Consumer Credit Conditions in the U.K.

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Abstract

It is widely perceived that credit conditions for U.K. consumers, particularly in the mortgage market, have been radically liberalised since the 1970s. The implications for the housing market and consumer spending are important. We examine quarterly micro-data from the Survey of Mortgage Lenders (SML) to learn about changes in credit conditions from loan-to-value and loan-to-income ratios of first-time buyers (classified by region and age). We combine data on the proportions of high loan-to-value and loan-to-income loans with aggregate information on U.K. consumer credit and mortgage debt to give 10 series for 1975-2000. We model these data in a ten-equation system, controlling for a comprehensive set of economic and demographic influences on the demand and supply for credit, and extract a single time-varying index of non-price credit conditions. The broad coverage of credit market indicators and thorough investigation of economic forces driving the credit market should make the resulting Credit Conditions Index more robust than previous estimates. The index increases in the 1980s, peaking towards the end of the decade. It retraces part of this rise in the early 1990s, before increasing again to levels apparently exceeding the previous peak. The index will be useful in modelling consumption and the housing market, and in interpreting current monetary conditions.

JEL classification**: C32, E44, E51, G21.**

1. Introduction

It is widely perceived that credit conditions for UK consumers, particularly in the mortgage market, have been radically liberalised since the 1970s. The implications for the housing market and consumer spending have been important. For example, the evidence is that consumption and the housing market were the principal agencies in the economic boom of the late 1980s and the subsequent recession of the early 1990s. More specifically, changes in credit availability during the 1980s and early 1990s are likely to have contributed to the boom and subsequent retrenchment in consumption.

The need for a credit-conditions index (CCI), which measures the non-price aspect of credit availability, has been widely recognised in the consumption literature. Indeed, proxies such as unsecured credit to income ratios and interest rate spreads have been used in empirical work (see Bayoumi, 1993a,b and Sarno and Taylor, 1998 as examples of the former; and Scott, 1996, for the latter). However, such proxies are unsatisfactory because they are too dependent on interest rates, asset prices, incomes, expectations and other aspects of the economic environment. The key aim of the present paper is to construct a CCI, which, as far as possible, is free of this endogeneity criticism because it controls for the effects of the economic environment.

A first attempt in this direction was made by Muellbauer and Murphy (1993), in their 'flib' index, based on the analysis of average loan-to-value ratios (LVRs) in the U.K. for first-time buyers from the 5 percent sample of Building Society mortgages[1]. For many of these buyers, the LVRs are at ceilings set by mortgage lenders. Effectively the method involved regressing the log average LVR on the log of the mortgage interest rate, the log house price to income ratio and the real mortgage interest rate, for 1969-1980 data, and using the post-1980 residuals as a measure of the easing of credit conditions due to financial liberalisation. Caporale and Williams (2001) and Fernandez-Corugedo and Price (2002) have extended the method to more recent data and have applied it to modelling consumption. However, the method is somewhat fragile since it relies on a single indicator, and plausible changes in the specification of the relationship can cause notable changes in the implied 'flib' estimates. Muellbauer (1997) used annual regional data for first-time buyers on average LVRs and on the proportion of LVRs over 0.9 to bring additional information to bear, using dummies to trace out the post-1980 easing of mortgage credit. As he acknowledges, see also Muellbauer (2002), there is a sample selection problem in relying on a sample which before 1992 contained only building societies. Thus, when the banks aggressively entered the mortgage market, loan terms offered by building societies became much less representative of the market as a whole.

From 1975 to 2001, there are over a million observations on mortgages for first-time buyers in the Survey of Mortgage Lenders (SML), and in its predecessor before 1992, the 5 percent Sample of Building Society Mortgages. We extract quarterly data on loan and household characteristics from this source, excluding sitting tenants and others buying at a price discount. The present paper uses quarterly data on distributions of LVRs and also loan-to-income ratios (LIRs), with a regional and age split, and combines these with aggregate data

[1] LVRs have also been used in studies of mortgage default as an indicator of lending quality, see Breedon and Joyce(1992), Brookes, Dicks and Pradhan(1994). Lending quality and 'ease of credit' tend to be negatively related, though better screening of individuals' credit histories and other characteristics could improve quality *and* access to credit.

on mortgage and non-mortgage household debt to generate time series data for 1975Q1 to 2001Q4 on ten credit indicators. These are modelled in a ten-equation system with extensive economic controls, and a common factor, the Credit Conditions Index, is extracted. The common factor restriction is also used to model the effects of uncertainty for the debt market environment, using a wide range of uncertainty proxies. Since the aggregate data are not subject to sample selection problems, we can use them to identify sample selection factors for the micro data.

The broad coverage of credit market indicators and the thorough and comprehensive investigation of economic forces driving the credit market should make the resulting index more robust than previous estimates. The economic variables we control or check for include survey based consumer confidence measures, unemployment rates, demography, measures of inflation and interest rate volatility, asymmetric rate of return measures for the housing market, recent history of mortgage possessions rates, yield gaps to reflect interest rate expectations, one year ahead income growth to reflect income expectations, as well as the more conventional interest rate, wealth and income effects. We use the term 'Credit Conditions Index' rather than 'Financial Liberalisation Index' because of the latter's connotations of process, rather than outcome. Nevertheless, the process of financial deregulation and other changes in financial architecture, described in Section 2, have had an important bearing on the credit availability outcome. We return in the conclusions to the question of whether our index solves the 'endogeneity' problem. As well as its use in econometric modelling of consumption, debt and the housing market, our estimated index has direct applicability in interpreting the current state of credit markets.

The layout of the paper is as follows. In Section 2, we examine the various aspects of liberalisation and other changes in U.K. credit markets since the 1970s. Section 3 discusses the information content of the Survey of Mortgage Lenders and its predecessor. It discusses reasons why lenders use credit ceilings, such as limits on loan-to-income and loan-to-value ratios. The information we extract consists of the proportions, by age and region, of first-time buyers with loan-to-income ratios of 2.5 or more and the corresponding proportions with loan-to-value ratios of 0.9 or more. We outline the empirical methodology: by controlling for economic and demographic influences on the demand for credit, we extract a single time-varying index of credit conditions from these SML data, combined with data on aggregate mortgage and unsecured consumer debt. The remainder of Section 3 explains the various economic influences on the proportions of high loan-to-income and loan-to-value ratios just defined.

Section 4 discusses the economic influences on unsecured and mortgage debt, in the context of the previous literature. Section 5 presents empirical estimates of the ten-equation system assuming there are no interaction effects between the Credit Conditions Index and the other economic variables. Section 6 discusses possible interaction effects of this type and presents estimates of the generalised model including interaction effects. Section 7 concludes and discusses possible applications of the Credit Conditions Index. A data appendix provides details of data construction and sources.

2. Financial liberalisation in the U.K.

The 1970s in the U.K. saw a period of negative, after-tax real interest rates. The authorities attempted to control credit with stringent liquidity ratios on banks, special deposits (popularly known as the 'corset'), regulations on minimum deposits and maximum repayment periods on hire purchase credit, and directives and persuasion aimed at building societies. There were several key events in the evolution of financial liberalisation under the Thatcher government, which came to power in 1979. First, exchange controls were removed in 1979, opening the banking sector to greater foreign competition and giving domestic institutions access to the developing Eurodollar markets. This was an important step in integrating the U.K. into international capital markets. The logical second step was to abolish the 'corset' on bank lending and banks could enter the mortgage market from 1980.

Increased competition in the mortgage market led to the relaxation of rules on building societies (e.g., their access to money markets) and the break-up in 1983 of the interest rate-fixing cartel. The Building Societies Act (1986) formalised the relaxation of rules.

Fourth, a second phase of new entry into the mortgage market from 1985 was heralded by the influx of centralised mortgage lenders without high street branches.[2]

Fifth, the Basel I accords on capital adequacy ratios for banks agreed in 1988, gave mortgage loans a preferred status, with a 50 percent risk weighting relative to other loans. This may have caused a further easing in an already quite liberal mortgage-lending regime in the U.K.

The first major demutualisation of a building society, that of Abbey National, occurred in 1989, demonstrating the new fluidity of the mortgage market. This was followed by a spate of others over the next decade. By 1990, differences in the average loan or the average income of borrowers between bank and building society customers had become relatively insignificant.

After 1990, following the start of the mortgage possessions crisis, financial liberalisation was partially reversed. The Building Society Commission increased prudential advice in 1991. Mortgage indemnity insurers moved the terms of insurance policies sharply against mortgage lenders, not just in pricing, but also in risk sharing. One symptom of the tougher conditions of the early 1990s was the loss of market share of centralised mortgage lenders (with substantially higher default rates than building societies).

The later 1990s saw another type of new entry - the internet mortgage lenders – and significant innovation in new products, such as fixed rate mortgages over longer terms and 'flexible mortgages'. The latter permit borrowers to repay loans more quickly, take payment holidays or extend loans flexibly, as long as loan-to-value ratios remain within pre-set bounds, see Munro et al (2001). The spate of special offers to new customers tended to improve mortgage terms for those willing to undergo the inconvenience of re-mortgaging, one symptom of the strength of competitive pressures, see Samuels (2001).

In 1998, a significant change in pricing behaviour by mortgage lenders occurred. Following the lead of the largest lender, the Halifax, lenders gave borrowers exemption from mortgage indemnity insurance (which insures lenders against mortgage default) if loan-to-value ratios were below 0.9. This gave borrowers considerable incentives to reduce mortgages to below this level.

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[2] These included Allied Irish Bank, Credit Lyonnais and other foreign banks.

Two aspects of this brief history are illustrated in Figure 1. This shows the value share of banks in mortgages outstanding, where Abbey National continues to be treated as a building society after 1988. The rapid rise from 1980 is notable, but after 1990, this share has little more meaning as a sign of competitive pressure. Figure 1 also shows the value share of centralised mortgage lenders, demonstrating the post 1985 rise (see the left axis for the scale).

Figure 2 shows consumption to income and house price to income ratios rising strongly in the 1980s. Part of the co-movement is almost certainly due to the liberalisation of credit markets, rather than the causal effect of house prices on consumption. Figure 3 shows the mortgage debt and unsecured debt to income ratios, both more than doubling between 1980 and 1990, and rising to new heights in recent years.

Another type of evidence is available from surveys of mortgage lenders, which have been regularly carried out since the end of 1968: As noted in the Introduction, the data on loan-to-income and loan-to-value ratios for first-time buyers, will often represent ceilings set by mortgage lenders. We turn next to further use of data from this source.

3. Extracting information on credit conditions from the Survey of Mortgage Lenders

3.1 Ceilings and the distributions of loan-to-income and loan-to-value ratios

The key reason for mortgage lenders applying ceilings to loan-to-income and loan-to-value ratios is to avoid the risk of default, both in payment arrears, and, more seriously, mortgage possession. Consider the immediate causes of mortgage possession. Such default can be seen as the intersection of two events: the 'debt/equity ratio rising above some threshold' and 'a trigger function (of debt service ratio, income shocks, house price shocks) exceeding another threshold'. The first of these events makes it difficult or impossible for the borrower to trade down to cheaper housing or out into the rental sector, given the difficulty of obtaining substantial unsecured debt. In the absence of unexpected income losses or unexpected rises in interest rates, mortgagors and lenders have an interest in avoiding default, even with a bad debt/equity ratio, since mortgage possession in the U.K. is extremely unpleasant for borrowers. The latter are liable for the lenders' transactions costs, pursuit in the courts for years and denial of access to future credit. However, if unexpected cash flow problems arise - the trigger function exceeding some threshold, there will often be no alternative to default.

Formally, the probability of default equals the probability of a bad debt/equity ratio multiplied by the probability of a bad trigger, given a bad debt/equity ratio.[3] By limiting the

[3] The U.K. differs in important ways from many U.S. states, where borrowers' liabilities end as soon as they return the keys to the mortgaged property to the lender. This means that in the U.S. the first factor, the debt/equity ratio should have a more dominant role in defaults, largely decided on by borrowers. Thus the U.S. 'rational default model', which applies option pricing theory to find bad debt/equity threshold, in absence of transactions costs and credit restrictions, is unlikely to apply in the U.K., where most defaults were instigated by lenders,

initial loan-to-value ratio, lenders can reduce the probability of a later bad debt-equity ratio, which can arise through a fall in house prices, and/or through accumulated payment arrears.

By limiting initial loan-to-income ratios, the probability of a later bad 'trigger' is reduced. For example, with a loan-to-value of 2.5, the initial debt service ratio is 2.5*r, where r is the tax-adjusted mortgage interest rate plus pro-rated loan repayments, initially a small fraction of monthly mortgage payments, plus pro-rated insurance costs. For example, with r at 10 percent, 25 percent of income is committed to debt service. However, with r at 15 percent, 37.5 percent of income would be committed to debt service, a percentage many households would find hard to tolerate, particularly if they had not planned for it. Thus, in an environment of high nominal interest rates, lenders are likely to apply tighter loan-to-income criteria, while in a low interest rate environment of, for example, 2001-2, the opposite will be the case.

For given interest rates, house prices etc., financial liberalisation as occurred in the U.K. in the 1980s, is likely to have raised both types of loan ceilings. Note that, while borrowers and lenders have significant common interests in wanting to avoid loan defaults or coming under severe financial pressure from debt service costs, there seems no reason why financial liberalisation should cause *borrowers* to want to raise these ceilings.[4] The rise in loan-to-income and loan-to-value ceilings, which occurred, and which cannot be explained by conventional demand side variables, is therefore likely to have been a shift on the credit supply-side.

