

“Modelling and Forecasting Mortgage Delinquency and Foreclosure in the UK.”

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Abstract: In the absence of micro-data in the public domain, new aggregate models for the UK’s mortgage repossessions and arrears are estimated using quarterly data over 1983-2014, motivated by a conceptual double trigger frame framework for foreclosures and payment delinquencies. An innovation to improve on the flawed but widespread use of loan-to-value measures, is to estimate difficult-to-observe variations in loan quality and access to refinancing, and shifts in lenders’ forbearance policy, by common latent variables in a system of equations for arrears and repossessions. We introduce, for the first time in the literature, a theory-justified estimate of the proportion of mortgages in negative equity as a key driver of aggregate repossessions and arrears. This is based on an average debt-equity ratio, corrected for regional deviations, and uses a functional form for the distribution of the debt-equity ratio checked on Irish micro-data from the Bank of Ireland, and Bank of England snapshots of negative equity. We systematically address serious measurement bias in the ‘months-in-arrears’ measures, neglected in previous UK studies. Highly significant effects on aggregate rates of repossessions and arrears are found for the aggregate debt-service ratio, the proportion of mortgages in negative equity and the unemployment rate. Economic forecast scenarios to 2020 highlight risks faced by the UK and its mortgage lenders, illustrating the usefulness of the approach for bank stress-testing. For macroeconomics, our model traces an important part of the financial accelerator: the feedback from the housing market to bad loans and hence banks’ ability to extend credit.

Key words: foreclosures, mortgage repossessions, mortgage payment delinquencies, mortgage arrears, credit risk stress testing, latent variables model.

JEL codes: G21, G28, G17, R28, R21, C51, C53, E27

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1. Introduction

A record number of UK households (cumulatively 3 percent of mortgage borrowers, containing perhaps one million individuals) suffered mortgage reposessions (foreclosures) in the 1990s, following the house price and credit boom of the 1980s. Payment arrears (delinquencies) also reached record proportions. A subsequent boom ending in mid-2007 again increased the proportion of households with overstretched budgets and over-extended debts relative to their assets. At its peak in early 2009, however, the UK reposessions rate reached only about half that of the 1990s reposessions peak. By comparison, the US foreclosure rate¹ peaked at 4.6 percent in 2010, around ten times the 2009 UK rate and far above previous US peaks. A deeper UK reposessions crisis was avoided mainly through dramatic monetary policy interventions, lenders' forbearance policy and increased government income support for those with payment difficulties. With low inflation and a flexible exchange rate, a key difference from 1990-92, the Bank of England's policy interest rate (base rate) was brought down rapidly to half a percentage point. This lowered mortgage rates given the predominance of adjustable rate mortgages in the UK.

Fluctuations in UK reposessions (annualised) and arrears rates are shown in Figure 1, using data from the Council of Mortgage Lenders². The flow into reposessions peaked in 1991, at an annual equivalent rate of 0.8 of one percent of the number of mortgages. The arrears rates peaked in 1993 (proportions of mortgages with greater than 6 months or greater than 12 months payment arrears), two years after the reposessions peak of 1991. The lag can partly be attributed to a shift in government policy and coordinated efforts by mortgage lenders from the end of 1991 to exercise forbearance (Muellbauer and Cameron, 1997).³ The policy shift reduced the reposessions rate, but the count of mortgages in arrears rose. There are strong parallels between these earlier and the later (2008-9) government interventions and suasion on lenders towards leniency.⁴

A careful study of the aggregate data is pertinent in the UK given the paucity of micro data on mortgage defaults in the public domain. By contrast with a long history of US empirical literature on borrower mortgage default or lender foreclosure, the set of UK empirical studies on repossession and arrears is strikingly limited. Reviews of the US

¹ The US data measure the total number of mortgage loans in the foreclosure process at year-end, not quite comparable to the UK measure. It exceeds the number of households affected as one household can have several mortgages and not all foreclosure proceedings end in the loss of the home.

² Characteristics of the available data on UK mortgage reposessions and arrears are documented in an appendix table in Aron and Muellbauer (2010).

³ Policies then included the shift to direct payment of income support to mortgage lenders and a Stamp Duty holiday, in return for a collective agreement by lenders to exercise leniency.

⁴ Later policy shifts included more generous Support for Mortgage Interest, the Mortgage Pre-action Protocol from November 2008, and other measures (Wilson, 2014).

literature into the 1990s on mortgage default and delinquency (e.g. Quercia and Stegman, 1992) and a special focus on empirical testing of option theoretic models of default (Vandell, 1995), reveal even then a wealth of micro-data⁵ based studies from both lender and borrower perspectives. The limited quality and availability of corresponding micro-data sets in the UK has constrained the possible analyses. The only micro-candidate for a random sample is the British Household Panel Study (BHPS), but these data are sparse and untimely, and there are problems drawing aggregate implications from them (section 2.2). This accounts for the small number of (predominantly macro-based) empirical studies, employing a hybrid of the recent default/delinquency theories in reduced form regression models (Table 1).

Even in the U.S., despite the now widespread availability of loan level data, it can be argued that analysis of aggregate data is useful.⁶ Loan level datasets in the U.S. do not equal the universe of all loans. Securities data cover only a subset of the market, which before 2002 was a small subset; service data is broader, but is only reliable from 2005 later, and covers only two-thirds of the market. For a long national time series, the only option is the Mortgage Bankers Association National Delinquency Survey (NDS), from the early 1970s, but which only provides the sort of aggregates we use for the UK. With a combination of Federal Housing Finance Agency (FHFA) price indices (back to the 1970s), the Federal Reserve Financial Obligations Ratio (back to 1980) and the NDS, one could construct a model of delinquency for the U.S. going back at least as far back as 1980. There are, however, limits with aggregated data. The stability of national house price indices can conceal dramatic regional variation.

Using UK data on aggregate mortgage repossessions and mortgage arrears, we present new quarterly models for forecast simulations. The fundamental economic drivers in our models are the debt-service ratio (the product of the mortgage interest rate and the level of debt divided by disposable income), negative equity and the unemployment rate. We devise an innovative “latent variables” method for modelling lending standards and forbearance policy as a type of “residual” (i.e. going beyond what is measurable such as the extent of negative equity and unemployment rates). Arrears and repossessions are estimated jointly in a system of equations together with ‘loan quality/credit access’ (the *LQ* function) and forbearance policy proxies (the *FP* function). The *LQ* indicator measures the impact on current rates of repossessions and arrears of variations in earlier lending standards, in access to refinancing, and in government income support for borrowers with payment difficulties.

⁵ The underlying data sets include individual/family loans and their characteristics from Freddie Mac, Federal Housing Administration, Department of Veteran Affairs, Federal Home Loan Bank Board, Morgan Guarantee Insurance Corporation and other banking institutions or institutional bodies (e.g. Mortgage Bankers Association) or Savings and Loans by US states. Panel data sets of income dynamics e.g. by the University of Michigan have also been employed.

⁶ We are grateful to a referee for this point.

The *FP* proxy captures “leniency” of lenders that lowers the rate of repossession but raises the rate of arrears. The *LQ* and *FP* functions are mainly linear combinations of time dummies. Cross-equation constraints are imposed on the arrears and repossessions equations through the common *LQ* and *FP* functions. This latent variables approach improves on the widespread use of loan-to-value measures for first mortgages as indicators of loan quality, as these are not comparable over time and omit further advances of credit.

Our second innovation is the theory-justified use of an estimate of the proportion of mortgages in negative equity, calibrated to micro data, which is based on the ratio of average mortgage debt to average home prices, with a correction for regional deviations. A third innovation is the systematic treatment of a measurement bias in the published “months-in-arrears” statistics, previously neglected in modelling studies. Finally, the universal assumption in previous UK studies of a proportional relationship between repossessions and arrears is relaxed in our system. By including proxies for ‘loan quality/credit access’ and forbearance policy, just five variables are needed in the parsimonious empirical model to explain the history of arrears and repossessions over 1983-2014 and to assess future trends.

The aggregate implications of defaults are important for understanding the feedback loops in the financial accelerator⁷ missing in standard macro-econometric models. We discuss this issue further in the conclusions. Our models allow the separation of various factors contributing to the evolution of arrears and repossessions. In the 1990s, the persistence of negative equity prevented a faster decline in repossessions, despite lower interest rates and the forbearance policy introduced at the end of 1991. Post 2009, the repossessions rate was lowered and stabilized by radical reductions in mortgage rates in 2009 and greater income support for those with payment difficulties, while negative equity was somewhat less persistent than in the 1990s.

The next section develops a model for the economic drivers of aggregate repossessions and arrears using a double trigger framework for foreclosures and payment delinquencies, and discusses the UK empirical literature on defaults. Estimation methodology and the empirical specification are presented in section 3. Data issues, including the formulation of the latent variables, the *LQ* and *FP* functions, are discussed in section 4. Section 5 presents results for a joint estimation of arrears and repossessions with proxy functions for ‘loan quality/credit access’ and forbearance policy. Section 6 illustrates with forecast scenarios to the end of 2020. Section 7 concludes.

⁷ For a discussion of the feedback of bad loans on credit availability and feedback loops via residential construction and consumption, illustrated by the US sub-prime mortgage crisis, see Duca et al. (2010).

2. The Economic Drivers of repossessions and Arrears

2.1 Conceptual Framework: the Double Trigger Model for Defaults

There is general agreement that mortgage defaults or repossessions result from a mix of excessive debt relative to home equity, and cash flow problems. This is consistent with the ‘double trigger’ approach to modelling of defaults, a more general view of mortgage repossession than the option pricing approach (popular in some of the US literature, see Kau et al. (1992) and Deng et al. (2000), and applied to UK data by Ncube and Satchell (1994)). In the option pricing model, default is chosen by the household once housing equity falls below the mortgage debt level by a given percentage, which depends mainly on house price uncertainty. Even in the US, where mortgages in many states are non-recourse loans⁸, doubt has been cast on this ‘ruthless default’ literature (Vandell, 1995). Recent empirical literature also encompasses cash flow problems, for example, Gerardi et al. (2008), Foote et al. (2008), Bhutta et al. (2010) and Fuster and Willen (2012).⁹ Appendix A gives a brief overview of the evolution of the US empirical literature on mortgage default and delinquency.

A thorough early exposition of a double trigger model is by Elmer and Seelig (1998). Abstracting from variations in interest rates and cash flows, default for household i at time t , due to a *weak net equity position* can be triggered when

$$\log(\text{mortgagedebt}_{it} / \text{equity}_{it}) > \tau_{it} \quad (1)$$

where the threshold τ_{it} depends positively on the expected growth rate of house prices, given transactions delays, and also on house price volatility.

