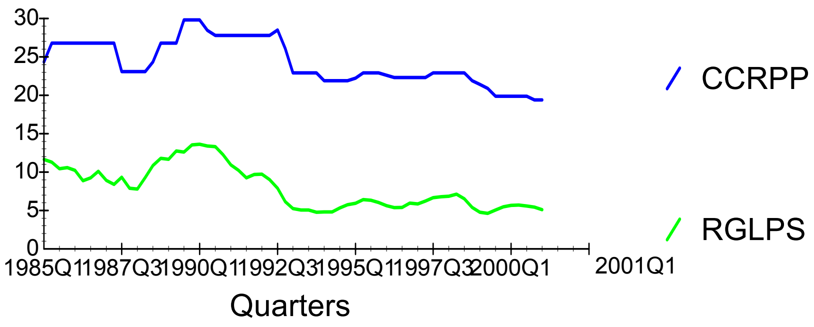
Log (consumption-income ratio)



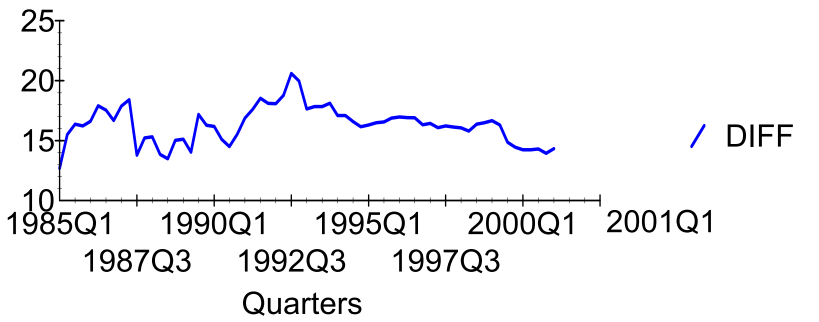
Log (money-income ratio)



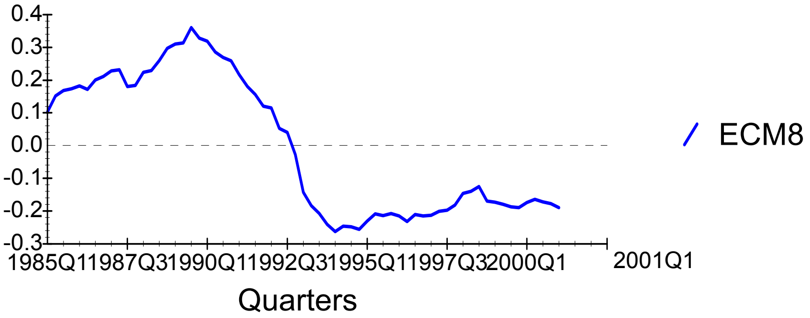
Log (credit-income ratio)



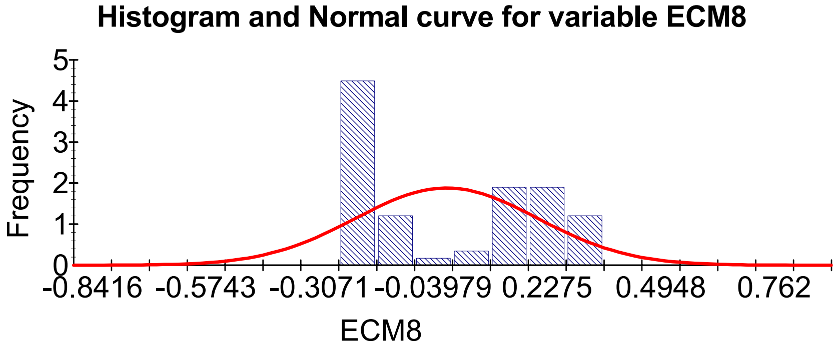
Credit card and Treasury Bill interest rates



Interest rate differential (credit card rate - Treasury Bill rate)



Disequilibrium in credit-income ratio



Disequilibria in credit-income ratio, 1985q1-2001q1

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