The structure of decision-making behind the observable LIRs and LVRs, has been discussed by Muellbauer (1997). A credit-unconstrained household chooses a mortgage loan M^d and a house of value V^d by maximizing utility subject to their budget constraint and the housing quality-house price trade-off. This generates $LVR^d = M^d/V^d$ and $LIR^d = M^d/Y$, where Y is the household's current income. The household is faced with a maximum mortgage offer LVR^s, LIR^s from the supply side. There are then three possibilities:

(a) $LVR^d < LVR^s$, $LIR^d < LIR^s$ so that $LVR = LVR^d$, $LIR = LIR^d$

(b) $LVR^d > LVR^s$, $LIR^d < LIR^s$ so that $LVR = LVR^s$ and $LIR = \min(LIR^{d*}, LIR^s)$ where LIR^{d*} is obtained by re-maximizing utility subject to the $LVR \leq LVR^s$ constraint.

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not borrowers. Unpublished research on arrears and possessions for a large mortgage lender in the U.K. (Cameron, Hendry and Muellbauer) provides evidence consistent with these points.

4 Whilst we make the point that financial liberalisation should not lead to an increase in the ceilings chosen by borrowers, habit formation may suggest the contrary. With financial liberalisation, the consumption of housing goods increased in the economy as agents were able to borrow to purchase a house. As the consumption of housing goods increased, individuals falling behind would have come under reference group pressure to 'keep up with the Joneses' and so increase their housing consumption and debt levels. However, note that the story begins with financial liberalisation. It certainly seems plausible that the diffusion process by which it affected behaviour could have been via consumer habits as well as their and the lenders' information sets. These channels cannot be empirically distinguished in our estimates of the long-run impact of the credit conditions index on behaviour.

(c) $LVR^d < LVR^s$, $LIR^d > LIR^s$ so that $LIR = LIR^s$, $LVR = \min(LVR^{d*}, LVR^s)$ where LVR^{d*} is obtained by re-maximizing utility subject to the $LIR \leq LIR^s$ constraint.

Note that the outcome where both constraints bite, so that $LVR = LVR^s$ and $LIR = LIR^s$, is a possibility subsumed under (b) and (c). Then $V/Y = LIR^s/LVR^s$

This is the decision making structure underlying data on the observed distributions of LVRs and LIRs. We cannot observe the LVR^s and LIR^s ceilings directly. Clearly they vary to some extent over lenders and certainly vary with time.

3.2 The empirical methodology

We use 25 years of quarterly data on mortgage credit conditions from the Survey of Mortgage Lenders (SML) and, as noted, its predecessor[5]. Specifically, we examine distributions of loan-to-value (LVR) and loan-to-income (LIR) for first-time buyers (FTBs), concentrating particularly on vulnerable tails for LVR $\geq$ 0.9 and LIR $\geq$ 2.5. We examine data by age (under 27/27+) and by region (North/South) giving 8 series on the proportion of FTBs in these respective vulnerable tails. By including also aggregate data on mortgage debt/income and unsecured consumer credit/income, illustrated in Figure 3, we have 10 series. We then use economic and demographic variables to control for variations in credit demand, and a spline function is used to measure the common unobserved supply side component, our Credit Conditions Index, over the last 25 years. Such an index can then be used to model consumption, house prices, housing turnover and subsequent loan defaults in separate equations. Alternatively, such equations could be added by extending the 10-equation system to 12 or more equations, for example, by modelling the consumption and house price data illustrated in Figure 2.

Usable electronic records for the LIR and LVR distributions begin in 1975 but average loan-to-income and loan-to-value ratios for first-time buyers (excluding discounted ‘right to buy’ sales to social housing tenants) are available back to 1969 and are illustrated in Figure 4. The loan-to-income graph shows an early peak in 1972 during the first of the post-war house price booms, a strong rise between 1980 and 1990, and a weaker upward drift in more recent years. Despite some definitional issues, to be discussed, the data suggest a considerable positive correlation between average house price/income ratios and loan-to-income ratios.[6] The graph of the average loan-to-value ratio suggests the opposite correlation with average house price/income ratios, and a strong rise between 1980 and 1984, with levels thereafter remaining higher than before, but otherwise no immediately obvious pattern emerging.

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5 The survey and its predecessor consisted of a 5 percent sample until 2000. The survey includes information on income, size of loan, value of house being purchased, previous tenure, the age of the main borrower, whether the price was discounted, type and duration of mortgage, and the interest rate charged. From 1980, single borrowers and multiple borrowers, such as couples, are distinguished, but not so in earlier years.

6 They also contain at least a hint that the temporary early 1970s "Competition and Credit Control” policy shift by the Bank of England was associated with some easing of credit market conditions.

Figures 5 and 6 show PLIR, the percentage of FTBs with loan-to-income ratios of 2.5 or more by age and region, rising from under 10 percent in 1980 to over 60 percent in 1989 in the case of the South and to over 35 percent in North. The correlation with average house price to income ratios is apparent as in Figure 4: both the 1989-90 peak and the early 1990s decline in the South are consistent with the pronounced Southern boom/bust in house prices in this period. The systematic tendency of PLIR to be higher in the South than the North is also consistent with higher house price/income ratios in the South. Differences by age are less pronounced than by region: older FTBs tend to have slightly lower percentages of high LIR mortgages in both regions.

Figures 7 and 8 show PLVR, the percentage of FTBs with loan-to-value ratios of 0.9 or more. The graphs show a very clear difference between borrowers aged under 27 and those aged over 27: in both regions, systematically higher percentages of younger borrowers have LVRs of 0.9 or more. One should expect such differences since younger borrowers tend to have lower cash resources and so are less able to provide substantial deposits. For these younger borrowers, PLVR rose from averages of 25-30 percent in 1975-80, to 60-80 percent and 50-70 percent for North and South, respectively, for 1984-2000. The decline since 1998 is notable.

3.3 Economic factors impinging on PLIR

The structure of decision-making, involving both households and mortgage lenders, underlying the observed LIR and LVR distributions was discussed in Section 3.1. In many respects mortgage lenders and households have the same interest in avoiding default. The direction of effects of interest rate and risk factors on the proportion of high LIR loans will therefore be the same, whether they operate on LIR^s or LIR^d. The directions of most of the economic forces operating on the proportion of high LIR loans are easy to understand, see Muellbauer (1997) for more microeconomic detail.

We now list the key economic variables and the signs of their expected effects on PLIR, the percentage of FTBs with LIR ≥ 2.5:

(-) Nominal interest rate: to avoid uncomfortably high debt service ratios, see Section 3.1, PLIR should fall as the nominal interest rate rises.

(-) Real interest rate: a high real rate raises the probability of mortgage arrears and lower house prices.

(-) Interest rate expectations: the yield gap between gilts at durations of one or more years and short rates, should reflect the market view of the direction of movement of short rates.

(+) House price/ income ratio: a high ratio puts pressure on borrowers to get the highest possible loan (and so helps explain higher PLIR in South).

(+) Consumer confidence: greater confidence in economic prospects should increase the willingness of lenders to lend and borrowers to borrow.

(-) Perceived risk: we use four indicators. The first two are inflation and interest rate volatility. Greater historical volatility is likely to be interpreted, by lenders and borrowers, as a sign of greater riskiness and should discourage borrowing on high multiples. The third risk indicator is an asymmetric indicator[7] of returns on housing and the fourth is the rate of mortgage possessions, in the form of two or three year moving averages.

(-) The change in unemployment: a rise in unemployment is an indicator of the risk of income declines.

(+) Expected income growth: using actual income growth over the next 4 quarters as a proxy.

(-) Cut in ISMI (income support for mortgage interest): in 1995 such income support was sharply reduced, increasing the risk of cash flow problems in the event of unemployment.

(-) Share of couples: since lenders apply lower LIR ceilings to joint incomes, a rise in the share of couples among first-time buyers, would lower the proportion of high LIR loans.

(-) Sample selection: before 1990, when the survey refers to building societies only, an increase in the share of banks, and later, in centralised mortgage lenders, makes the building society sample a more distorted representation of the whole market. We represent the first effect by weighting the 4-quarter change in the share of banks in mortgages outstanding by the average loan to FTBs by banks minus the average loan to FTBs by building societies, scaled by the average loan to FTBs by building societies. When banks first entered the market, they catered to the upper end, particularly of existing bank customers with stable jobs and known credit and income records, driving the building societies down-market, where loan-to-income ratios were lower but loan-to-value ratios were higher. By the late 1980s, the average loans from banks and building societies had become fairly similar, so that the sample selection effect would have been much lower. The evidence is that centralised mortgage lenders catered to the riskier end of the market, so that their entry would have pushed down PLIR and PLVR reported by building societies.[8]

3.4 Economic factors impinging on PLVR

One would expect the economic factors acting on PLVR, the percentage of FTBs with loan-to-value ratios of 0.9 or more, to work similarly to those acting on PLIR, with the following exceptions:

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[7] This indicator is defined as the rate of return when this is negative and zero when the rate of return is positive.

[8] Note that the information from aggregate mortgage debt data is helpful for identifying such sample selection effects. While the centralised mortgage lenders are gaining market share, this is reflected in rising aggregate mortgage debt/income ratios - even though the building society data on PLIR and PLVR apparently suggests no rise or even a contraction of credit conditions.

(-) Nominal interest rate: though the effect on PLVR is still likely to be negative, it should be weaker than the effect on PLIR, which stems directly from the definition of the debt-service ratio.

(-) House price to income ratio: this should act on PLVR in the opposite direction to the effect on PLIR. There are two mechanisms: a high house price indicates a greater probability of a fall in house prices, other things being equal. Second, in areas with high house price/income ratios, households are more likely constrained by LIR ceilings than by LVR ceilings. Since the risks in the two dimensions interact, as noted in Section 3.1, lenders should be more cautious about offering very high LVRs to borrowers already at LIR ceilings.

(-) Rate of change of house prices: valuations by surveyors for mortgage lenders are likely to be conservative, tending to lag behind the market when prices are rising strongly. Loan offers are based on these valuations but loan-to-values reported for completed transactions are based on prices actually paid, which will tend to exceed mortgage valuations in rising markets. The time lag in the mortgage approvals process can induce similar effect in rising markets, where the incidence of 'gazumping' - the seller demanding a higher price than initially agreed - is higher. Note that this effect should be absent from the PLIR equation.

(-) 'Pricing' mortgage indemnity premia: in 1998, Halifax removed mortgage indemnity premia for LVR < 0.9 and the market followed. This gave borrowers an incentive to bring LVRs below 0.9, e.g. by increasing unsecured borrowing to raise cash deposits.

(-) Increased access to unsecured lending: by the route just outlined.

(-) Average age: though we divide borrowers into under 27, and 27 and over, age groups, variations do occur of average ages within these groups, e.g. an upward drift in the 1990s. Since the accumulation of financial assets available as a housing deposit increases with age, we expect a negative effect on PLVR[9].

(?) Sample selection with respect to the rising share of banks: there are likely to be two offsetting forces at work. The first, with a negative influence on the proportion of high LVR loans reported by building societies, comes from the simple fact that in competing for similar customers, gains in market share by banks are likely to be the result of more generous terms, viz. higher LVRs and LIRs. This would mean the proportion of high LVRs reported by building societies understates the proportion for the market as a whole. However, there is an effect in the opposite direction, which comes from the fact that the building societies were forced downmarket where LVRs tend to be higher. Note that this offsetting effect is not present for LIRs, since LIRs tend to be lower for lower income borrowers.

3.5 Functional forms for PLIR and PLVR equations

[9] One would expect a negative effect on PLIR also. However, given the stylised fact from Figures 4 and 5, of only a small age difference in PLIR between the under 27 and 27+ groups, it seems likely that this effect will be weak.

Section 3.1 set out the decision structure behind the observed LIRs and LVRs. We do not have precise ideas about the functional forms for LIR^s, LVR^s, LIR^d, LIR^{d*}, LVR^d and LVR^{d*} and about the stochastic structure of disturbances at the level of individual households and mortgage lenders. Identification of these structural relationships is hopeless. Moreover, the observed distribution of LIRs and LVRs is for completed transactions of first-time buyers. Some may not have been able to obtain finance at all, or have been unsuccessful in housing search, or to have encountered sellers unable to transact within the relevant period. We know that the number of transactions by first-time buyers has fluctuated considerably over the last 25 years, see Holmans (1996, 2001) and it is possible that the shape of the LIR and LVR distributions may have been affected by the transactions volume. However, as indicated above, we use an extremely rich set of controls effectively to model reduced form equations for PLIR and PLVR.

Suppose reduced forms for observed LIRs and LVRs at the individual level are given by

$$\log \mathrm{LIR}_{\mathrm{it}} = f(x_t) + e_{it} \tag{3.1}$$

$$\mathrm{ly\ LVR}_{\mathrm{it}} = g(x_t) + h_{it} \tag{3.2}$$

where ε_i and η_i are household specific error terms with zero means.