Default can also occur because of *cash flow problems*, when a function of the debt-service ratio exceeds a threshold. But such default depends also on the credit worthiness of the household, its employment status and its expected income growth. This can be expressed by a second trigger function combining the debt service ratio and these factors, being positive. However, even when there are cash flow problems, it makes little sense for a household with *positive* net housing equity to default. With positive equity, such households may have refinancing possibilities or could sell the home rather than lose it through repossession. With the possibility of refinancing, therefore, combining both these triggers, a plausible default condition therefore is:

⁸ In non-recourse loans, the lender's rights are restricted to the equity in the home, excluding recourse to the borrower's income or other assets

⁹ For example, Foote et al. (2008) show that in their 1990s sample of Massachusetts home owners, more than 90 percent of those in negative equity continued to make mortgage payments. Fuster and Willen (2012) show that reductions in interest rates in adjustable rate mortgages have a dramatic effect on the foreclosure hazard even in the presence of negative equity.

$$\begin{aligned} f(\text{debt service ratio}_{it}, \text{ur}_{it}, \text{cs}_{it}, \Delta y_{it}^e) &> 0 \\ \text{and } \log(\text{mortgage debt}_{it} / \text{equity}_{it}) &> \tau_{0t} \end{aligned} \quad (2)$$

where ur is the household's unemployment rate, cs its credit score and Δy^e represents its expected income growth. The parameter τ_{0t} is likely to be negative since significant positive equity is likely to be needed for refinancing, while transactions costs need to be covered when selling.

Default in the double trigger model occurs if *either* condition (1) *and/or* condition (2) are fulfilled. Default due to a weak net equity position can occur even if the household does not have cash flow problems. This is particularly relevant in the US where, in states such as California, borrowers have a 'walk away' option so that their liability is confined to the value of the home. In the UK, unlike the US, it is likely that relatively few repossessions cases arise through condition (1) alone, as the consequences of repossession are more painful in the UK. Mortgage borrowers can be pursued for up to six years for negative equity after the lender has sold a home in repossession (contrasting with non-recourse mortgage loans and 'walk away' options in much of the US). The double trigger inherent in condition (2) is thus the more relevant for most UK repossessions.

The above, incorporating idiosyncratic error terms, defines a probability model specified for an individual. Averaging over heterogeneous individuals generates the *aggregate* proportion of defaults. Without knowledge of the distributions of observables and unobservables, the functional form of the relationship between the aggregate proportion of defaults and the means of the observables is unknown, but in general will be non-linear. With knowledge of or plausible assumptions on the micro-level distributions of the observables (such as the debt/equity ratio) and of the unobservables (such as tastes) ¹, individual hazard rates could be aggregated into the aggregate proportion of defaults, as a function of the *means* of the observables and of the *parameters* of the distributions. There is an important common element in conditions (1) and (2) involving a threshold for $\log(\text{mortgage debt/equity})$. Although c_{0t} is expected to be a little below zero (e.g. from transactions costs), while option pricing theory implies c_{it} would be a little above zero (e.g. there is a small probability that equity might recover with volatile house prices), the proportions of households satisfying each condition should be highly correlated with the proportion in *negative equity* (i.e. the proportion for whom $\log(\text{mortgage debt/equity})$ exceeds zero).

With negative equity closely correlated with the trigger conditions, it is important to estimate aggregate negative equity. On specific assumptions, it would be possible to derive a simple relationship between the proportion of households with negative equity in terms of the means of the distribution, the mean debt and the mean equity. Suppose, for example, that

mortgage debt and equity have log-normal distributions; then the log (mortgage debt/equity) is also normally distributed. The proportion of mortgages with negative equity is then given by the normal distribution function: $F(\mu, \sigma; 0)$, with the mean of log (mortgage debt/equity) denoted by μ and its standard deviation by σ . As the mean of the distribution shifts to the right, the area under the tail increases proportionately *more* than does the mean, suggesting the proportion with negative equity is highly non-linear relative to the mean. For the log-normal distribution, there is a simple relationship between the mean of log debt, which we do not observe, and the log of mean debt, which we do observe (and, correspondingly for the mean of log equity and the log of mean equity). This relationship implies a simple intercept adjustment where the size of the adjustment depends on the variances of debt and equity.¹⁰ Applying this relationship to the logistic function, a good approximation to the normal, the distribution function will imply:

$$\begin{aligned} \text{proportion of negative equity} &= 1 / (1 + \exp(-\lambda (\text{mean logdebt/equity}))) \\ &= 1 / (1 + \exp(-\lambda (\log(\text{mean debt/mean equity}) - \lambda_0))) \end{aligned} \quad (3)$$

where λ_0 is half the difference in the variances of log debt and log equity. Given data on the ratio of mean debt to mean equity, and distributional parameter estimates based on micro data of the proportion of households with negative equity, the coefficients λ and λ_0 could be calibrated to match the estimated proportion of negative equity to the micro data. In the application below we generalize the term in the exponential bracket to a cubic (rather than a linear) function.

The next step is to derive an expression for the aggregate proportion of repossessions based on condition (2) that incorporates aggregate negative equity. The probability of default associated with condition (2) can be written as the product of the probability of ‘bad (debt/equity)’ and the probability of a ‘bad cash flow and related aspects’ given ‘bad (debt/equity)’. Modelling the probability in logs, that is with the aggregate log repossessions rate, results in an additive model in logs. If the two events in condition (2) were independent, the log repossessions rate would simply be given by a function of (debt/equity) plus a function of the means of the variables appearing in the cash flow function. This would suggest a log-linear approximation, in which the log repossessions rate is driven by the log of the unemployment rate, the log of the debt-service ratio, the expected growth rate of income, the log of the imputed proportion with negative equity, and an aggregate ‘loan quality/credit access’ indicator (in the absence of data on the aggregate credit score).

The reasoning just set out for modelling the repossessions rate can be adapted for modelling mortgage arrears or ‘payment delinquencies’. The count of mortgages exceeding a

¹⁰ To be specific, it is well-known that if X is log normally distributed, then $\log(EX) = E \log(X) + 0.5 \text{var}(\log(X)) = \mu + 0.5\sigma^2$, where E is the expectations operator, and μ and σ are the mean and standard deviation of X .

threshold level of arrears (such as 6 months of regular payments, or 5 percent of mortgage debt) measured relative to the total number of mortgages, should be governed by a less stringent version of condition (2). If the threshold is exceeded there are one of four outcomes: repossession; partial (or full) repayment in order for arrears levels to fall below the threshold; the sale of the property; or refinancing. The last two options may be blocked by low net equity. Thus, the proportion of mortgages in negative equity is likely to have a significant effect on the arrears count, though with a smaller relative weight (compared to the debt-service ratio and unemployment) than in the repossessions equation. While a poor debt-equity ratio is a necessary condition for repossession for rational households, arrears can arise without the household necessarily being close to negative equity.

2.2 *Micro- versus macro-data in the analysis of UK repossessions and arrears*

The UK literature on arrears and repossessions is summarized in Table 1¹¹. Repossessions models tend to be sequential or simultaneous models with arrears (Breedon and Joyce, 1992; Brookes et al., 1994; Allen and Milne, 1994; Cooper and Meen, 2001). None attempts to measure and use negative equity. Some work is flawed by incorrect measurement of variables¹². When modelling repossessions conditional on arrears, all impose the constraint that in the long run, the flow of repossessions moves in proportion to the number of households in long-term arrears. This is a questionable restriction, see below. Notably, the non-linearity linking the debt-equity ratio with defaults is neglected in all aggregate UK studies. Moreover, shifts in lenders' forbearance policy, shifts in credit constraints and changing lending quality are usually omitted, though some of the dummies used by Cooper and Meen (2001) can be interpreted this way. Indeed, econometric studies of aggregate mortgage possession data, such as Breedon and Joyce (1992), Brookes et al. (1994) and Allen and Milne (1994), estimated on data up to 1990 or 1991, break down on later data. There is some limited treatment of credit factors (e.g. Whitley et al. (2004) in modelling arrears find a role for competing unsecured borrowing (via credit card arrears)). A rise in the loan-to-value ratio for new first-time buyers *reduces* the level of arrears in the short run, suggesting that the loan-to-value ratio acts as a proxy for refinancing opportunities for those facing risk of delinquencies. The short-run role of the loan-to-value ratio as a proxy for refinancing opportunities and its long-run role as a proxy for one aspect of lending quality (with opposite signed effects), can produce apparently contradictory findings in different studies with loan-to-value controls.

¹¹ There are other types of quantitative study not summarised here e.g. by Ford (1993), who analyses borrower characteristics of repossessions and in arrears using data from one major lender.

¹² Two examples are that unwithdrawn equity is measured by Brookes et al. (1994) as net equity divided by the number of mortgages, a *nominal* variable. Figueira et al. (2005) correctly use the ratio of net equity to the stock of debt, but define the debt service ratio as mortgage payments divided by *real*, instead of nominal disposable income.

A small sub-set of the UK studies use semi-aggregated or micro data sets. The determinants of *regional* repossessions are explored by Muellbauer and Cameron (1997), Cooper and Meen (2001) and Aron and Muellbauer (2011), using regional repossession court orders for England and Wales. Lambrecht et al. (1997, 2003) employ *proprietary* data on individual mortgages supplied by a mortgage insurance company. Their 1997 study extends the traditional option theoretic approach to examine both ability-to-pay and equity variables influencing default, finding that the former variables have more influence on default than the latter. Their 2003 study examines similar influences over the timing of delinquency and repossessions, using a hazard model. The loan-to-value ratio was found to be *positively* associated with time to default; this was rationalized by the increased use of second mortgages, when initial loan-to-value ratios were low, with a higher ultimate probability of default. The sample used is not random, consisting only of a set of defaulting borrowers. The available data limit borrower characteristics to the loan-to-value ratio, salary, marital status and the interest rate, measured at point of mortgage origination (on ensuing drawbacks, see Cooper and Meen (2001)). Theoretical and empirical ambiguities in the role of the loan-to-value ratio in micro-studies are replicated in macro studies. Two principal *micro-data* surveys offer some housing-related information. The Survey of English Housing (SEH), operating since 1993, covers about 20,000 households, and is a series of cross-sections not a panel. It is rich in information on individual characteristics, but is not suitable to analyse trigger events (Cooper and Meen, 2001). Burrows (1998) use the SEH to analyse mortgage arrears with a logit model, as a function of borrower and lender characteristics, measured not at time of origination or default but in the current sample wave.

Other studies use the British Household Panel Survey (BHPS), an annual survey since 1991, covering approximately 10,000 individuals in 5,000 households (extended since 1999). The BHPS sample under-represents some types of households; the repossessions data are too sparse to make full use the panel structure (see Cooper and Meen, 2001); some variables are poorly measured; and the history is too short to identify complex, time-varying influences, such as policy variations. Even with pooling, Cooper and Meen suggest that a focus on owner-occupiers alone would generate only 46 default observations (during 1991-2000).

3. Empirical specification and methodology

Empirical models for repossessions and arrears are motivated by the double trigger approach outlined in section 2.1. The models utilize dummy-based equations capturing difficult to measure institutional changes in lending quality and forbearance policy. The timing and shapes of these institutional dummies are discussed in section 4.