Then

$$\mathrm{PLIR}_{\mathrm{t}} = P(f(x_t) + e_{it} \geq \log 2.5) \tag{3.3}$$

and

$$\mathrm{PLVR}_{\mathrm{t}} = P(g(x_t) + h_{it} \geq \log 0.9) \tag{3.4}$$

If the distributions of ε_{it} and η_{it} could be approximated by logistics, so that, for example

$$P(e_{it} \geq z_t) = \frac{1}{1 + \exp(a\, z_t)} \tag{3.5}$$

Then

$$\exp(a\, z_t) = (1 - P_t) / P_t$$

and

$$\log(P_t / 1 - P_t) = -a\, z_t \tag{3.6}$$

This suggests using the log odds ratios log(PLIR/1-PLIR) and (PLVR/1-PLVR), as the dependent variables. As we shall see, we allow for a possible mis-specification of eq. 3. 6 by introducing a cubic in z_t as well.

4. Economic factors impinging on aggregate unsecured and mortgage debt to income ratios

One would expect the economic variables affecting debt to income ratios to work in the following direction:

(+) Demography: proportions of working age individuals in the key house buying age groups

(+) Income: higher income should allow individuals to be able to service a given amount of debt more easily.[10]

(+) Expected income growth: if individuals are consumption smoothers and expect higher income growth in the future, they will increase their consumption of housing and non-housing goods for a given level of income and will therefore be more likely to get into debt.

(-) The change in the unemployment rate: this variable may proxy income uncertainty. A higher unemployment rate is consonant with higher uncertainty leading to higher savings for precautionary reasons.[11] Moreover, higher unemployment is likely to lead to lower current and expected aggregate labour income, leading to a reduction in consumption.

(-) Liquid financial wealth: at the individual level, greater liquid wealth reduces the need to borrow. At the level of the economy, a higher level of household liquid assets/income suggests a greater ability for the financial system to recycle assets into debt, though with financial deregulation, household deposits would no longer constrain lending to households. In other words, controlling for the Credit Conditions Index, greater liquid wealth should reduce indebtedness.

(+) Illiquid financial wealth, e.g. tied up in pensions, provides long-term asset backing for debt, and so should have a positive effect on the demand for debt.

(+) Housing wealth: the greater gross housing wealth, the greater the available collateral for mortgage debt.

(+) Consumer confidence: the measure of consumer confidence used in our work corresponds to the GfK survey and measures consumers' confidence about their finances and the state of the economy. An increase in confidence should be consonant with better prospects for the economy.

(-) Change in consumer credit controls: consumer credit controls, which regulated down-payments and repayment periods for 'hire purchase' borrowing to buy durable goods, were an important policy instrument in the 1950s to 1970s. A tightening in controls

[10] See Ludvigson (1999) for a theoretical model of unsecured debt as a function of consumers' income. In that model an increase in the debt to income ceiling enables consumers to get into more debt, a fact Ludvigson finds consistent with the data. Also see Japelli (1990) for the finding that a major reason households in the Survey of Consumer Finances are denied credit is because they had insufficient income.

[11] See Carroll and Dunn (1997) for forceful arguments that unemployment expectations are a good predictor of consumption.

should have a negative impact on unsecured debt in the 1970s, in addition to its role as a proxy for CCI at this time.

(-) Stock of debt in the previous period/income: the higher is debt, the more debt has to be repaid each period under typical debt contracts. Another aspect is equilibrium correction: the tendency of the steady state level of debt not to be exceeded.

(-) Nominal interest rate: as we saw in section 3, a higher nominal interest rate and so debt service ratio is likely to reduce the amount of debt that individuals are likely to undertake and to which lenders will agree.

(-) Real interest rate: a higher real interest rate should lower debt through two channels. In the first, a higher interest rate will increase the debt service ratio making debt less affordable. The second channel is through saving since a higher real interest rate increases the price of current consumption.

(-/+) Spreads between the credit card interest rate and mortgage rate: a negative effect on unsecured debt; a positive effect on mortgage debt

(-) Perceived risk: we use the four indicators discussed in Section 3.3.

(-) Cut in ISMI (income support for mortgage interest): the increase in the risk of future cash flow problems should reduce demand at the margins.

(+) Ratio of credit cards outstanding to adult population: a positive effect on unsecured credit. The more credit cards available to consumers the higher the probability that these will be used.

(+) Mortgage indemnity premium pricing dummy: a positive effect on unsecured credit from 1998 as lenders abolished the premium for LVRs under 0.9; a corresponding negative effect on mortgage debt, but proportionately smaller.

5. Empirical results: the base-line model

Sections 3.2 to 3.4 have outlined the economic variables impacting on loan-to-income and loan-to-value ratios for first-time buyers, as represented by the eight series on PLIR and PLVR, and on aggregate unsecured and mortgage debt to income ratios. As explained in Section 3.2, the effect of the altered credit supply environment, linked to the institutional changes discussed in Section 2, is introduced in each equation through the Credit Conditions Index, CCI, common to all ten equations. This is represented by a linear spline function, which apart from 1980s, consists of connected straight-line segments, which can change slope at the beginning of each year. The CCI also depends on the change in consumer credit controls, phased out in 1983. In addition, in the unsecured debt equation, we incorporate the ratio of the number of credit cards outstanding to the number of adults, to capture changes in credit supply not reflected in CCI, the latter being more tuned to the mortgage market.

The data appendix gives details of data construction (e.g., of tax-adjusted interest rates, after-tax disposable non-property income, and the use of annual data from the New Earnings

Survey on earnings by age, gender and region, interpolated using the quarterly average earnings index to obtain income data by age and region[12]).

Even without the interaction effects discussed in Section 6, estimating this 10-equation system was not trivial: we imposed our extensive prior expectations on sign patterns of coefficients outlined in Sections 3.2-3.4, as well as on the broad outline of the CCI index, given the institutional evolution described in Section 2. Moreover, to the extent practicable, we allowed the lag structures (e.g., of responses to interest rates and house price changes) to be determined empirically. The priors were extremely helpful in reducing very flexible general specifications to a parsimonious one.

We now explain schematically the set-up of the 10-equation system and some identification issues. We write the equations in the form:

$$?\, y_{it} = a_i\,(?_i\, CCI_t + \mu_i VOL_t + Sß_{ij}x_{jt} - y_{it-1}) + e_{it} \qquad (5.1)$$

for i=1,10

$$CCI = S\ d_s\ Dum_{st} + ?_1 ?\,4CC_t + ?_2\ liqr_{t-1} \qquad (5.2)$$

$$VOL = S\ ?_j z_{jt} \qquad (5.3)$$

The y variables in (5.1) are the two log debt measures and the eight log odds-ratios of LVRs and LIRs exceeding given threshold values, by region and age. We model each as an equilibrium correction model, with the dependent variable in quarterly change form, Δy. Here a_i is the speed of adjustment. For the $x_{jt,}$ which can be given a long-run interpretation, β_j is the long-run coefficient. Note that the x's include variables in Δ form, and so not in the long-run solution. We also impose some homogeneity across equations, for example, setting most slope coefficients to be the same across regions and age for the four PLVR equations and the four PLIR equations, respectively.

The definition of the credit conditions index CCI given in (5.2) incorporates split trends, the Dums, the 4-quarter change in consumer credit controls, ?4CC and liqr, defined as the liquidity ratio of building societies before 1980Q3 minus its 1980Q4 value, and zero thereafter. The definition of VOL incorporates measures of inflation volatility, interest rate volatility and the rate of mortgage possessions.

It is clear that the a_i and therefore the $ß_{ij}$ are identified in (5.1). However, a scalar multiple of the coefficients in (5.2) cannot be separated from a similar multiple of $?_i$, so that either one of the coefficients in (5.2) or one of the $?_i$ has to be normalised at some value. Exactly the same applies to μ_i and the coefficients of (5.3). We choose to set $?_i$=10 and μ_i=10, for the PLIR equations.

5.1 The equation for unsecured debt.

[12] Such data could have been extracted from the SML but are likely to be too subject to sample selection problems. For example, if unemployment rises, the income profile of those selected both by themselves and by lenders to be successful FTBs may well improve, as more risky prospects are selected out, giving a spuriously positive impression of the economic environment.

Previous research on the determination of unsecured household debt in the U.K. is relatively sparse.[13] The most recent study is that of Chrystal and Mizen (2001), who examine a simultaneous system including consumption, household M4 and unsecured credit using a VECM approach. Chrystal and Mizen identify 3 cointegrating vectors. That for unsecured lending has the form (Table C):

$$\log ud/pc = 1.41 \log \text{real income} - 0.68 \,(\text{credit card interest rate} - \text{bank base rate}) + 0.65 \log \text{real net worth} - 2.89 \,\text{dlog } pc, \tag{5.4}$$

where ud is unsecured debt and pc is the consumer expenditure deflator. However, in the context of the VAR, the Johansen cointegration approach finds empirically that the ECM terms for consumption and broad money also enter the model for Δlog ud/pc with significant coefficients, see their Table C. In a model, which conditions on the growth rate of current consumption and in current M4, the former enters negatively with a coefficient of –1.6 (t=3.5) and the latter positively with a coefficient of 3.9 (t=6.9), while the change in the unemployment rate has a positive coefficient, 0.039 (t=4.5) and consumer confidence has a significantly positive effect. The ECM for log real ud itself enters with a coefficient of –0.11 (t=5.2), see their Table E. It is clear that such an equation cannot be given a conventional demand for credit interpretation: unsecured credit can only be understood as part of the system.

Our approach is, in one sense, more conventional: unsecured credit is interpreted in terms of a function of income, lagged assets, interest rates, consumer confidence etc., which, unlike current consumption and money holdings, can plausibly be regarded as given to the individual household. Though at the micro level, asymmetric information is endemic, so that lenders use rules to limit their risk exposure, information about macro aggregates should be broadly symmetric between lenders and borrowers. Data on unsecured credit will therefore incorporate lending rules, as well as what credit demand could have been in the absence of lending ceilings, both, in turn, reflecting the aggregate data on income, lagged assets etc. As

[13] At the level of theory, most of the research on unsecured debt has been undertaken with respect to the effects that unsecured debt can have on consumption/saving decisions. See Antzoulatos (1994), Scott (1996), Ludvigson (1999), Carroll (2001), Fernandez-Corugedo (2002) for the theoretical effects of the relaxation of liquidity constraints on consumption decisions. The main result that comes from these papers is that with a relaxation of credit ceilings individuals are able to increase their consumption for a given level of cash-on-hand. However, such an increase in consumption reduces precautionary savings and therefore makes individuals more exposed to uncertainty. Maki (2000) provides an excellent summary of some of the U.S. empirical literature on consumer credit and the household debt service burden. Recent papers include Murphy (1999), who demonstrates that the debt burden of households is helpful in forecasting future consumption growth, and in particular durable consumption growth. Gross and Souleles (2001) examine credit demand and supply using US credit card data. They find that an increase in the credit limit leads to an immediate and significant rise in debt. Westaway (1990) considers a consumption model where a proportion of individuals are able to finance part of their consumption expenditure using debt (both secured and unsecured debt). Westaway obtains mixed results on U.K. data. He finds that a sensible long-run cointegrating vector does not exist between consumption and the variables thought to determine it, but he also finds that a model, which includes debt, does perform better than equations, which do not include debt.

already noted, the distinctive feature of our approach is in the treatment of credit conditions through the CCI measure.

The difficulties of modelling unsecured debt are considerable. The first is that this is a far from homogeneous category. It includes hire purchase debt – in fact, often secured on the value of a car or other expensive durable purchase. The duration of such debt can be as long as four years, and the interest rate can sometimes be discounted as part of a purchase package. It also includes personal bank loans, with not dissimilar durations. Student loans, however, tend to have longer durations. These are the main types of closed-end loans. The other important ingredients are in the nature of 'revolving' credit, with short durations. Maki (2001) points out that, in the U.S., revolving credit has grown from around 1 percent of personal disposable income in 1970 to around 8 percent in recent years, now accounting for around 40 percent of total unsecured consumer credit. It seems likely that much of this growth is accounted for by the growth of credit card debt, the rest being largely bank overdrafts up to pre-arranged ceilings. The second difficulty, that of measuring the relevant interest rate, stems from the first. Not only do interest rates differ by type of loan and by lender, but much of credit card debt, where bills are fully paid off monthly, is interest free. The third difficulty, measuring debt-service ratios, which add interest costs to repayment rates, is related. The Bank of England calculates 'official' estimates of debt service ratios, excluding repayments of principle, but only for the last few years, see Financial Stability Review, June 2002, p.82.. As Maki (2000) makes clear, the U.S. estimates are, in part, based on crude assumptions such as that the minimum monthly payment on credit card debt is 2.5 percent of the outstanding debt, and on approximate data on the durations of closed-end loans.

We model unsecured debt as an equilibrium correction model, with the dependent variable, the log change of unsecured debt, Δlog ud. We estimate the equation in the form (5.1), where α_u is the speed of adjustment. For the $x_{jt,}$ which can be given a long-run interpretation, β_j is the long-run coefficient. Note that the x's include variables in Δ form, and so not in the long-run solution. The key component of the ECM, is the log ratio of ud(-1)/income. But the ECM includes other levels effects: log per capita real income, the log nominal interest rate,[14] the real interest rate, interest rate spreads, the rate of return in housing, the log of the ratio of the number of credit cards outstanding to the adult population, log ratios of liquid, illiquid financial and housing assets to income, the proportion of the population in the 20-35 age group, consumer confidence, and various risk indicators discussed above. Dynamic terms included the change in the unemployment rate and a measure of demographic change, which weights age groups by their importance in mortgage borrowing. Table 1a shows the base line model estimated for 1976Q1 to 2000Q4.

The parameter estimates are consistent with almost all the sign priors stated in Section 4, though some effects are insignificant. The most important exception is that, while, as we shall see, the mortgage interest rate has a strong negative effect in the mortgage equation, we were never able to establish a negative effect for an interest rate for unsecured debt, measured either with the credit card rate (from Barclays Bank) or with bank base rates, in the unsecured debt equation. Perhaps this is not surprising in view of the measurement problems described

14 The repayment part of the debt service ratio is implicitly proxied by a constant proportion of the lagged stock itself, already included in the equation.

above. The effect is therefore excluded[15]. However, the interest spread as measured by the credit card rate of Barclays Bank minus the tax-adjusted mortgage interest rate, is highly significant in the unsecured debt equation. Other features of this equation are the long-run income elasticity of around 1.4, despite both the significant CCI effect and a significant effect of the ratio of the number of credit cards outstanding to the adult population. In contrast, the long-run income elasticity is clearly one in the mortgage equation. Expected income growth has a significantly positive effect on unsecured debt, consistent with intertemporal consumption smoothing, while the equivalent effect in the mortgage debt equation is insignificant.

The asset effects suggest a negative coefficient for liquid assets, consistent with out prior. The illiquid financial asset effect is positive, suggesting that the personal sector is more willing to take on unsecured debt when its equity and pension investments are high. The housing wealth effect, however, is close to zero. This may reflect the simple fact that unsecured debt is non-mortgage debt: had housing security been available, the household would have borrowed in the form of cheaper mortgage debt.

No seasonal dummies were significant, not surprising given consumer credit is seasonally adjusted. A dummy consisting of 1 followed by -1 proxies the announcement of coming windfalls from building society demutualisations in 1997. A more permanent change occurred in early 1998, when, as discussed in section 3, mortgage lenders decided to exempt mortgages with LVRs below 0.9 from mortgage indemnity insurance premia. This created an incentive, at the margin, to increase the unsecured component of borrowing and to reduce the mortgage component. According to our estimates, this raised the long-run stock of unsecured credit by 8 percent.

The speed of adjustment is 0.27. This suggests a relatively rapid speed of adjustment or short average loan duration for unsecured borrowing. Our composite indicator, VOL, of interest rate risk and expectations, proxied respectively by recent volatility of inflation and the log of the base rate, and by the yield gap between one-year gilts and base rate, is very significant. This suggests that the climate of low inflation and the stable monetary policy framework of recent years has encouraged borrowing.

The standard error of the equation is around one third of the Chrystal-Mizen unsecured debt equation even after a degree of freedom adjustment, reflecting our richer specification, as well as the use of the Credit Conditions Index. The long-run effect of the latter can be computed by taking its peak value of 0.235 in 2000, multiplying by its long-run coefficient of 2.15 to give 0.503. The implication is that about 0.5 of the rise in the log of unsecured debt from 1980 to 2000 can be attributed to the rise in the CCI. This corresponds to a 65 percent rise.

Tests for serial independence up to the 4th order and homoscedasticity of the residuals are all satisfactory. A check on parameter stability is provided by the last two columns of Table 1a, which shows the estimates over the 1975Q1 to 1990Q4 sample. The standard error is higher

15 Part of the problem may be in not having a good measure of the relevant interest rate on unsecured debt, which is a mixture of credit card debt, bank loans and hire purchase loans. A large and variable part of credit card debt is effectively interest free, to those who pay off their bills every month. For those who do not, credit card rates differ across lenders by large amounts.

for the shorter sample and the great majority of the parameters are under two standard deviations from the full-sample estimates.

5.2 The equation for mortgage debt

There is a large volume of previous research on the determination of the U.K. stock of building society mortgages, but this peters out by the mid-1980s, as the entry of the banks into the mortgage market made this both harder to model and less relevant. Anderson and Hendry (1984), Meen (1985) and Wilcox (1985) are the last significant studies. Meen reviews previous work comprehensively. As he makes plain, all the previous studies took into account that before 1980 mortgage demand had been in an almost continuous excess demand state. Indeed, Meen estimates a measure of excess demand and so the severity of mortgage rationing, MRAT to be the percentage deviation between the flow demand for mortgages and the actual mortgage flow, which is positive for 1963Q1 to 1980Q3, before turning positive.

Meen's model does not give a long-run solution for mortgage demand, though there is a solution for the long-run stock of building society mortgages conditional on the stock of deposits in building societies. Meen's equation for the rate of growth of building society mortgages, estimated for 1963 to 1977, has a standard error of around 0.0026.

Wilcox (1985) follows a different approach. He takes the average LVR for FTBs as an indicator of mortgage rationing, following Kent (1980). The long-run solution for his equation, estimated for quarterly data 1969-1983 on building society mortgages, given the reported standard errors, can be parameterised as follows:

$$\log(bsd/pdi) = \text{constant} + 0.4*\log \text{real pdi} - 0.32*\log abmr + \log \text{housing stock} + 1.4 \log LVR$$

where bsd is the stock of building society mortgages, pdi is personal disposable income, abmr is the tax-adjusted mortgage interest rate, the housing stock is defined as housing wealth scaled by the mix-adjusted house price index and LVR is the average for first-time buyers for building societies. The equation, estimated in equilibrium correction form, also contains dynamic terms in log house prices, the interest rate and LVR and has a coefficient of –0.062 on log bsd(-1), measuring the speed of adjustment. The equation standard error is 0.0029.

We have outlined the relevant variables in our equation for the total stock of mortgage debt in Section 4. The equation has the same general form as eq. 5.2, with the dependent variable Δlog sd, where sd is the stock of mortgages held by the personal sector. After extensive reduction from a more general dynamic specification, we arrive at the model shown in Table 1b. This has a speed of adjustment of 0.062, virtually the same as that estimated for building societies by Wilcox (1985), and about one quarter of that corresponding to unsecured debt.

A key component is log income where, after testing, we impose a long-run coefficient of 1. The long-run coefficient of the log housing wealth to income ratio is 0.58. The long-run coefficient on log abmr is -0.39, close to the estimate of Wilcox (1985). The spread between the credit card rate and the mortgage interest rate has a positive coefficient indicating that a fall in the mortgage rate relative to the credit card rate encourages a switch from unsecured to mortgage borrowing, other things being equal, though the effect is less significant than the parallel effect in the unsecured debt equation. However, the real rate of interest is not significant. The implications are quite important: a decline in inflation, with the real rate constant, reducing nominal rates and the 'front-end loaded' current debt service ratio, will increase mortgage debt. A decline in inflation, with no change in the nominal rate, and so a rise in the real rate, leaves the mortgage debt to income ratio unchanged, even though future debt service ratios are higher than with higher inflation. One could argue that this finding suggests that household suffer from an element of inflation illusion. An alternative interpretation is that low inflation is associated with lower risks of interest rate rises and of income surprises, and that it this, which is encouraging households to carry heavier debt burdens. However, we have already controlled for at least part of this effect though our volatility measures of inflation and interest rates.

The rate of mortgage possessions in the previous three years has a significant negative coefficient. The dynamics include the demographic change variable reflecting changes in population in the key mortgage borrowing age groups, and the four-quarter changes in consumer confidence and the unemployment rate. However, a proxy for income growth expectations, using the actual growth rate of income four quarters ahead, proved insignificant, unlike in the unsecured debt equation, where it had been strongly significant. It seems that mortgage debt is less relevant for intertemporal consumption smoothing at a one-year horizon than is unsecured debt. Our measure of volatility of inflation and interest rates and of interest rate expectations is significant, indicating that mortgage-borrowing is also encouraged by a low volatility environment.

The equation includes seasonals, given the mortgage debt data are not seasonally adjusted, implying that the second and third quarters experience greater mortgage growth. A dummy taking the form of +1 followed by -1 measures the advancement effect of Chancellor Nigel Lawson's announcement in March 1988 that multiple mortgage interest tax relief would be withdrawn on August 1^{st}. The long-run effect of the CCI on mortgage debt can be computed by taking its peak value of 0.233 in 2000, multiplying by its long-run coefficient of 3.28. The implication is that about 0.76 of the rise in the log of unsecured debt from 1980 to 2000 can be attributed to the rise in the CCI. This corresponds to a 114 percent rise.

The equation standard error is 0.00281, without correcting for degrees of freedom. Assuming that 21 degrees of freedom are lost, from the 18 parameters in the function, plus another 3 apportioned to the contribution of that equation in the estimation of the CCI, gives a standard error of 0.0031.[16] This is a little higher than that for Wilcox's model, and even higher than Meen's equation, but since these covered only the more homogeneous building society component of mortgages, this can be considered to be reasonable.

Tests for serial independence up to the 4th order and homoscedasticity of the residuals are all satisfactory. A check on parameter stability is provided by the last two columns of Table 1b, which shows the estimates over the 1976:1 to 1990:4 sample. The asymptotic standard error is slightly lower for the shorter sample, but correcting for degrees of freedom, it is higher. As for the unsecured debt equation, the great majority of the parameters are under two standard deviations from the full-sample estimates.

5.3 The equations for PLIR

16 This suggests that the reported t-ratios in Table 1b should be scaled down by a factor 0.895 to incorporate the degree of freedom correction.

We know of no previous work modelling the proportion of high loan-to-income mortgages to first-time buyers. As noted above, we have data on PLIR, the proportion of FTBs with LIR of 2.5 or over, classified by age (under/over 27) and region (North/South). Our priors for the economic influences on the PLIR equations were set out in detail in Section 3.3. The equation has the form

$$\Delta y_t = a\,(f\,(z_t) + b\,(f\,(z_t) - f_0)^3 - y_{t-1}) \tag{5.5}$$

where y is the log odds-ratio of PLIR, $f(z_t)$ is a linear function of the various drivers of y, and f_0 is the average across age and regions of the maximum observed value of y. When $f(z_t) = f_0$, the long-run value of y is f_0, and near this value the non-linearity is unimportant. However, with β positive, as $f(z_t)$ falls further and further below this value, the cubic term becomes more and more negative, so that y falls below the value otherwise predicted by $f(z_t)$ and y_{t-1}. Without this non-linearity, the model finds it slightly more difficult to capture the low values of PLIR reached in 1980, before credit conditions eased, and at a time of high interest rates and recession. Otherwise, the type of curvature, implied by the log odds-ratio, seems to capture well the behaviour of PLIR

The speed of adjustment α is estimated at 0.38. The coefficient on the CCI is set to the value 10. Note that the CCI coefficient in one equation must be set, to achieve identification, given that the parameters of the spline function, which governs the shape of the CCI are estimated.

The long-run coefficient on the log income/house price ratio is –2.08, though all the negative income effect is offset by the coefficient of 2.65 on log real income, leaving a positive long-run income effect. The implication is that high real house prices tend to force up LIRs, as argued in Section 3.3. The log of the mortgage rate has a strong negative effect with a long-run coefficient close to -1, suggesting that debt-service considerations are relevant for LIR rules followed by lenders and probably for the borrowing motive. But increases in mortgage rates over the previous two years also have a strong negative effect on PLIR. It is possible that the effect being captured is not just on interest rate expectations, since changes in interest rates tend to be positively auto-correlated, but perhaps also on economic conditions in the labour and housing markets. This may be why the change in the unemployment rate and consumer confidence, relevant in the debt equation, prove to be insignificant here. A risk indicator defined as the eight-quarter average of negative housing returns is correctly signed though not significant at the 5 percent level. As discussed further below, the coefficient on our other risk indicator, the 3-year moving average of the rate of mortgage possessions, is set rather than estimated.

The effect of the ISMI dummy, representing the tightening of rules governing income support for unemployed mortgage borrowers, has a negative coefficient, though completely insignificant[17]. The dummy for the 1998 elimination of mortgage indemnity premia for LVRs below 0.9 would be expected to have a larger effect in the PLVR equation. Indeed, its coefficient is negative but insignificant in the PLIR equation, and the term is omitted in this specification.

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[17] Note that the effect of the ISMI dummy, a step dummy 0 before 1995Q2 and 1 from 1985Q3, is hard to distinguish from the effect of D96. We have restricted D96 to zero. We similarly restrict D98 to zero, to improve identification of the mortgage indemnity pricing dummy.

An important consideration when modelling mortgage data, which before 1992, reflects only building societies, is the sample selection issue. When the banks entered the mortgage market in 1980, it is believed that they began by targeting existing current account customers, who would previously have gone to building societies for mortgages. They therefore will have taken customers away from building societies who were, on average, more affluent, with secure jobs, and with larger potential cash deposits. This is likely to have pushed up the proportion of building society customers with small cash deposits - *controlling for the general easing of credit conditions* - and so high LVRs, but lowered the proportion of building society customers with high LIRs. Banks are likely to have given higher LIRs to their own current account customers with secure jobs and a satisfactory banking and credit record. Figures 5 and 6 confirm that PLIR for building societies rose at the time. However, it is likely that PLIR for building societies and banks together, rose by even more. From 1983, data are available on average loans advanced by banks and building societies. The data show average bank loans to be around 30 percent higher than building society loans in 1983-5, but declining to be close to the level of building societies by 1990. For 1980-82, we assume bank advances to be 40 percent higher. We define our proxy for the sample selection bias to be (average bank advance/average building society advance –1)* annual change in the share of banks in total mortgages outstanding, and zero after 1990, when banks and building societies have very similar lending profiles. The change in the share of banks is a proxy for the volume of new advances to FTBs by banks relative to building societies, which is not available. Table 1c confirms a significant negative coefficient for this variable in the PLIR equation.