The models for repossessions and arrears are formulated in general equilibrium correction form, illustrated as follows for the log repossessions rate:

$$\begin{aligned} \Delta \log poss_t = & \kappa^p (a_0 + \sum_{l=1}^3 a_l X_{l,t} + a_4 LQ_t + a_5 FP_{t-1} - \log poss_{t-1}) + \sum_{l=1}^3 \sum_{j=0}^k \alpha_{l,j} \Delta X_{l,t-j} \\ & + \alpha_4 \Delta LQ_t + \alpha_5 \Delta FP_t + \sum_{j=1}^k \phi_j \Delta \log poss_{t-j} + \varepsilon_t \end{aligned} \quad (4)$$

The dependent variable is the quarterly change in the log repossessions rate.¹³ The equilibrium correction term is defined in terms of levels of the key drivers in a vector X of variables, and the ‘loan quality/credit access’ and forbearance policy functions, LQ and FP . Worse loan quality or credit access *increases* LQ ; harsher policy on forbearance *increases* FP . The set of X variables includes an estimate for the proportion of mortgages in negative equity, the log mean debt-service ratio, and the log unemployment rate. The speed of adjustment to long run equilibrium is κ^p . The long-run relationship between the log repossessions rate and the long-run X variables, and LQ and FP policy functions, is thus:

$$\log poss = (a_0 + \sum_{l=1}^3 a_l X_l + a_4 LQ + a_5 FP) \quad (5)$$

The equilibrium correction form is a small generalization of the standard partial adjustment model of $\log poss$ towards this target. The ΔX_l terms, ΔLQ and ΔFP in equation (4) can be thought of as shifts in time of the dating in the target components $a_l X_l$, LQ and FP . The lagged $\Delta \log poss$ terms could arise if, for example, adjustment is for span of two quarters for some market participants and for one quarter for others.

The two arrears models have a broadly similar structure to the repossessions equation (4), and are applied to data on the proportion of mortgages that are more than 6 months and more than 12 months in arrears. There are two key differences from the repossessions equation: the first arises from the correction of a serious bias in the commonly used “months-in-arrears” measure (Appendix B), which has not previously been corrected for in the literature; the second concerns the role of forbearance policy, which has the opposite-signed effect on arrears from that on repossessions.

To begin with the bias, a long history of arrears data is available only for a count of arrears measured as “months in arrears” (i.e. an accumulated level of arrears in excess of an

¹³ The log formulation, used in our models, has the advantage of plausible multiplicative effects in levels. However, it may exaggerate movements at *low* levels of repossessions, e.g. in 2004, unless the explanatory variables similarly reflect these extremes. In practice, however, the log of the estimated proportion of mortgages with negative equity, together with the log of the debt service ratio and the log of the unemployment rate, captures these low levels. In the empirical application, this was checked by comparing log and Box-Cox transformation of the repossessions rate.

equivalent number of months of normal payments). Thus, when mortgage rates fall, normal payments fall and the “months-in-arrears” count actually *rises* (see Appendix B for an illustration). The correction involves substituting for arr^* (a count of arrears by the ratio of arrears to mortgage debt) by the sum of $arrm$ (the month in arrears count which best matches the percentage in arrears count represented by arr^*)¹⁴ and $\theta^a \log dsr$ (which proxies the measurement bias). The parameter θ^a will differ for 6-month and 12-month arrears rates, see discussion in section 5.1.

Turning to forbearance policy, there are two possible channels affecting arrears. One arises from a stock-flow relationship with repossessions. The change in the count of any measure of arrears equals the inflow minus the outflow of arrears. The total outflow consists of the ‘good’ outflow into repayment or refinancing, minus the ‘bad’ outflow into repossessions. Let the $(\text{inflow into arrears}_t - \text{‘good’ outflow from arrears}_t) / (\text{stock of arrears}_{t-1})$ be a function of a vector Z_t , $F(Z_t)$. Hence the net change in the flow of arrears is

$$\text{total change in arrears}_t / \text{arrears}_{t-1} = F(Z_t) - \varsigma \text{flow into repossession}_t / \text{arrears}_{t-1} \quad (6)$$

where ς is the proportion of the total flow into repossession which comes from the stock of the specific measure of arrears under consideration. Hence approximately,

$$\Delta \log \text{arrears}_t \approx F(Z_t) - \varsigma \text{flow into repossession}_t / \text{arrears}_{t-1} \quad (7)$$

Thus, the ratio of negative repossessions to lagged arrears was included in each arrears equation to account for this link between repossessions and arrears. A second channel operates via an incentive effect on the borrower (an instance of moral hazard). The knowledge that lenders and courts are exercising forbearance makes borrowers less concerned about the risk that a rise in their arrears levels will induce repossession. Such borrowers may pay off credit card debt before mortgage debt, or cut back less on other household expenditure. The parameter $-b_5$ (note the negative sign) where b_5 is positive in equation (8) below, incorporates the incentive effect of increased forbearance on arrears.

The two policy effects are shown in an equilibrium correction model corresponding to equation (4), for the proportion of mortgages measure by “months-in-arrears” which corrects for the bias:

¹⁴ Basing the bias correction on the log or level of the tax-adjusted mortgage rate instead of the log debt service ratio gives similar results for the arrears and repossessions equation, but fits less well.

$$\begin{aligned}
\Delta \log arm_t = & \kappa^a (b_0 + \sum_{l=1}^3 b_l X_{t,l} + b_4 LQ_t - b_5 FP_t - (\log arm_{t-1} - \theta^a \log dsr_{t-1})) \\
& + \theta^a \Delta \log dsr_t - \varsigma poss_t / arm_{t-1} + \sum_{l=1}^3 \sum_{j=0}^k \beta_{l,j} \Delta X_{t,l-j} + \beta_4 \Delta LQ_t + \beta_5 \Delta FP_t \\
& + \sum_{j=1}^k \chi_j (\Delta \log arm_{t-j} - \theta^a \Delta \log dsr_{t-j}) + \varepsilon_t
\end{aligned} \tag{8}$$

for the same three X variables and LQ and FP functions, with k lags, and applying to both 6-month and 12-month arrears. The speed of adjustment to long run equilibrium is κ^a .

To summarise, a system of three equations is jointly estimated for the 6-month and 12-month arrears measures and the repossession measure, with cross-equation constraints imposed on the LQ and FP functions in each specification. The equation specifications for repossessions and for arrears have a general lag structure in the dynamic terms. Given the heterogeneity in individual circumstances, including the timing of the initial mortgage and behaviour by lenders and the courts, there will be fluctuations in debt-service ratios and in the proportion of mortgages in negative equity. These probably have drawn-out effects in aggregate that can be well-represented by moving averages of these variables¹⁵. Parsimonious models, with much simplified short-term dynamics, for repossessions and arrears confirm the relevance of four-quarter moving averages for the log debt-service ratio and negative equity indicator. These formulations were applied in the three-equation system, and tested against more general lag structures.

4. Data issues

4.1 Measuring the debt-equity ratio and negative equity

One commonly used definition of the *ratio of mortgage debt to housing equity* divides the mortgage stock by the estimated value of the residential housing stock owned by the household sector (as published in the National Income and Expenditure Blue Book, and interpolated to a quarterly frequency). A substantial proportion of owners of housing equity, however, have no mortgages. We prefer, therefore, to adopt a measure defined as the average mortgage for those with mortgages relative to the average house price. We take the mix-adjusted index of second-hand house prices, normalized to the average value of houses traded in some year, as a proxy for the average house price of mortgaged properties.

To obtain an estimate of the *proportion of mortgages in negative equity*, $pneq$, we generalize equation (3) in two ways. First, we adjust the log mean debt/equity allowing for an

¹⁵ The re-parameterisation of the long-run solution in terms of a moving average can be illustrated with the example of a 2-quarter moving average: the two terms $x_{t-1} + \Delta x_t/2$ simplify to the moving average $(x_t + x_{t-1})/2$. Such simplifications, when warranted by the data, reduce the number of parameters to be estimated.

intercept and trend, to better match the Bank of England snapshots of negative equity. The adjusted log (mean debt/mean equity) is

$$alder = \log(\text{mean debt} / \text{mean equity}) + \rho_0 + \rho_1(t - 40) \quad (9)$$

Second, to fit the proportion of mortgages in negative equity, we generalize the functional form of equation (3) using the exponential function defined on a cubic in the adjusted log (mean debt/mean equity). Without available micro-data in the UK, it could not be checked whether the logistic function in equation (3) was a reasonable approximation to the tail of the log (debt/equity) distribution. However, we obtained from the Central Bank of Ireland, a random sample of around 138,000 observations for mortgages in Ireland in 2011. Modelling the upper tail of the distribution of log debt/equity for these data suggested that one could improve considerably on the logistic function by using a cubic instead of a linear term in equation (3). The proportion of negative equity is then

$$pnegeq = [1 / (1 + \exp(\lambda_1(alder) + \lambda_2(alder)^2 + \lambda_3(alder)^3))] \quad (10)$$

$$+ \omega_0 w_{bias} + \delta - \sum_{s=1}^{s=12} \omega^s poss_{t-s}$$

We were able to estimate the parameters of equation (10) from our time series data, with an improvement in fit compared to the logistic adopted in earlier versions of this paper.¹⁶ The coefficients ρ_0 and ρ_1 in the *alder* term (see equation (9)) are calibrated to match estimates of the proportion of UK households with negative equity in 2009 and 2003. Research by the Bank of England and the Financial Services Authority (FSA) suggests that 1.1m owner-occupiers and around 0.2 million buy-to-let mortgages were in negative equity out of around 11.55 million mortgagors at the peak in 2009. Some of the buy-to-let mortgages were multiple mortgages on the same property, suggesting a proportion in negative equity of perhaps 11 percent, a value to which we calibrate. Earlier, the Bank of England estimated about 1.8 million out of 9.91 million mortgaged properties in negative equity in 1993Q1, i.e. about 18.2 percent (Cutler, 1995). This almost certainly underestimates the true extent.¹⁷ We take 20 percent as a more appropriate figure.

We further adjust in equation (10) for a term, denoted *wbias*; this captures potential bias from omission of deviations in regional prices from the national average, see Appendix C. It also seems likely that a high number of recent repossessions would have temporarily depleted the

¹⁶ We are grateful to our referees and editor for encouragement to pursue this avenue.

¹⁷ There are two main reasons: first, the survey from which initial loan-to-value ratios are taken under-represents the riskier lenders, see section 4.2.1; second, the Halifax house price data used by the Bank of England also under-represents transactions for the riskier loans, and so likely understates the falls in house prices at the time.

count of mortgages in negative equity, below those implied by the average debt-equity ratio. To take account of this, we subtract a declining weighted sum of the repossessions rate over the previous 12 quarters¹⁸, from the proportion of negative equity otherwise implied by the cubic generalization of equation (3). The coefficient ω , when freely estimated, takes a value close to 0.9. The parameters: λ_1 , λ_2 and λ_3 are freely estimated, though λ_2 is set to zero because it is not significant. The parameter δ , is set at a very small positive value.¹⁹

4.2 *Latent variables for forbearance policy and ‘loan quality/credit access’*

Variations in lending standards can have large effects on subsequent default rates, as the US sub-prime crisis illustrates. Yet, lending standards are difficult to measure directly. We explain the shortcomings of the UK micro-data on lending quality, and then motivate the case for a “latent variables” approach using a ‘credit access/loan quality’ function, LQ , and a forbearance policy function, FP .

4.2.1 *Unsatisfactory micro data on mortgage credit indicators*

Data have been collected since 1968 from UK mortgage lenders on loan-to-value and loan-to-income ratios. These are used as indicators of lending quality or credit availability, or both, in the UK literature on arrears and repossessions. These indicators cannot be pure measures of lending quality as they are endogenous, depending also on interest rates, house prices, income and other factors (Fernandez-Corugedo and Muellbauer, 2006). Moreover, the available data are not fully comparable over time. The original survey was based on a five percent sample of building society mortgages, but became unrepresentative of the market when from 1980, banks entered the mortgage market, and from the mid-1980s, centralized mortgage lenders²⁰ increased their share of the market. Coverage was extended to the banks in the Survey of Mortgage Lenders (SML) from 1992, but not to the centralized mortgage lenders. Sample coverage after 2002 began to include full electronic records from some lenders (Tatch, 2003), but there were difficulties in classifying borrowers into first-time and repeat buyers.