The sample selection bias for centralised mortgage lenders is also likely to have been important. These entered the market from 1985, obtaining access to customers through financial advisers, estate agents and others because they did not have an established presence on the U.K.'s high streets. Their subsequent mortgage possessions rates were around three times as high as those of the building societies, see Ford (1994), suggesting a riskier lending profile, and hence probably a higher proportion of high LIR and high LVR loans. As they gained market share, the proportion of high LIR and high LVR loans by building societies would have declined - *controlling for the general easing of credit conditions.* Indeed, the annual change in the share of centralised mortgage lenders in total mortgages outstanding has a negative effect in the PLIR equations, though significant only at the 90 percent level.

There are some symptoms of negative first-order residual autocorrelation and of heteroscedastic residuals. The latter can be traced largely to large residuals in 1980, when the proportion of high LVR loans fell to the lowest level in the sample. Our reported parameter estimates do not incorporate a correction for these features, but it would be desirable to do so. A check on parameter stability is provided by the last two columns of Table 1b, which show the estimates over the 1975:4 to 1990:4 sample. The standard error is higher for the shorter sample and, as for the unsecured debt equation, the great majority of the estimated parameters are under two standard deviations from the full-sample estimates.

5.4 The equations for PLVR

The only previous work modelling the proportion of high LVR loans, of which we know, is Muellbauer (1997), though Wilcox (1985) and Muellbauer and Murphy (1993) had modelled the average LVR for FTBs [18]. Muellbauer analyses annual data, on the 11 U.K. regions, for PLVR for 1971-1995, extrapolating missing PLVR data for 1971-3 from average regional LVR data and a simple econometric model. Estimating a model, incorporating a CCI, confirms most of the priors regarding PLVR set out in section 3.4. The equation has the form,

$$\log(\mathrm{PLVR}/(1-\mathrm{PLVR}))_t = \underset{(9.0)}{0.33}^* \log(\mathrm{PLVR}/(1-\mathrm{PLVR}))_{t-1} - 0.083^*\log(hp_{it}/pc_t)$$

$$+\underset{(6.1)}{0.33}^*\Delta\log ry_{it} - \underset{(6.1)}{0.16}^*\Delta\log hp_{it} - \underset{(12.7)}{1.88}^* abmr_{it} + \underset{(4.9)}{0.48}^*\Delta\log pc_{it} + \underset{(2.8)}{0.08}^*\Delta(\mathrm{Gallup}/100)_t$$

$$-\underset{(6.5)}{0.15}^*\mathrm{arorse}^{**}t\text{-}1 + \underset{(2.3)}{0.12}^*\mathrm{rorsem}^{**}t\text{-}1 \qquad (5.6)$$

Here, hp refers to the house price in the ith region, pc is the consumer expenditure deflator for the U.K., ry is real regional non-property income, abmr is the tax-adjusted mortgage interest rate using the ith region tax adjustment, Gallup is the Gallup Poll measure of consumer confidence in December of the previous year, and arorse** and rorsem** are risk factors defined further below. Absolute values of t-ratios are shown in parentheses.

Thus, the log real house price index and its nominal rate of change have negative coefficients; the growth rate of income has a positive coefficient; the nominal interest rate has a negative coefficient, while inflation has a positive effect, suggesting an element of real as well as nominal interest rate effects. The annual change in an index of consumer confidence has a positive coefficient, while two risk indicators based on the rate of return in housing in the South East have the expected signs.

These indicators are defined as follows: let rorse be the rate of return in housing in the South East, defined as Δlog hpse – abmr, where hpse is the official mix-adjusted house price for the South East, including London, and abmr is the tax adjusted average mortgage rate for the U.K. scaled by 100. Let arorse be the absolute value of rorse and rorsem be zero if rorse is positive and equal to rorse if rorse is negative. Now define a Koyck lag by

$$\mathrm{arorse}^{**}_{t-1} = \mathrm{arorse}_{t-1} + 0.8^*\mathrm{arorse}_{t-2} + (0.8)2^*\mathrm{arorse}_{t-3}, \qquad (5.7)$$

and a similar lag in rorsem. These terms have respectively a negative coefficient, suggesting that greater volatility of returns dampens the proportion of high LVRs, and a positive coefficient, suggesting that a recent history of negative returns also dampens high LVRs.

As is acknowledged in Muellbauer (1997), one defect of the estimated model is that it fails to deal with the sample selection problem, so that the estimated CCI turns down temporarily in 1983 and 1987.

Turning to the current study, an equilibrium correction model for the log odds ratio of PLVR was specified in a similar form to that for PLIR discussed above, and incorporates a similar non-linearity through a cubic term, which, however, proved insignificant. Again, there are

18 Wilcox, however, does not control for market conditions, except through the ratio of building society deposits to building society mortgages, a proxy for the societies' liquidity.

fixed effects by age and region. The speed of adjustment at 0.54 is quite similar to that of the PLIR equations. The long-run CCI coefficient is estimated at 21.4 and is highly significant. The coefficient on the log income/house price ratio is 0.55 and significant, consistent with the posited negative real house price effect. The rate of growth of house prices also has the posited negative effect. The log mortgage rate enters with a four-quarter moving average, with a highly significant negative coefficient, and there is also a significant negative 'shock' effect of the current change in the mortgage rate, perhaps also forecasting further rises in rates. The real mortgage rate has a negative coefficient, but completely insignificant, and so omitted here. The VOL term, which captures volatility of inflation and interest rates and short-term interest rate expectations, is highly significant and its coefficient is about twice as large as in the PLIR equations. The three-year moving average of the mortgage possessions rate was relevant, as an indicator of perceived mortgage risk, in the two aggregate debt equations. It is also significant, with the expected negative coefficient, in the PLIR equations.

The log ratio of aggregate unsecured debt to income in the previous quarter has a negative coefficient, which we interpret as reflecting the greater ability to access unsecured debt, to help fund housing purchase deposits, at least indirectly. Note that, since this ratio depends positively on the CCI with a long-run coefficient of 2.16, and enters here with a coefficient of –2.34, the effect of the CCI from this source is around –5. The long-run coefficient of CCI in the PLVR equation is 21.4. Combining the two effects, gives a net long-run effect of CCI on PLVR of 16.4 rather than 21.4.

The step dummy for 1998Q1, which captures the abandonment of mortgage indemnity insurance payments for those with LVRs below 0.9, has a strong negative coefficient. As expected, this pricing shift created an incentive for borrowers over this threshold to bring their LVRs below 0.9, and so pushed down PLVR. The 1995 ISMI dummy also has a significant negative coefficient, reflecting the increased risks faced by borrowers, with the tightening of income support for the unemployed with mortgage commitments. The effect is substantially larger than for the PLIR equations, for no obvious reasons.

As Figures 7 and 8 illustrate, PLVRs for older borrowers tend to be substantially lower than for younger borrowers, while the PLIR differences are much less pronounced. Clearly younger borrowers have had less opportunity to save for a deposit. From the early 1990s, there has been a substantial rise in the average age of FTBs.[19] Since the under 27 category is bounded by the age 27, the rise has been more noticeable in the over 27 age group. One would expect this to account for some of the downward drift in PLVRs in the second half of the 1990s. Indeed, when we enter the deviation in the average age of the over 27 group in each quarter from the average over the whole sample, we find a significant negative coefficient.

Finally, to turn to the sample selectivity proxies discussed in Section 5.3, the proxy for banks, where the prior is unclear, is insignificant, but a negative coefficient for centralised mortgage lenders is consistent with prior expectations. Thus, when the downmarket centralised mortgage lenders gained market share in the second half of the 1980s, this pulled down the

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19 It is noteworthy that 'first-time buyer' is defined as someone whose previous tenure was not in owner-occupation. Some in this category may therefore have had a spell as owner-occupiers, returned to renting, before switching back, see Holmans (2001).

PLVRs reported for building societies. This effect is not enormous, however, and significant only at the 90 percent level.

Tests for serial independence up to the 4th order and homoscedasticity of the residuals are all satisfactory. A check on parameter stability is provided by the last two columns of Table 1d, which shows the estimates over the 1976Q1 to 1990Q4 sample. The standard error is higher for the shorter sample and, as for the other debt equations, the great majority of the parameters are under two standard deviations from the full-sample estimates.

5.5 The estimated VOL

To define inflation volatility, we first define $a\inf_t = abs(\Delta_4 lpc_t - \Delta_4 lpc_{t-4})$ where lpc is the log of consumer expenditure deflator, and abs( ) indicates the absolute value. Then, $ainfma4_t + 0.5\ ainfma4_{t-4}$ defines inflation volatility, where ma4 is the 4-quarter moving average. To define interest rate volatility, we first define $albr_t = abs(\Delta_4 lbr_t)$, where lbr is the log of the base rate. Then $albrma4_t + 0.5\ albrma4_{t-4}$ defines interest rate volatility. One year ahead interest rate expectations are measured by $spread1_t$ = yield on 1 year $gilts_{t-1} - br_t$, where br is the base rate and the yield is the end of quarter definition. Then, we define

$$\begin{aligned} VOL = v_1(a\inf ma4_t + 0.5aimfm4_{t-4}) + v_2(albrma4_t + 0.5albrma4_{t-4}) \\ + v_3 \text{ spread1}_\text{t} \end{aligned} \tag{5.8}$$

where the v_i's are parameters. We also checked for longer lags in the 4-quarter moving averages of volatility and for the 5 and 10 year spreads, but none of these were significant. As noted above, the coefficient on VOL needs to be fixed for one equation to identify the v_i's. We fix the coefficient in the LIR equation at 10 so that we expect the v_i's to be negative. The results are in Table 1e. The most significant of the three terms is v_1: a fall in inflation volatility has sizeable positive effects on both types of debt and on the proportion of high LVRs and LIRs. Our measures of interest rate volatility and of interest rate expectations are of more marginal relevance.

5.6 The estimated CCI

Table 1f shows estimates of the parameters of the CCI function. Note that the last quarter of 1980 marks the start of the rise in CCI, handled by a 4^{th} quarter dummy. Otherwise, piecewise linear splines, shifting in quarter one of each year, are used to model CCI. These are constructed by defining step dummies for each year, stepping from 0 to 1 in the first quarter. The 4-quarter moving average converts the step into a trend going from 0 at the end of the previous quarter to 1 at the end of the current quarter, thenceforth remaining at 1. We estimate the coefficients on each of these terms, subject to the restriction that, in the 1980-89 and 1995-2000 periods, no negative reversals take place: such reversals can be ruled out given the institutional background set out in Section 2. These restrictions imply a zero coefficient in 1983. As noted above, a zero restriction was also imposed on the coefficients in 1996 and in 1998 to help identify the effects of ISMI (income support for mortgage interest) and the MIP dummy (for the change in pricing of mortgage indemnity insurance).

Without this restriction, the CCI would have risen in 1998, standing marginally higher in 2000.

To account for possible variations in CCI before 1980, we include the 4-quarter change of the consumer credit controls dummy. This is likely to reflect the stance of the authorities to expansion of credit more generally. Its coefficient is negative and significant. We also investigated the mortgage-rationing indicator, MRAT, from Meen (1995) for the period up to 1980 Q3, after which the CCI dummies begin to operate. The coefficients are *positive* for the current value and lags up to two quarters, and significantly so at a lag of one quarter. This suggests, perversely, that greater rationing is associated with higher values of debt growth and looser ceiling on LVRs and LIRs. In our view, this casts some doubt on the short run dynamics of Meen's indicator, though it does show a fall at the end of 1980 and remains low, indicating an easing of rationing. One other possibility, which we have not investigated, is to use a liquidity ratio for building societies up to 1980Q3 for the same purpose.

Figure 9 graphs the estimated CCI, showing also the real tax-adjusted mortgage interest rate[20]. As noted, the steepness of the fall between 1990 and 1993, and of the subsequent recovery depends on the calibrated values of the possessions effects in the PLIR and PLVR equations. Thus, under other assumptions, we could have obtained a smaller fall and subsequent rise than the one illustrated here. Figure 9 also plots the CCI, which results when the possessions coefficients are set to zero in the PLIR and PLVR equations. As can be seen, the fall between 1990 and 1993 is more pronounced, as is the subsequent recovery. Otherwise, the overall shape of the CCIs is similar.

An important question concerns the downturn in the CCI from 1990, reaching a trough in 1993, before turning up again. One might ask whether this is a genuine credit supply shift, or reflects the risk perceptions and negative outlook on both sides of the market during this period when mortgage possessions ran at the highest levels since records begin. We control for risk perceptions as noted above, and the consumer confidence indicator and income growth should control for economic conditions, but one cannot be entirely sure that these controls are adequate. The description of the evolution of credit conditions given in Section 1 suggests that the biggest source of a downward supply shift was the change in mortgage indemnity insurance contracts available to lenders. In the post-war period, there had never before been a time of sustained falls in nominal house prices, and with hindsight, the insurers had severely under-priced credit risk in the late 1980s. However, the result of these misperceptions was that, for given economic conditions, mortgage borrowers had had greater access to credit in the 1987-89 period than in 1990-94. For modelling consumption, house prices, housing turnover and subsequent mortgage defaults, this does seem to point in the right direction.