The new Regulated Mortgage Survey (RMS) was introduced in 2005, with broader coverage by types of lender. There was jump in the fraction of high loan-to-value loans recorded for first-time buyers, and other differences with the SML, Tatch (2006). The SML

¹⁸ The average debt-equity ratio eventually captures attrition from repossession since defaults by vulnerable cases reduce the average debt-equity ratio for remaining mortgages. In the short term, removing negative equity cases through repossession temporarily reduces the negative equity count by more. Limiting the adjustment to the previous 12 quarters captures the temporary nature of the effect.

¹⁹ The log of the proportion in negative equity is a key driver in our model, so equation (10) needs always to be strictly positive. A value of δ of 0.0007, in practice guaranteed that this was the case.

²⁰ These suffered repossessions rates around three times as large as those of high street banks and building societies, Ford et al. (1995).

and its predecessors capture only first mortgages, omitting second mortgages and the home equity loans that later added to mortgage debt.²¹ Moreover, the data do not fully capture the quality of the screening carried out by lenders. The shares of self-certification and of securitized mortgages rose sharply in 2005-7 (Turner, 2009), which have shown higher default rates more recently. Comparable data were not collected in the SML for earlier years.

4.2.2 *Latent variables: the FP and LQ functions*

We derive two indicators based mainly on dummies that capture lending quality and the differential access to credit (the *LQ* function) and forbearance policy (the *FP* function). Table 2 sets out priors for ‘loan quality/credit access’ and forbearance policy, explains the dating of shifts in our models and the expected effects on repossessions and arrears.

The ‘loan quality/credit access’ function *LQ* represents hard-to-measure factors which shift arrears and repossessions in the *same* direction. The *LQ* function is a linear combination of ogive and step dummy variables²² and a survey-based credit conditions index from the Bank of England. Lending standards evolve slowly with *gradual effects* on mortgage defaults. The heterogeneity of individual borrowers and of lenders’ behaviour results in *smoothness* in aggregate default rates in responding to shocks. An ogive dummy, which makes a smooth transition from zero to one over eight quarters, capturing the slow evolution, is a promising proxy for changes in lending standards in *LQ*. Linear combinations of ogive dummies provide a simple way of representing successive smooth transitions. Shifts in income support are subject to sharper shocks and are well-captured by step dummies.

The *LQ* function captures three effects: lending quality; improved government income support for those with mortgage payment difficulties that enhances *apparent* lending quality; and improved credit access through refinancing opportunities.

More risky lending in recent years has *increased* both current rates of arrears and possessions. The late 1980s and early 1990s and 2007 onwards are test-beds for the impact on defaults of earlier lax lending standards. Following a default crisis, loan-to-value ratios typically decline as credit standards are tightened. Subsequently, improved methods of credit scoring and arrears management probably raise lending quality. Policy relaxing the economic constraints faced by households will shift repossessions and arrears in the same direction. Improved (temporary) government support *decreases* both arrears and repossessions below what they would have been. In the short-term, easier refinancing improves ‘loan quality/credit access’, and *decreases* both arrears and repossessions from rescheduling or absorbing the arrears into a larger mortgage. This resembles ‘forbearance’ but as it reduces *both* repossessions and recorded arrears, it forms part of the *LQ* function.

²¹ LaCour-Little et al. (2009) give US evidence on the relevance of further loans for defaults.

²² The ogive and step dummies are defined in Table 3.

Refinancing opportunities may arise with market movements in mortgage credit availability. The deteriorating quality of lending during 1986-89 and 2005-07 was probably temporarily offset by the ease with which borrowers were able to refinance. It is important to note that in both periods more risky lending conditions were also reflected in rising debt levels. This variable enters both our debt service ratio and negative equity expressions; our model shows these to be the two most important drivers of mortgage defaults in the UK. Increasing capital requirements for banks (from the Independent Banking Commission (2011) and Basel III reforms) restricted credit availability from 2007. However, the Bank of England's Credit Conditions Survey suggests some easing of mortgage credit constraints from 2010, and following the Funding for Lending Scheme from July 2012.

The forbearance policy function FP is based on a mix of step and ogive (i.e. smooth-transition) dummies common to the system of repossessions and arrears equations. Governments can alter repossessions rates by influencing forbearance policies of mortgage lenders and court procedures. Increased forbearance *lowers* repossessions but it *increases* arrears unless it takes the form of refinancing debt or forgiving debt (in which case, as noted above, we capture it in the LQ function). Increased forbearance without refinancing has a *positive* effect on arrears because every mortgage in arrears which does not move into repossession swells the arrears count. There may also be an incentive effect: if lenders are lenient on repossessions, households may prove less motivated to reduce their debt.

The above discussion can be linked with the literature on loan level data using survival analysis.²³ Lower LQ reduces the hazard of arrears, and conditional on arrears, lower LQ reduces the hazard of repossession and increases the hazard of cure, meaning that better LQ uniformly lowers the level of both arrears and repossessions. Lower FP (i.e. greater forbearance), simply reduces the hazard of repossession, conditional on arrears, but does nothing to the hazard of cure. In a U.S. cross-section, one can think of low FP as states which require judicial foreclosure. Gerardi et al. (2013) show that judicial laws have exactly these effects: slowing the foreclosure rate and dramatically increasing the stock of delinquent loans. Lower FP actually reduces the hazard of cure; they argue the reason is that lower FP prevents lenders from repossessing on borrowers for whom cure is impossible.

4.3 *Interpolation of bi-annual arrears, repossession and mortgage count data*

Measures of arrears of 6-12 months and arrears of greater than 12 months were added together to give arrears greater than or equal to 6 months. Thus, the 6-months arrears dependent variable includes loans that are 12-months in arrears.

²³ We are grateful to a referee for this point.

The choice of arrears measures to be modelled was affected by the available data. Data for arrears greater than 3 months, or arrears of 3 to 6 months, are available only from 1994 in bi-annual data; this compares with bi-annual data from 1981 for measures of both 6-month and 12-month arrears. Applying an equilibrium correction framework supports using longer time series where possible. CML publishes quarterly data for arrears, repossessions and the outstanding mortgage stock beginning in 2008, but made available unpublished quarterly data from 1999Q1. Half-yearly data for the earlier years can be interpolated into quarterly data from the early 1980s, and linked to the quarterly data from 1999Q1. The interpolation for arrears, which are stock data, is straightforward.²⁴ The switch from interpolated data to quarterly data is allowed for by permitting short-run dynamics to switch in 1999. A subsequent check of the sensitivity of our results to the interpolation procedure was carried out. When the long-run coefficients were restricted to their full-sample estimates, and the model run from 1999Q2, all the other coefficients were within one standard deviation of their full sample estimates. There was no evidence of residual autocorrelation. This suggests that the use of biannual interpolated data before 1999 does not pose a problem.

5. Empirical results for a joint model for mortgage repossessions and arrears with variable lending quality and policy shifts

Models are simultaneously estimated²⁵ for total repossessions and 6-month and 12-month arrears measures, with two linear functions, *LQ* for the dummy proxies of ‘loan quality/credit access’, and *FP* for forbearance policy. Details of the precise forms of the estimated equations are given in Appendix D, with the variables defined in Table 3. The parameter estimates for the long-run solutions of these equations are shown in Table 4. Full equation estimates are given in tables in Appendix E. Parameter stability is demonstrated for two samples, by also running the model to the earlier cut-off point of 2005Q4. For 45 out of 51 parameter estimates for the shorter sample, these are within one standard error of the full sample estimates and the remaining six estimates are within two standard errors. Tests for homoscedastic residuals are passed for the arrears equations but not for the repossessions equation so that we report *robust* standard errors in the tables. Durbin-Watson tests are satisfactory.

Repossessions and arrears, as explained in section 3, are driven by three long-run economic fundamentals: the debt-service ratio; the proxy for the proportion of mortgages in

²⁴ The H1 value is given to Q1 and Q2 and the H2 value to Q3 and Q4. Then logs are taken and a two-quarter moving average is taken of the log values. For the flow of repossessions, the interpolation is a bit more complex. The quarterly data are created and scaled using H1 and H2 biannual data (scaling ensures that the total of the implied quarterly flows into repossession add up to the published biannual data). $Q1_t = H2_{t-1}/6 + H1_t/3$, scaled by $H1_t/(Q1_t + Q2_t)$; $Q2_t = H1_t/3 + H2_t/6$, scaled by $H1_t/(Q1_t + Q2_t)$; $Q3_t = H1_t/6 + H2_t/3$, scaled by $H2_t/(Q3_t + Q4_t)$; and $Q4_t = H2_t/3 + H1_{t+1}/6$, scaled by $H2_t/(Q3_t + Q4_t)$.

²⁵ The maximum likelihood computations were performed in Hall, Cummins and Schnake’s Time Series Processor (TSP 5) package.

negative equity; and the unemployment rate. The jointly estimated LQ and FP functions are the remaining long-run drivers. In sharp contrast to the earlier UK literature, there is no significant effect on the rate of repossessions from either measure of arrears, when controlling for the fundamental drivers. This important finding is discussed further below.

5.1 *The long-run repossessions equation*

The dependent variable in the dynamic equation for repossessions (see equation (4)) is the change in the log repossessions rate. The long-run equation for repossessions was given in equation (5) and the coefficients on LQ and FP indicators are normalized at 1.²⁶ The speed of adjustment is given by the parameter κ^P which multiplies the long-run solution for the log repossessions rate. The quarterly speed of adjustment, see Table 4, estimated at 0.39, suggests that appropriately lagged, the regressors have most of their effect within a year.²⁷ The debt-service ratio is highly significant with a robust t-ratio of 16.2. The estimate suggests that a 1 percent rise in the debt-service ratio raises the repossession rate by 1.6 percent. The log proportion of those in negative equity is also highly significant with a t-ratio of 11.2. A one percent rise in this proportion is estimated to increase the repossessions rate by 0.28 of one percent. The effect of the log unemployment rate has a point estimate of 0.61, and a t-ratio of 4.3. Short-run dynamics of the equation are reported in Appendix E.²⁸

The long-run effects²⁹ on the repossessions rate are shown in Figure 2 for the debt-service ratio, the estimated proportion in negative equity and the unemployment rate. Figure 3 shows the long-run impact of ‘loan quality/credit access’ and forbearance policy, discussed further below. In the *first* repossessions crisis in 1989-93, the initial rise in repossessions was driven mainly by the rise in the debt-service ratio and lower ‘loan quality/credit access’, but later the rising incidence of negative equity emerged as an important driver. The persistence of negative equity prevented a faster decline in repossessions, despite lower interest rates and

²⁶ The debt-service ratio, $\log dsr$, enters as a lagged four-quarter moving average, as does negative equity, $\log negeq$, while the unemployment rate, $\log ur$, has a lag of four quarters. This is because a reparameterisation of the long-run solution with lagged or moving average terms allows a more parsimonious expression in the short-run dynamics.

²⁷ Given the four quarter lag on the unemployment rate, the effect of a rise in the unemployment rate begins after 4 quarters and is largely complete after 10 quarters. For the four quarter moving average of the debt-service ratio, which is lagged by a quarter, the effect is largely complete after 9 quarters.