6. Empirical results: interaction effects with the Credit Conditions Index

[20] And so helping to explain, given the positive correlation in the early 1980s, why it is common to find weak or perversely signed real interest rate effects in mortgage equations, which omit a CCI effect.

Sections 3.2 to 3.4 have outlined the economic variables impacting on loan-to-income and loan-to-value ratios for first-time buyers, as represented by the eight series on PLIR and PLVR, and Section 4 the economic variables acting on aggregate unsecured and mortgage debt to income ratios. As explained in Section 3.2, the effect of the altered credit supply environment, linked to the institutional changes discussed in Section 1, is introduced in each equation through the Credit Conditions Index, CCI, common to all ten equations. In addition, in the unsecured debt equation, we incorporate the ratio of the number of credit cards outstanding to the number of adults, to capture changes in credit supply not reflected in CCI, the latter being more tuned to the mortgage market. In Section 5, we presented estimates of this 10-equation model, in which the CCI enters as an additive effect in each equation[21]. We now consider a range of interaction effects.

With more liberal credit conditions, housing collateral is likely to receive a larger weight in the mortgage equation and liquid assets an even more negative one. And since intertemporal substitution should have been more important as a motive for borrowing, the real interest rate and expected income growth should play a bigger role as CCI rises, see Aron & Muellbauer (2000) for the parallel effects on consumption. Meanwhile, income uncertainty should have a less negative effect on debt and consumption as CCI rises, since with more liberal credit availability, temporary income downturns can be managed by additional borrowing.

As far as the PLIR and PLVR equations are concerned, one might expect also that the real interest rate and expected income growth should play a bigger role as CCI rises for similar demand side reasons and because of lenders' views on the ability of households to repay. It seems likely that the nominal interest rate would play a smaller role since, in a more liberal credit regime, refinancing is likely to be easier as a possible escape route, to ease pressure on cash flows when nominal rates rise. As far as average house price/income ratios are concerned, one might expect the negative effects in the PLVR equations to moderate somewhat as CCI rises since, in a more liberal credit regime, lenders will have taken a more relaxed attitude to the risk of house prices falling. The effect on the PLIR equations is less clear, *a priori*.

Extending the model to include these interaction effects is fairly straightforward. Estimation is more difficult, as the complexity of the model generates local peaks in the likelihood function. This is particularly so when the CCI interacts with an I(1) variable. It is also important to demean the variables whose interactions with the CCI are to be estimated, since otherwise arbitrary shifts in the intercept roles of the CCI will take place. In Table 2, we present estimates of a model with interaction effects, after some insignificant terms have been eliminated.

The unsecured debt equation alters little. Income growth expectations were already significant and the interaction with the CCI adds nothing. Interacted with the CCI, the real interest rate now has a marginal negative effect. In the mortgage debt equations, however, the changes are bigger, though even interacted with CCI, the real interest rate is still not significant. The mortgage risk proxy, the possessions rate, still has a negative coefficient, but

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[21] This corresponds to a concept Hendry (1999) has termed 'co-breaking'**.** The CCI represents the intercept-equivalent effect of the structural breaks associated with financial liberalisation. When the effect is additive in each equation, then by taking a simple linear transformation of pairs or other combinations of equations, it is possible to eliminate the effect of the structural breaks.

is not insignificant. The interaction of the CCI with the change in the unemployment rate is positive, reducing the negative impact of rising unemployment on mortgage debt. This suggests that great credit availability reduces the effect of income uncertainty on debt. The biggest effect, however, is the interaction of CCI with the log ratio of housing wealth to liquid assets. This implies that when CCI is zero, the point estimate of the long-run elasticity of housing wealth on mortgage debt is 0.18. At the CCI peak of 0.234, the point estimate has risen to 0.86

In the PLIR equation, the interaction effect with CCI suggest a small reduction in the effect of the income to house price ratio - though we had no prior on the direction of this effect. As expected, the composite nominal interest rate effect is reduced as CCI rises, while the interaction with the real interest rate is negative. This suggests that, as refinancing becomes easier, the front-end-loading problem associated with a rise in nominal rates matters less, but a rise in real rates matters more. However, given that an income growth expectations effect already appears, the extra effect when CCI rises is negligible.

In the PLVR equations, the interaction effect with CCI implies a roughly 40 percent reduction in the log (income/house price) effect suggesting a reduced concern over future house price falls. As in the PLIR equations, the negative effect of nominal interest rates on the proportion of high LVR loans shrinks somewhat as credit conditions ease, while the negative real interest rate effect expands. There is also a notable interaction of income growth expectations with credit conditions, as theory predicts, though it is not very precisely estimated.

The shape of the estimated CCI, estimated with the interaction effects discussed, is not very different from the one coming from the base specification of Section 5. Figure 10 plots the two against each other. The log-likelihood of the equation system improves by 22 when the interaction effects are included and the goodness of fit of all the individual equations improves, notably the mortgage equation, where the asymptotic equation standard error falls from 0.00281 to 0.00253.

7. Conclusions

We have estimated an index of non-price credit conditions facing households in the 1976-2000 period. The index was derived as a common factor in ten credit indicators subject to broad priors, consistent with the historical account of financial deregulation and other developments in Section 2. Two of the ten credit indicators were aggregate unsecured debt and mortgages (secured debt). The remaining eight consisted of the fractions of high loan-to-income and high loan-to-value mortgages for UK first-time house buyers split by age and regions. Around 1m individual observations from the Survey of Mortgage Lenders, and its predecessor, were aggregated to produce the 832 data points in these eight indicators. To ensure that, as far as possible, our CCI is not subject to the criticism that it is endogenous, we have tested for and included, where relevant, an exhaustive set of economic controls. Working with such general specifications was only made feasible by careful consideration of sign priors to ensure the estimation of meaningful relationships. The economic controls included nominal and real interest rates, a measure of interest rate expectations and of inflation and interest rate volatility, mortgage risk indicators, house prices, income, income growth expectations, the change in the unemployment rate, demography, consumer confidence, portfolio wealth components, proxies for sample selection bias and various institutional features.

Effectively, by construction, our CCI should be independent of these controls. For a major rise in CCI to be sustainable, rational lenders should either have priced in the possible risk consequences, or be using better credit screening methods, or be able to offload the risks more easily on other financial institutions perhaps because of more efficient system-wide risk sharing, or be prepared to experience an increase in losses on their household lending portfolios, or some combination of the above. It is true, as we have seen, that real interest rates on mortgage lending rose sharply in the early 1980s, paralleling the rise in the CCI, and consistent with the first of these points. Research by one of us, with Gavin Cameron, on possessions rates for a large mortgage lender does suggest an improvement in the 1990s not explicable by the distribution of LVRs and changes in the economic environment. The increased use of securitisation of mortgage loans in recent years is a sign that risk sharing may be more extensive than previously. However, whether all lenders are fully rational is questionable, see Herring(1999) for an analysis of herd behaviour and myopic tendencies of banks. Hoggarth and Pain(2002), suggest that provisioning policy by UK banks has a relatively short horizon, anticipating formal accounting write-offs by about two years. Since the latter lag behind loan losses, the horizon appears to be under two years. The fact that we are unable to find any very significant real interest rate effects in any of our ten equations, suggests that lenders, like borrowers, are fixed on short term cash debt-service ability. This suggest systematic neglect of the longer term outlook for the debt service burden in an economic environment, where real interest rates are likely stay relative high, but coinciding with weak nominal income growth.

Be that as it may, major applications of the CCI will be in modelling aspects of personal sector behaviour including consumption, the demand for money, the housing market and mortgage default rates. If it is argued that our CCI includes influences other than the supply-side evolution of consumer credit conditions in the UK - perhaps some gradual evolution in preferences regarding risk - which we have not controlled for, then the same influences will be omitted from extant models of consumption etc. The empirical usefulness of the CCI is therefore not compromised. And as long as the future evolution of the CCI is gradual, which seems to have been the case in recent years, it will be extremely useful in producing forecasting models.

The empirical literature on the effects of financial liberalization on U.K. consumption does not always find significant or plausible effects. Despite some early successes, by Bayoumi(1993a,b), Muellbauer and Murphy(1993), Darby and Ireland (1994), Caporale and Williams (1997), and Sarno and Taylor(1998), more recently Fernandez-Corugedo and Price (2002)[22] find no role for financial liberalisation, and Bandiera et al (2000) find mixed results for a group of developing countries. Aron and Muellbauer (2000) suggest two reasons for this: poor measurement of financial liberalization or of credit conditions indicators, and an

[22] Darby and Ireland found that the degree of financial liberalisation, measured by Muellbauer and Murphy's (1993) FLIB indicator had a significant role in a forward-looking consumption function for the United Kingdom estimated over the period 1969 Q1 to 1990 Q2. Caporale and Williams use the same methodology as Darby and Ireland at extending their sample to 1995 Q4 and find that FLIB continues to explain consumption behaviour. Fernandez-Corugedo and Price (2002) extend the sample to 1998 Q4 but find that FLIB does not help to explain consumption behaviour in the United Kingdom.

inappropriate empirical model, particularly differencing data, as in Euler equations, so removing long-run information. They argue that the CCI has three effects in a consumption function: an intercept effect, an interaction effect with housing wealth, and interaction effects with uncertainty, growth expectations and the real interest rate. They estimate a credit conditions index, using institutional priors, from a two-equation debt and consumption system. Their results suggest that in South Africa, beginning in 1983, credit conditions for consumers were liberalized progressively and that this played a major role in explaining rises in debt to income and consumption to income ratios, despite the absence of any house price boom in this period.

If similar results are obtained for the U.K., we can expect a faster speed of adjustment and more sensible and precise estimates of interest rate and wealth effects, including lower housing wealth effects, than in current U.K. consumption functions[23].

As far as the interpretation of recent conditions is concerned, in recent years the percentage of loan-to-value ratios of 0.9 or over and of loan-to-income ratios of 2.5 or over appear to have been at relatively moderate levels. One of the most striking implications of our findings is that this may give too reassuring an impression of the exposure both of households and of mortgage lenders to risk. Garratt and Panel (2001) address the related issue of whether credit standards have again fallen by marshalling evidence from the SML. They note the downward drift in the proportion of high LVR loans and the moderate rise in aggregate mortgage/income ratios, though there is some upward drift in high loan-to-income loans, particularly in London in 1997- 2000. However, they acknowledge the lack of household data on unsecured lending, which by 2000 had reached twice the ratio relative to GDP attained in the late 1980s. This leaves some concerns that households and lenders with both mortgage and unsecured loan books might be exposed to a down-turn in the economic environment, for example, caused by a fall in the exchange rate and a subsequent rise in interest rates.

Our econometric evidence is that an index of credit supply conditions, is indeed at an all-time peak. And note that we have controlled for the effects of low nominal interest rates and the low inflation and interest rate uncertainty environment of recent years, as well as for other features of economic conditions. Moreover, we have evidence that borrowers have been substituting unsecured debt for mortgage debt at the margin, to bring down loan-to-value ratios to levels below 0.9, where mortgage loan terms are more favourable. However, given a relatively benign view of interest rate prospects, as well as changes in the composition of first-time buyers, and probably, improvement in credit scoring methods[24], it seems unlikely that the underlying situation is as risky as it was in 1988-9. Between 1988 and 1990, the base rate rose from a trough of 7½ percent to 15 percent. A rise from 4 percent to 8 percent, the current equivalent, appears a remote possibility, particularly in the context of weak global demand conditions.

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[23] Earlier work by Muellbauer and Murphy (1993) incorporated interaction effects but not the intercept role of a credit conditions index.

[24] Unpublished research (Cameron and Muellbauer) for a large lender on possessions data by vintage of loan is consistent with a significant improvement in lending quality in the 1990s.

Data Appendix

The following appendix explains how our data set was constructed.

A. National data

- Non-property income (LY). These series are nominal and seasonally adjusted. Its construction is based on the guidelines produced in the Medium Term Macro Model by the Bank of England, pages 58 and 62. More specifically the formula to construct the series is given by the following ONS series: (rpqk-royl+royt-nrjn+royh) where rpqk denotes total disposable income, royl is property income received, royt is property income paid, nrjn is households gross operating surplus including gross mixed income and royh is mixed income. Effectively, LY is personal disposable income (pdi) minus pre-tax property income (propy). However, pdi - (1-tp)* propy would have been more appropriate, where tp is the unobserved tax rate on property income. Thus, if npdi is the desired measure of personal disposable non-property income,

  $\log npdi \cong \log LY + tp*propy/LY.$

  We do not have good estimates of tp and take a proxy for tp to be 0.5*(total direct taxes paid by households/personal income). Since part of property income is untaxed imputed rent and since other parts of interest income are untaxed, it seems likely the tax rate on property income is lower than the average tax rate on all income, hence the 0.5 factor. It seems likely that this is closer to the true value than the value of zero, implicitly assumed by the Bank.