²⁸ In the dynamics, a significant positive coefficient on the two-quarter change in the rate of negative equity may reflect changes in expectations on both sides of the market. The negative coefficient on the lagged two-year change in negative equity can be interpreted in terms of lenders’ incentives or processing capabilities: rising rates of negative equity may make it harder to sell homes taken into repossession, or to process quickly the higher number of cases then arising, and conversely for falling rates. A small effect from last quarter’s change in the log debt service ratio complements the dominant effect of the moving average of this variable.

²⁹ Repossessions are forecast for 2014-2020, assuming the Base Scenario (section 6.1) for interest rates, house prices, unemployment, income and average debt.

the forbearance policy introduced at the end of 1991. In the *second repossessions* crisis, the rise in repossessions from a low level in 2004 was again driven by a growing debt-service ratio and later the increasing incidence of negative equity. This rose sharply in 2008-9, at the same time that ‘loan quality/credit access’ deteriorated. Falling mortgage rates in 2009 and improving ‘loan quality/credit access’ due to greater income support for those with payment difficulties, and the easing of the credit crunch, lowered and stabilized the repossessions rate.

5.2 *The long-run arrears equations*

The two arrears equations have a similar structure; the three main drivers are the log debt-service ratio, the log imputed proportion in negative equity and the log unemployment rate. The dependent variables in the dynamic equations for arrears (see Appendix D) are the changes in the log of arrears measures (greater than 6 months and greater than 12 months). The long-run equations for the two measures of arrears are:

Arrears > 12 months

$$\log arr12 = b_0 + b_1 \log dsrma + b_2 \log neqma + b_3 \log ur + b_4 LQ - b_5 FP + \theta^{a12} \log dsr \quad (13)$$

Arrears > 6 months

$$\log arr6 = c_0 + c_1 \log dsrma + c_2 \log neqma + c_3 \log ur + c_4 LQ - c_5 FP + \theta^{a6} \log dsr \quad (14)$$

In each equation, the long-run debt-service and negative equity terms are lagged four quarter moving averages. The speed of adjustment for log 12-month arrears is estimated at 0.29 per quarter and 0.28 for log 6-month arrears. Without adjusting for the outflow into repossessions, however, the estimated speeds would be rather lower.³⁰ The estimate of the long-run effect of the debt-service ratio, with t-ratios of 8.5 and 11.5, suggests that a 1 percent rise in the debt-service ratio raises both arrears rates by between 1.7 and 1.8 percent. The log proportion of those in negative equity is highly significant, with t-ratios of 5.4 for log 12-month arrears and 6.7 for log 6-month arrears: a one percent rise is estimated to increase the former by 0.17 percent and the latter by 0.15 percent. The estimate of the long-run effect of the log unemployment rate is 1.03 for log 12-month arrears, and 0.86 for log 6-month arrears.³¹

³⁰ We assume that 90 percent of the quarterly flow into repossession is from those with arrears of six months or more. Our model explains the quarterly change in the proportion of 6-month arrears cases after removing this flow into repossession. For the 12-month arrears model, 30 percent is assumed.

³¹ Whitley et al. (2004) estimate the unemployment effect to be broadly similar at 0.7 for 6-month arrears, using the claimant count measure of unemployment, not the Labour Force Survey measure. They report a t-ratio of only 1.3 for the long-run coefficient of a measure of un-withdrawn equity on 6-month arrears, intended to capture a similar effect to negative equity. However, probably compensating for the weak role of debt to equity, they estimate the long-run effect of the debt service ratio to be about double that reported above.

The long-run effects of ‘loan quality/credit access’ on stocks of arrears are measured by the parameters b_4 and c_4 , with the same-signed effect on arrears as on repossessions. The incentive or demonstration effect of forbearance policy is measured by the parameters b_5 and c_5 , whose negative signs indicate the *opposite-signed* effect of FP on arrears compared with repossessions. The formulation allows a lag in the incentive effect of policy as FP enters the arrears equations as a two-quarter moving average. The long-run effects of ‘loan quality/credit access’ on stocks of arrears are higher than on the flow into repossessions.

The correction factors for the bias in the arrears count when interest rates change are strongly significant. This explicit correction has not previously been made in studies of UK arrears. The measurement bias hypothesis implies a dynamic restriction imposed on each arrears equation (see Appendix B).

Figures 4 and 5 plot the long-run contribution on the log 6-month arrears rate of the log debt-service ratio, log proportion in negative equity and the log unemployment rate, and of ‘loan quality/credit access’ and policy variables, respectively. The rise in arrears in 1989-93 (as was found for repossessions) was initially driven by the rise in the debt-service ratio and lower ‘loan quality/credit access’, and later mainly influenced by negative equity, higher unemployment and forbearance policy. Contributions from ‘loan quality/credit access’ and the unemployment rate were larger than for repossessions, while that of negative equity was lower. This makes sense since payment delinquencies are more immediately connected with cash-flow difficulties than are foreclosures. The rise in arrears in 2008-9 is explained by previous rises in the debt-service ratio, the increased incidence of negative equity, the combination of poor lending quality and restricted access to credit, the effect of forbearance policy, and in 2009, by the rise in the unemployment rate.

All published repossessions models for UK macro data impose a one-for-one long-run effect of the arrears rate on the repossessions rate. Our point estimates of the long-run coefficient on log 6-month arrears in the repossessions equation are *negative*, given the other drivers, but insignificant, and strongly reject a coefficient of one.³² Though most repossessions cases would first have been in arrears, this rejection of the ‘one-for-one’ relationship looks paradoxical. Most arrears cases do not end in repossession, however. Our evidence also implies that repossessions are less sensitive to unemployment (and ‘loan

³² We tested this restriction, imposing a long-run coefficient of 1, and selecting, from general specifications, parsimonious equations consistent with sign priors on the economic variables and the LQ function. This gave a repossessions model where the log arrears rate (corrected for measurement bias, Appendix B) was the only long-run driver of repossessions since the debt-service ratio, negative equity, the unemployment rate and the LQ indicator, were all insignificant, or appeared with the wrong sign. The speed of adjustment of the repossessions equation fell from 0.35 to 0.12. The fit of the resulting repossessions equation was substantially worse. Estimates for the two arrears equations and the LQ and FP functions were little changed. A likelihood-ratio test for the three-equation system strongly rejects this restriction.

quality/credit access') than are arrears. Forcing a one-for-one effect of arrears on repossessions then requires a counter-intuitive *negative* impact of unemployment (and 'loan quality/credit access') on repossessions, to offset the too strong effect coming through arrears.

5.3 *The selected 'loan quality/credit access' and forbearance policy shift equations*

The selected 'loan quality/credit access' function, LQ , and forbearance policy shift function, FP , are graphed in Figure 6, with annotations for corresponding institutional events. From a long-run perspective, the 1980s now look 'abnormal'. This was the decade of the most radical liberalization of mortgage credit markets, see Fernandez-Corugedo and Muellbauer (2006). At the beginning of the decade, lending standards were still quite conservative so that negative equity, repossessions and arrears were at low levels. The LQ indicator begins to rise in 1985-6, with worsening lending quality, probably connected with the market entry of centralized mortgage lenders. As credit standards progressively relaxed, the underlying deterioration in credit quality was disguised for several years due to easy access to refinancing and strong competition from the centralized lenders whose market share was rising strongly. The LQ indicator leapt in 1989-90 with the credit crunch, and the collapse of new lending from the centralized mortgage lenders blocked refinancing possibilities. In 1995-96, the easing of credit conditions, together with more careful lending practices in the intervening years began to show up in an improvement – a fall in LQ . In 1996-7, a small deterioration in LQ was driven by less generous provision of income support (Support for Mortgage Interest or SMI) for borrowers with payment difficulties. In the credit boom after 2000, improved access to refinancing once more disguised an underlying deterioration in credit quality.³³ The LQ indicator jumps only after mid-2007, when money market funding evaporated and UK mortgage lenders were caught in the global financial crisis. Generous assistance for borrowers with payment difficulties paid directly to lenders and increased refinancing³⁴ is shown in a falling LQ indicator in 2009Q2. However, effective from 2010Q4, the interest rate paid directly to borrowers with payment difficulties fell from 6.08% to 3.63%. The reduction in support would have induced a small increase in LQ from 2011Q1 but for the ongoing effects of gradually improving credit conditions as measured by the Bank of England's Credit

³³ Refinancing opportunities also increased through sale and rent-back deals with the development of the buy-to-let market. This involves the sale of an owner-occupied home to an investor, shifting the occupier to a rental contract. Concerns about lack of regulation and of misinformed selling led to an Office of Fair Trading Inquiry in 2008, revealing perhaps 50,000 sale and rent-back deals up to mid-2008, with up to 60 percent related to households at risk of repossession.

³⁴ The Financial Stability Report of the Bank of England (December 2011) highlighted the role of forbearance via refinance (e.g. extending the repayment period or refinancing in the form of an interest-only mortgage). The pressure to extend this kind of refinancing to people with payment difficulties coincided with a continuing credit crunch for new borrowers in 2009-2011. FSA evidence confirms small proportions of new mortgages at high loan-to-value ratios and high risk spreads on such loans, and a small share of low documentation loans in 2009-2011.

Conditions Survey. The *LQ* indicator falls more sharply from mid-2012, with the ‘Funding for Lending Scheme’ launched in July 2012, and mortgage credit conditions measured by the Bank of England continue to improve.³⁵ By 2014Q1, *LQ* is down by 0.52 compared to its 2009Q1 peak, returning the level to close to the post-1990 ‘normal’ level, and declines a little more in 2015.

We tested an alternative formulation of the ‘loan quality/credit access’ indicator based on median loan-to-value ratios for first-time buyers (CML data). The estimates suggest a negative short-run effect of loan-to-value ratios (probably reflecting access to refinancing), but positive effects when expressed as four-quarter moving averages at lags of four or more quarters (which probably reflects more slowly evolving loan quality). Though adopting the alternative specification was far less successful at fitting the data, the estimates of the key economic drivers on repossessions and arrears were little affected.

The selected forbearance policy shift function graphed in Figure 6 indicates the increase in forbearance after December 1991 with a pronounced fall in the *FP* function in 1992Q1. In 1996-7, the withdrawal of forbearance and resumption of ‘normal’ practice is confirmed by the data. The *FP* function rises again in 2005-6; this is interpreted as a shift in the composition of mortgage lending; evidence suggests there was an increase in the proportion of lenders extending riskier loans but resorting to the courts more quickly when default problems arose.³⁶ In 2008Q4, the *FP* function falls sharply, representing newly-reinforced forbearance, mainly through the Mortgage Pre-Action Protocol, see Wilson (2014). Part of the shift in 2008 would have been temporary in nature since the mortgage code of practice delayed some repossessions actions. Experimenting with lags in the 2008Q4 step dummy, suggested the *FP* function is flat for a quarter, presumably because the increased application of the protocol roughly balanced the partial reversal expected as previously delayed repossessions proceedings were enacted. After 2009Q2, the *FP* function drifts up as more delayed repossessions proceedings came through. By 2010Q2, we estimate a net effect on the log repossessions rate compared to 2008Q3 (i.e. just before forbearance policy shifted) of around 0.12, about half of the initial impact. One might have expected a renewed fall in the *FP* indicator in 2010Q4, with increased forbearance associated with new FSA rules on mortgage providers. However, this is not significant and instead from 2011Q1 there is a small rise in *FP*, probably because mortgage lenders perceived the reduction from October 2010 in

³⁵ The Funding for Lending Scheme was mainly directed at new lending, so the subsequent further easing of credit conditions measured in the Bank of England survey almost certainly exaggerates the improvement in refinancing opportunities for existing mortgagors. We therefore halve the coefficient in *LQ* for rises in the credit conditions index beginning in 2012Q4 (confirmed by free estimation).

³⁶ There is evidence in the FSA’s Turner Report (2009), for example, for a rise in the share of ‘Intermediate Mortgage Lenders’ and of the share of securitised lending in 2005-7. Northern Rock and other lenders were engaging in aggressive competition for market share, with low margins on mortgage rates and high loan-to-value ratios on offer. The share of low documentation loans peaked in 2005-7.

mortgage interest paid to them under SMI as the government partially reneging on the implicit contract under which the lenders exercised forbearance. Our estimates suggest that the joint effect of income support, re-financing relief and forbearance policy, lowered the log repossessions rate between 2008Q3 and 2014Q1 by around 0.48 (0.36 from the *LQ* indicator and 0.12 from the *FP* indicator). Over the same period, the net effect on the log 6-month arrears rate was close to zero.³⁷

6. Forecasting performance and forecast simulations

The principal purpose of our model is not to produce unconditional forecasts, but to consider alternative forecast scenarios for repossessions and arrears. We can ask how well the model would have done estimating to a range of endpoints: to 2010Q4, to 2011Q4, to 2012Q4 and 2013Q4, and compare the forecasts from dynamic simulations with the outcomes to the most recent data point in 2015Q3, *using actual out-turns of the economic drivers*.³⁸ This is a particularly favourable period for model stability, without major further policy interventions, apart from the easing of mortgage credit conditions as measured in the bank lending survey. Table 5 shows the full-sample root mean square error (RMSE) and the respective out-of-sample RMSE for each of the three foreshortened forecast equations. The latter are close to or below the full-sample RMSE, reflecting the parameter stability of the equations over the different samples.

Then three forecast *scenarios* from 2014Q2 to 2020 are compared: a base scenario with more and less favourable variations. Common to all is the assumption of no further change after 2014 in *FP*, the forbearance policy function; but there are shifts in *LQ*, the combined loan quality/credit access function. It is plausible that new lending since 2008 under tighter prudential controls, will, on average, have been of higher quality. Eventually this should reduce default rates and we assume a gradual improvement (reduction in *LQ*) after 2015Q2. For the changes in SMI announced in July 2015 (after April 2016, the waiting period before payment is extended from 13 to 39 weeks; and from April 2018, it will be a loan rather than a benefit), we assume the increase in *LQ* from the reduced income support exactly offsets the reduction in *LQ* from the improved regulation of lending quality.

Forecasts of total mortgage repossessions, 6 and 12-month arrears for 2014Q2 to 2020Q4, based on the three economic scenarios, were generated using the model outlined in

³⁷ This is computed by the $1.15LQ - 3.44FP$ term in the 6-months arrears equation. The 2008Q3 reference point may not fully capture the improvement (fall) in the *LQ* indicator due to more generous income support, and may therefore understate the total impact of policy and of improvements in credit conditions on arrears.

³⁸ UK default data for 2015 were subject to revision at the time of writing. Indeed the CML believe that in provisional data for 2015Q1 to Q3, arrears were overstated and repossessions understated.

section 3. The implications of the scenario assumptions for the annualized mortgage rate, the debt-service ratio, the house price index, the proportion in negative equity and the unemployment rate are shown in Table 6. Table 7 summarises the three contrasting forecast scenario outcomes with annualized forecasts of arrears and repossessions.

The *Base Scenario* uses November 2015 forecasts from Oxfordeconomics.com for the underlying exogenous variables: the unemployment rate, mortgage interest rate, debt levels (and hence debt-service ratios), house prices (and hence debt-equity ratios). Unemployment declines from 5.4 to 5 percent between 2015 and 2018, stabilizing just under that level in 2019-20. The average mortgage rate is down from 3.17 percent in 2015 to 3.14 percent in 2016, and begins to rise in 2017 to 4.14 percent in 2019 and 4.43 percent in 2020. Nominal house prices rise steadily at an average rate of around 4 percent per annum, while the rise in the average mortgage is somewhat less pronounced. The average debt service ratio troughs at 12.2 percent in 2016; it then rises with the interest rate and the rise in average mortgage debt relative to income, to 15.2 percent in 2018, 16.6 percent in 2019 and 17.9 percent in 2020. The estimated average percentage in negative equity drops to 0.71 percent in 2015 and to 0.54 percent in 2016, and rises a little and falls to 0.51 percent in 2020. On these assumptions, the number of 6-month arrears cases as a percentage of the number of outstanding mortgages falls from 0.52 percent in 2015 to 0.36 percent in 2017, and then drifts up to 0.47 percent in 2020. The annual rate of repossessions similarly drops from 0.13 percent in 2015 to 0.08 percent in 2017, then rising to 0.12 percent in 2020.

In the more favourable *Scenario 2*, the unemployment rate falls more sharply from 5.4 to 4.5 percent between 2015 and 2018, then settling just below this level in 2019-20. The average mortgage rate hovers between 3.1 and 3.2 percent until 2018, rises to 3.3 percent in 2019 and only to 3.6 percent in 2020. Nominal house prices rise at an average annual rate of 6.6 percent between 2015 and 2020, while average mortgage debt rises more slowly. The debt service ratio bottoms at 12.1 percent in 2016, rises to 12.5 percent in 2018, and 15.1 percent in 2020. The percentage in negative equity reaches its trough of 0.36 percent in 2019. On these assumptions, the rate of 6-month arrears continues to fall from 0.52 percent in 2015 to 0.29 percent in 2019, before rising gently. The annual rate of repossessions similarly falls from 0.13 percent in 2015 to 0.07 percent in 2019 before beginning to rise gently.

In the less favourable *Scenario 3*, the unemployment rate rises from 5.4 to 6.1 percent in 2017 and to 6.5 percent in 2020. Mortgage interest rates rise from 3.2 percent in 2015 to 3.4 percent in 2016, to 4.5 percent in 2017 and then more slowly to 5.7 percent in 2020. Nominal house prices rise slightly in 2016 before drifting down a little in 2018-2020. The debt service ratio rises from 12.4 percent in 2015 to 17.4 percent in 2017 and to 21.6 percent in 2020, while the percentage in negative equity rises from 0.71 percent in 2015 to 1.16 percent in 2019 and 2020. On these assumptions, the rate of 6-month arrears rises from a low

of 0.41 percent in 2016 and to 0.89 percent in 2020, while the rate of repossessions, rises from a trough of 0.09 percent in 2016 to 0.24 percent in 2020.

7. Summary and conclusions

Rates of mortgage repossessions (foreclosures) and payment arrears (delinquencies) remain high on the UK policy agenda, particularly with prospects of interest rates rising in future years from the current record low levels. Government policy has influenced the recent outcomes with monetary policy interventions, regulation of lenders' forbearance policy and income support for those with payment difficulties. However, unlike the US, the UK lacks the appropriate micro-data for the highly policy-relevant analysis of repossessions and arrears.

This paper has utilised the available *macro*-data to estimate equations for mortgage arrears and repossessions on data from 1983 up to the first quarter of 2014, taking account of institutional and policy changes with a latent variables approach, and has analyzed forecast scenarios to the end of 2020. The approach is motivated by a conceptual double trigger framework for foreclosures and payment delinquencies. Arrears and repossessions are estimated jointly in a system of equations together with 'loan quality/credit access' (the *LQ* function) and forbearance policy proxies (the *FP* function), imposing cross-equation constraints through the common *LQ* and *FP* functions. This results in plausible magnitudes for the effects of policy shifts and loan quality/credit access. This latent variables approach improves on the widespread use of loan-to-value measures for first mortgages as indicators of loan quality, as these are not comparable over time and omit further advances of credit, amongst other deficiencies.

Apart from the innovation of the latent variables approach, we introduce for the first time in the literature, a theory-justified estimate of the proportion of mortgages in negative equity as a key driver of aggregate repossessions and arrears. This is based on an average debt-equity ratio, corrected for regional deviations, and uses a functional form for the distribution of debt and equity checked on Irish micro-data from the Bank of Ireland, and Bank of England snapshots of negative equity. Moreover, measurement biases in the previous macro-empirical literature from using the available 'months-in-arrears' data, have been corrected utilizing parameter restrictions. A universal restriction in previous UK studies of a proportional relationship between repossessions and arrears is relaxed and rejected in our system.

Parsimonious arrears and repossessions models were tested successfully against more general specifications. The long-run impact of four major drivers, house prices, interest rates, debt levels, and income, is captured by just two coefficients: those on the debt-equity ratio, transformed into a proxy for the fraction of mortgages with negative equity; and on the debt-

service ratio. Highly significant effects on aggregate rates of repossessions and arrears are found for the aggregate debt-service ratio, the proportion of mortgages in negative equity and the unemployment rate. Tests for interaction effects, e.g. whether the effect of unemployment was higher in years where negative equity was more prevalent, found no supporting evidence.

The analysis of different forecast scenarios to 2020 allows an assessment of risks for different views on the UK and global economies, illustrating the usefulness of the approach for bank stress-testing. The mortgage default module in one of the more developed models for financial risk assessment, the RAMSI model developed at the Bank of England, Alessandri et al. (2009), could be considerably improved using the approach of this paper. Our parsimonious equations linking aggregate mortgage payments to a measure of defaults allow the separation of various factors contributing to the evolution of arrears and repossessions. In aggregate, this helps explain the *financial accelerator*, since mortgage defaults *amplify* the feedback effects between shocks and credit flows operating via asset prices. Such feedbacks are absent in all standard macro-econometric models (not only in DSGE models).

Data on defaults by vintage of issue would be particularly helpful to enhance our models, particularly at the level of individual lenders, where bank stress-testing is required. The ‘loan quality/credit access’ shifts then could be better identified, and with such data, it should also prove possible to better link lending quality measures with observable loan characteristics. Models linking macro-variables and micro-credit indicators with rates of mortgage default potentially have much to offer the stress-testing systems currently under development by central banks and supervisors, see Foglia (2009) and would also be highly relevant for developing early warning systems. One priority for future work is to endogenise house prices and the aggregate mortgage stock, checking for possible feedbacks from repossessions, and perhaps arrears, onto house prices and the mortgage stock, so capturing an important linkage in the financial accelerator.

Moreover, and relevant for understanding the role of consumer spending in the *financial accelerator*, linking information on new loan characteristics - and hence measuring access to credit - with information on bank balance sheets and on regulatory measures, the banking sector can be linked back to household portfolio and spending decisions and so the real economy. The modeling framework, with some adaptation, is also suitable for drilling down further to the level of individual loan histories, where the estimated ‘loan quality/credit access’ and forbearance policy dummies would be valuable controls to analyse time-varying drivers of arrears and repossession transitions.