- Unsecured debt (UD). These series, defined as consumer credit, come from the Bank of England's Monetary and Financial Statistics publication, code vzri in Table 6.1. Because the series are only available from 1987 we spliced them to 1975 using the consumer credit series analysed by Chrystal and Mizen(2001). The series are nominal and seasonally adjusted.

- Secured debt (SD). These series come from the ONS code amwt (see Financial Statistics, Table 3.2). The data are nominal and not seasonally adjusted.

- Consumer confidence. These series come from GfK, and represent the total balance, that is the sum of the percentage of positive responses minus that of negative responses, adding personal confidence about one's own finances and also confidence about the economy.

- Liquid Assets . These are defined as nnmp.q+nnmy.q, the sum of currency and deposits plus securities other than shares and are nominal and not seasonally adjusted (see table AA64 in Economic Accounts for more). Prior to 1987, the equivalent series are given by the old ONS codes aldo-rewg-amwv-aqhg-reyx-akui-aldj-rhht-amxf-rraq.

- Illiquid Financial Assets. Defined as the difference between total financial assets (definitions aldo.q (old ONS code) and nnml.q (new ONS code found in table AA64) in Economic Accounts) and liquid assets (defined above). The series are nominal and in current prices.

- Housing Wealth. Housing wealth is constructed by Bank staff and is nominal and seasonally adjusted. The end-of-year figures coincide with ONS data from the personal sector balance sheets.

- Price deflator (PC). This is the consumer price deflator obtained by dividing nominal by real consumption from the ONS.

- Unemployment rate. These series comes from Labour Market Statistics.

- The after tax mortgage rate. Series constructed by housing market analysts at the Bank of England. They build in a tax adjustment based on Inland Revenue estimates of the cost of mortgage interest tax relief.

- Population of working age. These series come from the ONS's Monthly Digest of Statistics and Labour Trends.
- The minimum lending rate.
- Hire purchase controls measure. This measure was used in the HM Treasury models of the 1980s.
- The change in demographic demand component. These series are defined as in Muellbauer and Murphy 1997. They apply SML fractions of new mortgages accounted for by different age groups to the population growth rates of each age group.
- The number of credit cards divided by the population of working age (CREDO). The number of credit cards in circulation come from the British Banking Association.
- Rate of return in housing. It is defined as the yearly change in house prices minus the after tax mortgage rate plus 0.02, an estimate of imputed rent minus taxes and maintenance costs as a proportion of the value of a dwelling.
- Demutualisation dummy. This is a dummy for expected windfalls from demutualisation of building societies in 1995 and takes the value 1 in 1995Q1.
- Mortgage Indemnity Premium Dummy. Step dummy for abolition of the premium from 1998Q1.
- Lawson dummy. Dummy for 1988's budget announcement that multiple tax relief would be abolished on August 1st, and restricted to one relief per property. The dummy is 0.25 in 1988Q2 and 1 in 1988Q3, and otherwise zero.
- Possessions . The series comes from CML's housing finance. They are the annual number of possessions divided by the number of mortgages outstanding.
- House prices (HP). Series from the Department of the Environment, Transport and the Regions.

B. Regional data

We first briefly define the main sources for our regional data, the Survey of Mortgage Lenders and the New Earnings Survey and then describe the data series in some detail.

B1. Data extracted from SBSM/SML

B1.1. Characteristics of SBSM/SML

The Survey of Building Society Mortgages (SBSM) and Survey of Mortgage Lenders (SML) were originally commissioned by Department of the Environment to construct a mix-adjusted house price series. These surveys are available in electronic format for the years 1975 to 2000 from the Data Archive at the University of Essex. Unfortunately, the year 1978 is missing and, though the data are in the archives of the Dept. of the Environment, Local Government, Transport and the Regions, they were unwilling to release it to us.

A structural break occurs in the surveys in 1992 Q2. Prior to that date, the survey only included Building Societies (the Abbey National being the exception as it is included after it became a Bank in 1988). The transformation of the Abbey National to a bank prompted the creation of the Council of Mortgage Lenders (CML) in June 1989. This led to the modification, in 1992 Q2, of the SBSM to accommodate all members of the CML, not only Building Societies.

The surveys correspond to the response of 5 percent of all loans granted (by Building Societies prior to 1992 Q2 and by all lenders thereafter). The questionnaire provides detailed information on the following characteristics:

- the loan amount,
- the price of the house at completion,
- the income of the borrower(s),
- the age of the borrower(s),
- the region where the house was purchased,
- the previous tenure of the borrower(s) (whether it is a first-time buyer, or an owner-occupier),
- whether price discounts were obtained (through right to buy schemes),
- the interest rate on the mortgage,
- the length of the mortgage,
- the number of borrowers (prior to 1983 the electronic records do not permit extraction of the number of borrowers),
- the sex of the borrowers,
- the type of the dwelling (such as a detached, semidetached, bungalow, etc)
- number of rooms.

B1.2. Variables extracted

From the SBSM/SML we obtained the quarterly series:

a) proportion of loan to value ratios in excess of 90 percent (PLVR)
b) proportion of loan to income ratios in excess of 2.5 (PLIR)
c) after tax mortgage interest rate

These series correspond to first time buyers only and exclude those receiving price discounts or those under the right to buy scheme. Moreover, each of these variables is constructed by region and age group (see below for more). These three series are derived after taking the following steps:

1) We first omit observations where relevant data are missing (such as age, income, house price, or information about price discounts or the previous tenure of the household).
2) We discard local authority and housing association tenants buying a house with a price discount.
3) We omit all sitting tenants not covered under 2).
4) We split the data into two age categories, those under 27 and those aged 27 and over.
5) We further split the data into those living in the South (defined as the regions Greater London, South East, South West and East Anglia) and the North (the rest of UK regions).
6) From this sub-sample of the data set, we construct PLVR, PLIR and the after tax mortgage rate.

The loan to value ratio is defined as the amount advanced by the lender divided by the house price.

The loan to income ratio is defined as the advance granted by the lender divided by the income or incomes of the borrowers (where appropriate).

The derivation of the after-tax mortgage rate is given by the following formula:

abmr=(x*bmr*(1-t)+(advance-x)*bmr)/advance

where x is the amount of the loan for which the tax discount is applicable (eg there was a maximum of 25000 from 1974 to 1983 and 30000 from 1983), bmr is the interest rate paid on the mortgage, advance relates to the advance made by the lending institution, and t is the appropriate tax rate for each individual (from 1991-93 it is just 25 percent, 20 percent in 1994, 15 percent from 1995, 10 percent from 1998 and zero from 2000).

B2. Extraction of NES data

The New Earnings Survey (NES) is an annual survey based on national insurance records providing comprehensive information about earnings and hours data each April. From an electronic file for 1975 to 2001, data were extracted on weekly earnings for full-time manual and non-manual men, and for women workers by age and region (North/South). The data in the electronic file are more complete than the data published each year in the annual reports of the NES.

B3. Regional income variable from NES, SBSM/SML; regional house prices

Construction of the Divisia index for regional income by age is done in the following steps:

1) Using the earnings data from the NES, we aggregate non-manual and manual men for each age and region using the following formula:

   0.75*non-manual earnings + 0.25*manual earnings to give men's earnings.[i]

2) For each age and region we construct couple's earnings as

   0.5*(men's earnings + women's earnings).

3) From 1983 onwards we have weights for each age and region of single men, single women and couples. These weights are obtained the SBSM/SML data sets and only include first time buyers and exclude individuals who have a price discount (see above).

4) We assume that the pre-1983 weights for males, females and couples are the same as the 1983 weights.

5) The average annual earnings index for each region and age is constructed as follows:

   average earnings = (female weight * female earnings) + (couple weight * couple earnings) + (male weight * male earnings)

6) We then construct the Divisia index using the previous year's weights across the 3 types of buyers - single men, single women and couples- making sure these weights add to one. We do this for each of the regions and age groups. The index is benchmarked to 1986.

7) To obtain quarterly series, we interpolate the data using the monthly average earnings index for Great Britain.

Regional house price data came from the mix-adjusted series published by the Dept. of Local Government, Transport and the Regions. These indices are scaled to the average value of first-time buyers’ dwellings in 1995.

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GLOSSARY of abbreviations

loan-to-value ratio (LVR)
loan-to-income ratio (LIR)
first-time buyer (FTB)
percentage of FTBs with loan-to-income ratios of 2.5 or more (PLIR)
percentage of FTBs with loan-to-value ratios of 0.9 or more (PLVR)
Credit Conditions Index (CCI)
income support for mortgage interest (ISMI)
inflation and interest rate volatility and expectations (VOL)

arameter estimates for the log change in unsecured
JD

	Variable	Sample 1976Q1-2000Q4		Sample 19
	Variable	**Coefficient**	**Absolute t-ratio**	**Coefficient**
	speed of adjustment	0.268	10.2	0.224
	Intercept	-0.053	0.2	-0.802
	CCI	2.16	4.9	2.48
	income growth (+4)	0.490	3.5	1.052
	Spread	-1.19	5.9	-1.12
	Demutualisation dummy	0.152	6.4	-
	MIP dummy	0.078	5.3	-
	log real income	0.367	2.5	0.811
	Δ_4 log base rate	-0.025	2.0	-0.020
	rate of return housing	0.258	4.1	0.372
	Asymmetric housing risk	0.359	3.3	0.063
	log liquid assets (-1)/income	-0.570	3.1	-0.568
	log illiquid financial assets (-1)/income	0.068	1.6	0.180
	log housing assets (-1)/income	0.004	0.1	0.065
	log proportion of credit cards (-2)	0.179	4.0	0.097
	rate of possessions ma12	-0.080	4.3	-0.268
	VOL (volatility of inflation etc)	3.217	3.6	4.632
	Std. Error of regression	0.00585		0.00616
	R-squared	0.900		0.812
	LM heteroscedasticity test	2.78 [P=0.096]		3.66 [P=0.056]
	Durbin-Watson	2.18		2.31
	LM AR4 test	F=0.87 [P=0.48]		

arameter estimates for the log change in secured (mortgage) debt, Dlogsd

		Sample 1976Q1-2000Q4		Sample 19
	Variable	**Coefficient**	**Absolute t-ratio**	**Coefficient**
	speed of adjustment	0.062	6.6	0.041
	Intercept	2.208	2.2	5.17
	Credit Conditions Index	3.263	4.4	5.61
	Spread	0.918	2.2	1.23
	seasonal 1	-0.064	4.6	-0.121
	seasonal 2	0.019	1.6	0.058
	seasonal 3	0.045	3.3	0.074
	Lawson dummy	0.263	4.2	0.331
	log adjusted mortgage interest rate	-0.394	4.4	-0.617
	Δ_4 consumer confidence index	0.00155	2.8	0.0099
	Δ_4 unemployment rate	-0.023	3.3	-0.005
	log liquid assets (-1)/income	-1.33	3.2	-2.30
	log illiquid financial assets(-1)/income	0.076	1.0	-0.173
	log housing assets(-1)/income	0.576	5.8	0.483
	Δ ldemography	11.7	2.9	-
	ISMI dummy(-1)	-0.175	3.4	-
	rate of possession ma12	-0.129	2.3	-
	VOL (volatility of inflation etc)	2.85	2.7	12.9
	Std. error of regression	0.00281		0.00265
	R-squared	0.961		0.865
	LM heteroscedasticity test	0.13 [P=0.72]		0.63 [P=0.43]
	Durbin-Watson	1.79		1.82
	LM AR4 test	F=0.47 [P=0.75]		1.82

arameter estimates of log odds ratio of PLIR (proportion of loan-to-income for FTBs of 2.5 or more

		Sample 1976Q1-2000Q4		Sample 1976Q	
	Variable	**Coefficient**	**Absolute t-ratio**	**Coefficient**	
	speed of adjustment	0.382	13.6	0.355	
	Intercept for NY	-24.3	6.8	-31.780	
	Intercept NO	-24.6	6.6	-32.423	
	Intercept SY	-23.7	6.5	-31.411	
	Intercept SO	-24.0	6.3	-31.780	
	CCI	10 (fixed)	-	10 (fixed)	
	share of couples	-0.640	2.2	-0.903	
	log income/HP	-2.08	9.3	-1.95	
	log UD (-1)/income	-2.34	6.8	-2.28	
	log mortgage rate	-0.892	5.0	-1.25	
	Δ_4 log mortgage rate	-0.564	2.7	-0.04	
	Δ_4 log mortgage rate(-4)	-0.380	3.2	-0.18	
	log real income	2.65	7.9	3.51	
	Income growth (+4)	1.24	1.9	1.83	
	Negative rate of return ma8	0.691	1.8	-	
	ISMI dummy(-1)	-0.150	1.2	-	
	Sample selection banks	-0.215	4.8	-0.159	
	Sample selection cent. lenders	-0.081	1.9	-0.096	
	Rate of possessions ma12	-0.43	2.9	0 (fixed)	
	VOL (volatility of inflation etc)	10 (fixed)	-	10 (fixed	
g	Std. error of regression	0.136		0.147	
	R-squared	0.972		0.952	
	LM heteroscedasticity test	11.9 [P=0.001]		10.8 [0.001]	
	Durbin-Watson	2.55		2.75	
	LM AR4 test	F=2.11 [P=0.86]			
	Std. error of regression	0.154		0.179	
	R-squared	0.971		0.953	
	LM het. Test	36.3 [P=0.000]		23.4 [P=0.000]	
	Durbin-Watson	2.62		2.67	