To conclude, comparing the recent UK crisis and that of the early 1990s, the most radical contrast is in the speed of the monetary policy response in reducing interest rates. In 1990-92, monetary policy was constrained by the high rate of inflation, and sterling’s membership of the European Exchange Rate Mechanism until the UK exited in September,

1992. The average cost of servicing mortgage debt as measured by the debt-service ratio rapidly fell in 2009 to below early 1990s levels, despite far higher levels of mortgage debt relative to income. The lenders' forbearance policy and the more generous government income support for those with mortgage payment difficulties also attenuated the rise in arrears and repossessions. The striking sensitivity of arrears and repossessions to higher interest rates in an economy where most mortgages are still at floating rates of interest has obvious policy implications. A sovereign debt crisis in which interest rates were forced higher, or a normalization of global interest rates while UK households remain with high levels of leverage, could raise arrears and repossession sharply, with unfortunate effects on undercapitalized UK mortgage lenders. Finally, our research highlights the importance of a sequence of earlier policy errors that allowed UK house prices and debt levels to rise to exposed levels, despite a serious structural fiscal deficit and a highly leveraged banking system.

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Table 1: A typology of UK empirical studies on mortgage arrears and repossessions

<i>Study</i>	<i>Dependent Variable & Sample</i>	<i>Equity Measures</i>	<i>Ability To Pay/Cash Flow Measures</i>	<i>Loan quality/ Policy</i>	<i>Methodology</i>
Selected Disaggregated Studies					
Muellbauer and Cameron (1997)	<i>Regional repossessions relative to mortgage stocks</i> Regional repossession court orders; constructed regional mortgage stocks; 1987-96 (annual)	Debt/equity	Debt-service ratio, change in unemployment rate, lagged business de-registration rate	Lending quality proxy based on market share of centralized mortgage lenders, policy dummies	Pool across 8 English regions and Wales; fixed effects panel regression
Burrows (1998)	<i>Mortgage arrears</i> SEH; 1993-94	Year of house purchase; loan-to-value dummy.	<i>Borrower characteristics:</i> rich set of household characteristics <i>Lender characteristics:</i> region, mortgage type, lender type.	First-time buyer status	Logit model
Cooper and Meen (2001)	<i>Unscaled regional repossessions</i> Regional repossession court orders; 1990-99 (annual)	Debt/equity for some regions	Debt-service ratio, change in unemployment rate, change in business de-registration rate	Shift and other dummies	Pool across 8 English regions and Wales, using regional shift dummies; stacked OLS
Lambrecht, Perraudin and Satchell (1997) (2003)	<i>Average time to default</i> <i>Times to forced repossession</i> 5,272 defaults, from an insurance co. database of claims for compensation from a UK building society; 1987-9	No treatment of current equity	<i>Borrower characteristics:</i> initial salary; initial marital status. Interest rate at which the mortgage was originally granted.	Initial loan-to-value ratio	Hazard model, using panel data
Boheim and Taylor (2000)	<i>Incidence of arrears</i> <i>Incidence of eviction</i> BHPS; 1991-97	No treatment of current equity or debt. Loan-to-value ratios are initial values only.	<i>Borrower characteristics:</i> Rich set of household characteristics; tenure; employment; income. Regional unemployment; interest rate.	Initial size of mortgage and initial house value	Pooled time series-cross sectional model, across all tenures
Gathergood (2009)	<i>Repayment difficulties</i> BHPS; 1992-2001	No treatment of current equity or debt. Loan-to-value ratios are initial values only.	<i>Borrower characteristics:</i> marital status, family size, employment, income etc.. Proxies for risk: health, employment & separation	First-time buyer status; initial loan-to-value and loan-to-income ratios	Random effects probit model, pooling household-observations over a 6 year period
Selected Macro-Based Studies					
Breedon and	<i>Arrears and repossessions</i>	Level of unused	Unemployment rate, debt-service	-	Three-equation model

<i>Study</i>	<i>Dependent Variable & Sample</i>	<i>Equity Measures</i>	<i>Ability To Pay/Cash Flow Measures</i>	<i>Loan quality/ Policy</i>	<i>Methodology</i>
Joyce (1992)	1971-91	housing equity	ratio		of house prices, arrears and repossessions
Brookes, Dicks and Pradhan (1994)	<i>Mortgage arrears rate 6m+ and repossessions as ratio of total mortgages outstanding</i> Quarterly interpolation of data from CML; 1970Q2 to 1990Q4	<i>Unwithdrawn equity</i> : net personal sector housing wealth /no. of mortgages.	Interest rates, inflation (instrument), debt-service ratio using PDI, inflow to unemployment, divorce rate	Loan-to-value ratio for first-time buyers in arrears but not repossessions equation	Engle-Granger two step method
Allen and Milne (1994)	<i>Mortgage arrears rate 6m+ and repossessions/arrears</i> Half yearly data from CML, interpolated before 1980. arrears: 70H1-91H2 repossessions:1974H1-1991H2	No equity treatment in arrears, but debt/equity drives repossessions/ arrears	Arrears equation: debt-service ratio, rates of change of house price/income and of employment	-	OLS
Cooper and Meen (2001)	<i>Repossessions and arrears data</i> Quarterly interpolation of bi-annual CML data 1985-2000	Debt/gross housing equity ratio in both arrears and repossessions	Debt-service ratio for first-time buyers, Labour Force Survey unemployment rate and income inequality in arrears equation	Impulse dummies	Equilibrium-correction model using OLS
Whitley et al. (2004)	<i>Aggregate UK household arrears: proportion of mortgage loans in arrears of six months or more</i> Quarterly interpolation of bi-annual CML data 1985-2000	<i>Undrawn equity</i> : gross housing wealth minus mortgage debt as a percentage of housing wealth.	Debt-service ratio: building societies' average mortgage interest rate x mortgage debt/PDI; unemployment rate (claimant count); lagged credit card arrears	Loan-to-value ratio for first-time buyers (<i>borrower quality</i>) Tested proportion of households with MPPI.	Error-correction representation using OLS
Figueira et al. (2005)	<i>Arrears in excess of 3 months relative to total mortgages</i> Monthly data for England and Wales, May 1993 to April 2001. Data on owner-occupier borrowers from a consortium of mortgage lenders (36 per cent of the total UK mortgage book)	<i>Level of unwithdrawn equity</i> : (average house price minus average mortgage)/average mortgage	Unemployment rate; lenders' mortgage interest rates; real personal disposable income <i>Debt-service ratio</i> : mortgage interest payments to real (sic.) PDI	Loan to income ratio for first-time buyers 1. Test for structural breaks. 2. Dummy for effect of changes to social security entitlement and increases in MPPI	Johansen methodology, VAR with 2 lags on monthly data. Error correction model is estimated for long-run and short-run dynamics in mortgage arrears.

Table 2: Priors on lending standards and policy shifts for past changes

<i>Date</i>	<i>Institutional Shifts</i>	<i>Impact on Arrears</i>	<i>Impact on Repossessions</i>	<i>Dummies for LQ function</i>	<i>Dummies for FP function</i>
1985-90	Poor quality lending, reduced credit access at end.	Raised	Raised	OD1986 OD1987 OD1989	
From 1992	Policy shift (increased forbearance) to reduce repossessions‡	Raised	Lowered		SD1992Q1
1995-6	Better lending quality	Lowered	Lowered	OD1995	
1996-7	Policy reversal (back to normal). Tightened SMI rules affected lending quality.	Raised	Raised	OD1996 OD1997	OD1996 OD1997
1999-2005	Good lending quality and/or easy credit access	Lowered	Lowered		
2005-6	Change in the composition of the mortgage market toward risk-taking lenders with less forbearance; easy refinance overwhelms poor quality lending	Lowered	Raised	OD2005	OD2005
2007-2009	Poor quality lending; reduced access to credit	Raised	Raised	OD2008Q2	
2008Q4	Policy shift (Mortgage Pre-action Plan increases forbearance) to reduce repossessions†	Raised	Lowered		SD2008Q4 SD2009Q1 SD2009Q2
2008-9	Income support (ISMI/SMI) made more generous; refinancing of mortgages	Lowered	Lowered	SD2009Q2	
2010Q4	Statutory interest rate paid to lenders under SMI falls	Raised	Raised	SD2010Q4 SD2011Q1	SD2010Q4 SD2011Q1
2010Q4	New FSA rules on mortgage providers increased forbearance	Raised	Lowered		SD2010Q4 SD2011Q1 SD2011Q2
From 2007Q2	Mortgage credit conditions: tightening 2007-2009, easing in 2010-14	Raised with tightening	Raised with tightening		

1. Abbreviations: Financial Services Authority (FSA); Income Support for Mortgage Interest (ISMI)/ Support for Mortgage Interest (SMI).
2. The definitions of an ogive (OD) and step (SD) dummies as used in the *LQ* and *FP* functions are given in Table 3. The *LQ* and *FP* functions are graphed in Figure 6.
3. ‡ In late 1991, before the 1992 General Election, an implicit contract was agreed between the Government and mortgage lenders. The government paid SMI direct to the lenders, stimulated the housing market by raising the Stamp Duty ceiling for a year and gave ear-marked grants to housing associations to purchase properties. In return, lenders agreed to greater leniency on repossessions. Practices by the County Courts also altered in the early 1990s, with longer repayment periods for households in payment arrears permitted.
4. † In 2008, the government again exerted pressure on lenders toward leniency (some were newly part-owned by the government). The SMI became more generous in January 2009, a Mortgage Pre-action Protocol was introduced from November 2008 and a Mortgage Rescue Scheme and Homeowners' Mortgage Support (see Stephens (2009)). The standard mortgage rate at which SMI was paid to lenders was set at 6.08 percent until October 2010, far above the average rate on outstanding mortgages of around 3.6 percent. Indirect support included another Stamp Duty holiday in 2009, and mortgage loan targets for wholly or partly-owned banks (Northern Rock, Royal Bank of Scotland and Lloyds TSB). The Funding for Lending scheme was introduced in July, 2012. Prudential controls from FPC on high loan to income ratio lending announced in June 2014 will also have been reflected in the credit conditions measure. There will be a reduction in the SMI from April 2016, see section 6.