	LM AR4 test	F=4.14 [P=0.004]			
g	Std. error of regression	0.138		0.145	
	R-squared	0.973		0.972	
	LM het. Test	5.6 [P=0.18]		4.3 [P=0.037]	
	Durbin-Watson	2.15		2.04	
	LM AR4 test	F=0.96 [P=0.43]			
	Std. error of regression	0.125		0.147	
	R-squared	0.977		0.973	
	LM het. Test	27.0 [P=0.000]		17.0 [P=0.000]	
	Durbin-Watson	2.56		2.62	
	LM AR4 test	F=2.30 [P=0.064]			

arameter estimates for log odds ratio of PLVR (proportion of loan-to-value for FTBs of 0.9 or more

		Sample 1976Q1-2000Q4		Sample 1976Q	
	Variable	**Coefficient**	**Absolute t-ratio**	**Coefficient**	
	speed of adjustment	0.544	15.9	0.440	
	Intercept for NY	-1.503	1.5	-0.447	
	Intercept for NO	-2.31	2.2	-1.168	
	Intercept for SY	-1.97	1.9	-2.616	
	Intercept for SO	-2.81	2.6	-1.179	
	CCI	21.4	6.2	22.7	
	log income/HP	0.553	2.8	0.320	
	log UD(-1)/income	-3.11	5.1	-2.354	
	log mortgage rate ma4	-1.22	6.3	-0.977	
	Δ log mortgage rate	-1.12	3.8	-0.153	
	Δ_4 log HP	-0.876	3.0	-0.98	
	ISMI dummy(-1)	-0.660	4.0	-	
	MIP dummy ma2	-0.190	2.8	-	
	Sample selection banks	-0.033	0.5	-0.15	
	Sample selection cent. lenders	-0.092	1.7	-0.095	
	age deviation for old	-0.0355	4.1	-0.044	
	Rate of possessions ma12	-0.49	2.5	0 (fixed)	
	VOL (volatility of inflation etc)	24.1	4.3	42.5	
g	Std. error of regression	0.125		0.117	
	R-squared	0.989		0.986	
	LM heteroscedasticity test	1.70 [P=0.19]		0.04 [P=0.84]	
	Durbin-Watson	1.80		1.60	
	LM AR4 test	F=0.40 [P=0.81]			
	Std. error of regression	0.117		0.142	
	R-squared	0.973		0.971	
	LM heteroscedasticity test	0.03 [P=0.87]		4.1 [P=0.043]	
	Durbin-Watson	1.68		1.57	
	LM AR4 test	F=1.94 [P=0.11]			
g	Std. error of regression	0.120		0.130	

	R-squared	0.977		0.979	
	LM heteroscedasticity test	0.03 [P=0.87]		0.37 [P=0.54]	
	Durbin-Watson	1.92		1.68	
	LM AR4 test	F=0.47 [P=0.76]			
	Std. error of regression	0.148		0.180	
	R-squared	0.962		0.952	
	LM heteroscedasticity test	0.19 [P=0.66]		0.37	
	Durbin-Watson	1.77		1.65	
	LM AR4 test	1.81 [P=0.14]			

arameter estimates for interest rate volatility and expectations

		Sample 1976Q1-2000Q4		Sample 1976Q
	Variable	**Coefficient**	**Absolute t-ratio**	**Coefficient**
	Inflation volatility	-0.685	4.1	-0.426
	Interest rate volatility	-0.024	2.2	-0.017
	1 year gilt yield minus base rate	-0.00062	2.0	-0.390

= [v_1*(inflation vol ma4+0.5*ma4(-4)) + v_2*(log base rate vol ma4 +0.5*ma4(-4)) + v_3*spread]

ırameter estimates for CC

	Sample 1976Q1-2000Q4		Sample 1976Q1- 1990Q4	
	Coefficient	Absolute t-ratio	Coefficient	Absol
	0.020	4.6	0.019	
	0.065	6.0	0.065	
	0.020	3.2	0.004	
	0.019	3.8	0.019	
	0.022	4.5	0.020	
	0.023	4.1	0.016	
	0.016	3.2	0.021	
	0.019	3.3	-	
	0.011	2.0	0.0095	
	-0.007	1.3	-0.005	
	-0.014	2.6	-	
	-0.025	4.4	-	
	-0.0002	0.0	-	
	0.038	3.9	-	
	0.008	2.0	-	
	0.011	2.4	-	
	0.007	1.6	-	
ıtrols	-0.00138	3.6	-0.00152	

ı.s 4-quarter moving average of step dummy=0 before year T, and 1 from quarter 1 of year T.
ıstep dummy 0 up to 1980Q3, 1 thereafter. CCI is the linear combination of coefficients and dummies.

arameter estimates for the log change in unsecured debt, D log UD

		Sample 1976Q1- 2000Q4	
	Variable	**Coefficient**	**Absolute t-ratio**
	speed of adjustment	0.286	10.3
	Intercept	-0.605	1.9
	CCI	2.57	3.8
	Income growth (+4)	0.574	4.2
	Spread	-0.943	5.0
	Demutualisation dummy	0.137	6.2
	MIP dummy	0.071	5.0
	log real income	0.518	3.5
	CCI* real base rate(-1)	-0.041	2.0
	Δ_4 log base rate	-0.008	0.6
	rate of return in housing	0.215	3.6
	Negative rate of return ma8	0.283	2.5
	log liquid assets (-1)/income	-0.504	3.0
	log illiquid financial assets (-1)/income	0.064	1.6
	log housing assets (-1)/income	0.090	1.9
	log proportion credit cards (-2)	0.126	2.5
	rate of possessions ma12	-0.104	5.4
	VOL (volatility of inflation etc)	9.22	1.2
	Std. error of regression	0.00608	
	R-squared	0.894	
	LM heteroscedasticity test	2.04 [P=0.154]	
	Durbin-Watson	2.03	
	LM AR4 test	F=0.09 [P=0.97]	

arameter estimates for the log change in secured (mortgage) debt, Dlog sd

		Sample 1976Q1- 2000Q4	
	Variable	**Coefficient**	**Absolute t-ratio**
	Speed of adjustment	0.084	7.5
	Intercept	2.32	4.3
	Credit Conditions Index (CCI)	4.23	4.1
	Spread	0.464	1.7
	Seasonal 1	-0.047	5.1
	Seasonal 2	0.019	2.3
	Seasonal 3	0.037	4.1
	Lawson dummy	0.190	4.9
	log adjusted mortgage interest rate	-0.286	4.8
	Δ_4 consumer confidence index	0.0083	2.0
	Δ_4 unemployment rate	-0.022	2.2
	CCI*Δ_4 unemployment rate	0.111	1.4
	log liquid assets (-1)/income	-0.906	3.4
	log illiquid fin assets (-1)/income	0.012	0.2
	log hous. assets (-1)/income	0.165	1.2
	CCI*log hous. assets (-1)/liq assets(-1)	2.83	2.7
	Δ ldemography	6.78	2.3
	ISMI dummy (-1)	-0.101	2.8
	rate of possession ma12	-0.022	0.5
	VOL (volatility of inflation etc)	8.33	1.2
	Std. error of regression	0.00254	
	R-squared	0.968	
	LM heteroscedasticity test	0.02[P=0.879]	
	Durbin-Watson	1.96	
	LM AR4 test	F=0.42 [P=0.79]	

arameter estimates of log odds ratio of PLIR (proportion of loan-to-income forFTBs of 2.5 or more)

		Sample 1976Q1- 2000Q4	
	Variable	**Coefficient**	**Absolute t-ratio**
	Speed of adjustment	0.412	14.3
	Intercept for NY	-5.54	0.7
	Intercept NO	-5.23	0.7
	Intercept SY	-4.59	0.6
	Intercept SO	-4.28	0.5
	CCI	10 (fixed)	-
	Share of couples	-1.56	4.1
	log income/HP	-2.80	8.4
	CCI*log income/HP	3.21	2.7
	log UD (-1)/income	-0.961	2.2
	log mortgage rate	-1.72	5.4
	Δ_4 log mortgage rate	-0.69	2.2
	Δ_4 log mortgage rate(-4)	-0.52	3.0
	CCI*composite mortgage rate	-3.30	3.2
	CCI*real mortgage rate(-1)	-0.411	2.1
	log real income	1.20	1.8
	Income growth (+4)	0.94	1.1
	Negative rate of housing return ma8	0.659	1.8
	ISMI dum(-1)	-0.253	2.5
	Sample selection banks	-0.172	3.9
	Sample selection centralised lenders	-0.102	2.4
	rate of possessions ma12	-0.43(fixed)	-
	VOL (volatility of inflation etc)	10 (fixed)	-
g	Std. error of regression	0.132	
	R-squared	0.974	
	LM heteroscedasticity test	13.3 [0.000]	
	Durbin-Watson	2.54	
	LM AR4 test	F=1.90 [P=0.12]	
	Std. error of regression	0.153	

	R-squared	0.972	
	LM heteroscedasticity test	33.2 [0.000]	
	Durbin-Watson	2.52	
	LM AR4 test	F=2.49 [P=0.049]	
g	Std. error of regression	0.133	
	R-squared	0.975	
	LM heteroscedasticity test	5.4 [0.020]	
	Durbin-Watson	2.11	
	LM AR4 test	F=0.87 [P=0.49]	
	Std. error of regression	0.125	
	R-squared	0.978	
	LM heteroscedasticity test	30.6 [0.000]	
	Durbin-Watson	2.63	
	LM AR4 test	F=2.79 [P=0.031]	

ortgage rate =(log mortgage rate*coeff + Δ_4 log mortgage rate*coeff +Δ_4 log mortgage rate(-4)*coeff)

arameter estimates for log odds ratio of PLVR (proportion of loan-to-value forFTBs of 0.9 or more)

		Sample 1976Q1- 2000Q4	
	Variable	**Coefficient**	**Absolute t-ratio**
	speed of adjustment	0.547	15.7
	Intercept for NY	-0.182	-0.1
	Intercept for NO	-0.182	-0.1
	Intercept for SY	-2.159	2.1
	Intercept for SO	-1.716	5.1
	CCI	23.6	4.5
	log income/HP	0.87	3.5
	CCI*log income/HP	-2.04	2.2
	log UD(-1)/income	-2.35	3.7
	log mortgage rate ma4	-1.70	5.1
	Δ log mortgage rate	-1.93	4.4
	CCI*composite mortgage rate	-3.45	2.9
	Δ_4 log HP	-0.339	1.8
	CCI*income growth(+4)	7.75	0.9
	ISMI dummy(-1)	-0.76	2.5
	MIP dummy ma	-0.57	3.8
	Sample selection banks	-0.0004	0.1
	Sample selection centralised lenders	-0.125	2.4
	age deviation for old	-0.027	2.8
	rate of possessions ma12	-0.49(fixed)	-
	VOL (volatility of inflation etc)	50.2	1.3
g	Std. error of regression	0.116	
	R-squared	0.981	
	LM heteroscedasticity test	1.84 [0.175]	
	Durbin-Watson	1.94	
	LM AR4 test	F=0.05 [P=0.995]	
	Std. error of regression	0.119	
	R-squared	0.972	
	LM heteroscedasticity test	0.02 [0.876]	

	Durbin-Watson	1.56	
	LM AR4 test	F=2.99 [P=0.023]	
g	Std. error of regression	0.117	
	R-squared	0.978	
	LM heteroscedasticity test	0.28 [0.59]	
	Durbin-Watson	1.99	
	LM AR4 test	F=0.37 [P=0.81]	
	Std. error of regression	0.155	
	R-squared	0.959	
	LM heteroscedasticity test	0.04 [0.839]	
	Durbin-Watson	1.59	
	LM AR4 test	F=2.81 [P=0.030]	

ortgage rate = (log mortgage rate ma4*coeff +Δ log mortgage rate*coeff)

arameter estimates for interest rate volatility and expectations

		Sample 1976Q1- 2000Q4	
	Variable	**Coefficient**	**Absolute t-ratio**
	Inflation volatility	-0.260	1.2
	log base rate volatility	-0.015	1.2
	Spread: 1yr gilt yield-base rate	-0.00016	0.9
	CCI interaction	-3.74	3.1

= [v_1*(inflation vol ma4+0.5*ma4(-4)) + v_2*(log base rate vol ma4 +0.5*ma4(-4)) + v_3*spread]*
where inflation and interest volatility and the spread have means for 1980Q4-2000Q4 subtracted.

ırameter estimates for CCl

	Sample 1976Q1- 2000Q4	
dentifier	**Coefficient**	**Absolute t-ratio**
	0.015	4.0
	0.039	4.3
	0.025	3.9
	0.021	4.1
	0.024	4.0
	0.019	3.6
	0.013	2.8
	0.008	1.6
	0.008	1.8
	-0.005	1.4
	-0.016	2.8
	-0.016	3.3
	0.009	2.1
	0.031	3.5
	0.012	2.5
	0.002	0.6
	0.009	2.1
ıtrols	-0.00067	2.4

s 4-quarter moving average of step dummy=0 before year T, and 1 from quarter 1 of year T.
step dummy 0 up to 1980Q3, 1 thereafter. CCI is the linear combination of coefficients and dummies.

tegory does not make the distinction between manual and non-manual workers.