Table 3: Definitions of variables used in the regressions

<i>Symbol</i>	<i>Variable definition</i>	<i>Sources</i>	<i>Means</i>	<i>Std. dev.</i>
$\log poss_t$	Log of the ratio of repossessions to number of mortgages outstanding	<ul style="list-style-type: none"> Number of repossessions from CML. Number of mortgages outstanding from CML. 	-7.30	0.59
$\log arr6_t$	Log of the ratio of 6-month arrears (defined as greater than or equal to 6 months) to number of mortgages outstanding. (Note that 6-month arrears include 12-month arrears.)	<ul style="list-style-type: none"> Sum of number of 6-12-month arrears plus 12-month arrears, both from CML. Number of mortgages outstanding from CML. 	-4.62	0.61
$\log arr12_t$	Log of the ratio of 12-month arrears (defined as greater than or equal to 12 months) to number of mortgages outstanding	<ul style="list-style-type: none"> Number of 12-month arrears from CML. Number of mortgages outstanding from CML. 	-5.82	0.81
$\log ur_t$	Log of unemployment rate	<ul style="list-style-type: none"> Unemployment rate by age (16 and over), seasonally adjusted, the Labour Force Survey, ONS (Code MGSX). 	2.00	0.28
$\log dsr_t$	<p>Log of cost of loan to income, measured as: $((arbm / 100)(avmort(-1)) / (avpdi))$</p> <p><i>arbm</i> = average mortgage interest rate; <i>avmort</i> = <i>amwt</i>/<i>mortno</i>, where <i>amwt</i> = mortgage lending stock and <i>mortno</i> = number of mortgages outstanding ; <i>avpdi</i> = <i>pdi</i>/<i>popw</i> where <i>pdi</i> = personal disposable income and <i>popw</i> = population of working age.</p>	<ul style="list-style-type: none"> Mortgage interest rate (adjusted for tax before 2000) is from FSA (MLAR statistics, Table 1.22 - Residential loans to individuals: Interest rate analysis. Overall weighted average interest rate on balances outstanding, all loans). From 2000 to 2006, linked to average of mortgage rate on balances outstanding for banks and building societies, previously reported in Financial Statistics, ONS. Before 2000, linked to average mortgage rate on balances outstanding for building societies, previously reported in Financial Statistics, ONS (Code AJNL). Number of mortgages outstanding from CML. Mortgage lending stock is loans secured on dwellings, from Financial Statistics, ONS (Code NNRP). Real household disposable income, seasonally adjusted, from United Kingdom Economic Accounts - Income and capital accounts, ONS (Code NRJR). Nominal disposable income is derived using the consumer expenditure deflator. Deflator is current price measure of consumer expenditure/chained volume index of consumer expenditure, both seasonally adjusted, from Consumer Trends, ONS. Population of working age, 15 to 64 (000s), ONS. 	-7.19	0.25

$\log neqeq_t$	Log of the debt-equity ratio, measured to proxy the ratio of the average mortgage to average house prices. Implied proportion of negative equity, see equations (9) and (10) in the text. $avdebt/equity = avmort(-1)/ph$ where $avmort = amwt/mortno$, see above, and $avmort$ = average mortgage, and ph = house price.	<ul style="list-style-type: none"> House prices are 2nd-hand mix-adjusted house prices of pre-owned dwellings, from DCLG (Table 694), from ONS. Converted from quarterly index to an average quarterly house price. The average mortgage is the ratio of the mortgage lending stock to the number of mortgages outstanding. Number of mortgages outstanding from CML. Mortgage lending stock is loans secured on dwellings, from Financial Statistics, ONS (Code NNRP). 	-3.73	1.35
$SD2008Q4_t$	Example of a Step Dummy: dummy =1 from 2008Q4, and 0 otherwise.	<ul style="list-style-type: none"> Constructed. 	-	
$OD1997_t$	Example of the Ogive Dummy which takes the values 0.05, 0.15, 0.3, 0.5, 0.7, 0.85, 0.95, 1 over an 8-quarter interval, beginning in 1997Q1 and ending in Q4 one year later.	<ul style="list-style-type: none"> Constructed. In this example, dummy=0 before 1997Q1; dummy=0.05 in 1997Q1; then rises each quarter (as shown in the preceding column) so that, for instance, dummy=0.3 in 1997Q3; until dummy=1 in 1998Q4 and thereafter. 	-	
$ID1984Q3_t$	Example of an Impulse Dummy for an outlier in 12month+arrears: dummy =1 for 1984Q3, and 0 otherwise.	<ul style="list-style-type: none"> Constructed. 	-	
$mcred$ and $mcred^{adj}$	Measure of mortgage credit conditions from Bank of England Credit Conditions Survey and adjusted measure: $mcred^{adj} = (mcred_t - 0.5(mcred_t - mcred_{2012Q3})SD2012Q4_t)$	<ul style="list-style-type: none"> Cumulated sum since 2007Q3 of net balance: percentage of banks reporting tighter unsecured credit for households compared with 3 months earlier, scaled by 100. http://www.bankofengland.co.uk/publications/Pages/other/monetary/creditconditions.aspx 	-0.28	0.61

Abbreviations: Office of National Statistics (ONS); Council of Mortgage Lenders (CML); Financial Services Authority (FSA); Department for Communities and Local Government (DCLG).

¹. The sample is the longest available for both arrears and repossessions, 1983Q2 to 2015. Biannual CML data, interpolated to a quarterly frequency are used before 1999.

Table 4a: Estimation results for long-run parameters of arrears and reposessions equations, 1983Q2-2014Q1 and 1983Q2-2005Q4.

<i>Variable</i>	<i>Parameter</i>	<i>Repossession equation</i>	<i>Repossession equation</i>	<i>Parameter</i>	<i>12-month arrears equation</i>	<i>12-month arrears equation</i>	<i>Parameter</i>	<i>6-month arrears equation</i>	<i>6-month arrears equation</i>
		1983Q2-2014Q1	1983Q2-2005Q4		1983Q2-2014Q1	1983Q2-2005Q4		1983Q2-2014Q1	1983Q2-2005Q4
Speed of adjustment	κ^p	0.39** (0.040)	0.37** (0.048)	κ^{a12}	0.28** (.026)	0.30** (0.039)	κ^{a6}	0.28** (0.028)	0.27** (0.041)
Constant	a_0	3.66** (0.77)	3.98** (0.87)	b_0	2.91 (1.73)	0.76 (1.96)	c_0	4.96** (1.18)	4.01** (1.47)
log dsrma(-1)	a_1	1.62** (0.099)	1.71** (0.097)	b_1	1.80** (0.214)	1.73** (0.223)	c_1	1.72** (0.152)	1.71** (0.175)
log negeqma(-1)	a_2	0.287** (0.025)	0.272** (0.027)	-		-	c_2	0.152** (0.022)	0.129** (0.024)
log negeqma(-2)	-			b_2	0.174** (0.032)	0.133** (0.032)			
log ur(-5)	a_3	0.57** (0.146)	0.665** (0.191)	b_3	0.99** (0.252)	1.56** (0.337)	c_3	0.84** (0.17)	1.16** (0.24)
LQ (loan quality)	a_4	1	1	b_4	1.75** (0.17)	2.05** (0.25)	c_4	1.15** (0.12)	1.30** (0.17)
FP (forbearance policy)	a_5	1	1	b_5	4.11** (0.76)	3.38* (1.37)	c_5	3.43** (0.63)	3.06* (1.21)
Correction factor	-	-	-	θ^{a12}	-0.285** (0.062)	-0.303** (0.071)	θ^{a6}	-0.162** (0.043)	-0.160** (0.047)
Diagnostics									
Eq. standard error		0.0410	0.0402		0.0341	0.0353		0.0244	0.0260
R squared		0.9951	0.9964		0.9982	0.9984		0.9984	0.9985
LM Het test P-val		0.000	0.002		0.212	0.264		0.350	0.217
Durbin-Watson		2.02	1.89		1.95	1.99		2.05	2.25

Table 4b: Estimation results for expression for negative equity, 1983Q2-2014Q1 and 1983Q2-2005Q4.

<i>Variable</i>	<i>Parameter</i>	<i>Negative equity equation</i>	<i>Negative equity equation</i>
		1983Q2-2014Q1	1983Q2-2005Q4
Intercept in <i>alder</i>	ρ_0	0.15 (fixed)	0.15 (fixed)
Trend in <i>alder</i>	ρ_1	-0.00122 (fixed)	-0.00122 (fixed)
Logistic in cubic	λ_1	-8.76** (0.98)	-8.71** (0.82)
Logistic in cubic	λ_3	-11.91** (4.07)	-12.48** (3.38)
Coefficient on <i>wbias</i>	ω_0	-0.153* (0.066)	-0.142* (0.071)
Add-on coefficient	δ	0.00066	0.00066
Decay factor	ω	0.9	0.9

Table 5: Forecast root mean square errors.

<i>Estimation period:</i>	1983Q2-2014Q1	1983Q2- 2010Q4	1983Q2- 2011Q4	1983Q2- 2012Q4
<i>Forecast period:</i>	full in-sample	2011Q1-2014Q4	2012Q1-2014Q4	2013Q1-2014Q4
<i>Equation</i>	<i>Root mean square errors (RMSE)</i>			
<i>Repossessions</i>	0.041	0.043 (0.021)*	0.011	0.022
<i>6-month arrears</i>	0.024	0.014 (0.014)*	0.026	0.004
<i>12-month arrears</i>	0.034	0.029 (0.022)*	0.032	0.021

1. RSME assuming knowledge of full sample estimates of 2011Q1 dummy coefficients, capturing consequences of reduction in interest rate paid to lenders under SMI.

Table 6: Summary of annualised data for three economic scenarios.*(a) Base Scenario*

	<i>Mortgage rate/%</i>	<i>Debt service ratio/%</i>	<i>House price index</i>	<i>Percentage in negative equity/%</i>	<i>Unemployment rate/%</i>
2014	3.31	13.19	200.5	1.41	6.17
2015	3.17	12.37	212.9	0.71	5.38
2016	3.14	12.17	222.0	0.54	5.17
2017	3.47	13.52	229.2	0.55	5.08
2018	3.85	15.17	236.4	0.59	5.01
2019	4.14	16.56	245.0	0.57	4.98
2020	4.43	17.89	255.3	0.51	4.97

(b) More Favourable Scenario

	<i>Mortgage rate/%</i>	<i>Debt service ratio/%</i>	<i>House price index</i>	<i>Percentage in negative equity/%</i>	<i>Unemployment rate/%</i>
2014	3.31	13.19	200.5	1.41	6.17
2015	3.17	12.37	212.9	0.71	5.38
2016	3.14	12.13	223.4	0.50	5.00
2017	3.22	12.50	234.9	0.46	4.60
2018	3.15	12.46	250.2	0.40	4.51
2019	3.34	13.59	267.2	0.36	4.48
2020	3.63	15.10	283.1	0.38	4.47

(c) Less Favourable Scenario'

	<i>Mortgage rate/%</i>	<i>Debt service ratio/%</i>	<i>House price index</i>	<i>Percentage in negative equity/%</i>	<i>Unemployment rate/%</i>
2014	3.31	13.19	200.5	1.41	6.17
2015	3.17	12.37	212.9	0.71	5.38
2016	3.44	13.35	219.4	0.61	5.67
2017	4.50	17.42	219.6	0.77	6.05
2018	5.10	19.72	218.2	0.96	6.16
2019	5.39	20.74	215.8	1.16	6.33
2020	5.68	21.60	215.8	1.16	6.52

Table 7: Annualised forecast simulations for various scenarios, in rates (%), 2015-2020

<i>Forecast year</i>	<i>Annual repossessions</i>	<i>12-month arrears</i>	<i>6-month arrears</i>	<i>Annual repossessions</i>	<i>12-month arrears</i>	<i>6-month arrears</i>	<i>Annual repossessions</i>	<i>12-month arrears</i>	<i>6-month arrears</i>
	<i>Scenario 1: Base</i>			<i>Scenario 2: More favourable</i>			<i>Scenario 3: Less favourable</i>		
2014	0.20	0.26	0.71	0.20	0.26	0.71	0.20	0.26	0.71
2015	0.13	0.17	0.52	0.13	0.17	0.52	0.13	0.17	0.52
2016	0.09	0.12	0.38	0.09	0.12	0.38	0.09	0.12	0.41
2017	0.08	0.11	0.36	0.08	0.10	0.33	0.11	0.15	0.48
2018	0.09	0.11	0.38	0.07	0.09	0.30	0.18	0.19	0.65
2019	0.11	0.12	0.42	0.07	0.08	0.29	0.22	0.23	0.77
2020	0.12	0.13	0.47	0.08	0.09	0.31	0.24	0.27	0.88

1. The scenarios are defined in section 5.

Figure 1: Repossessions and 6- and 12-month arrears in the UK

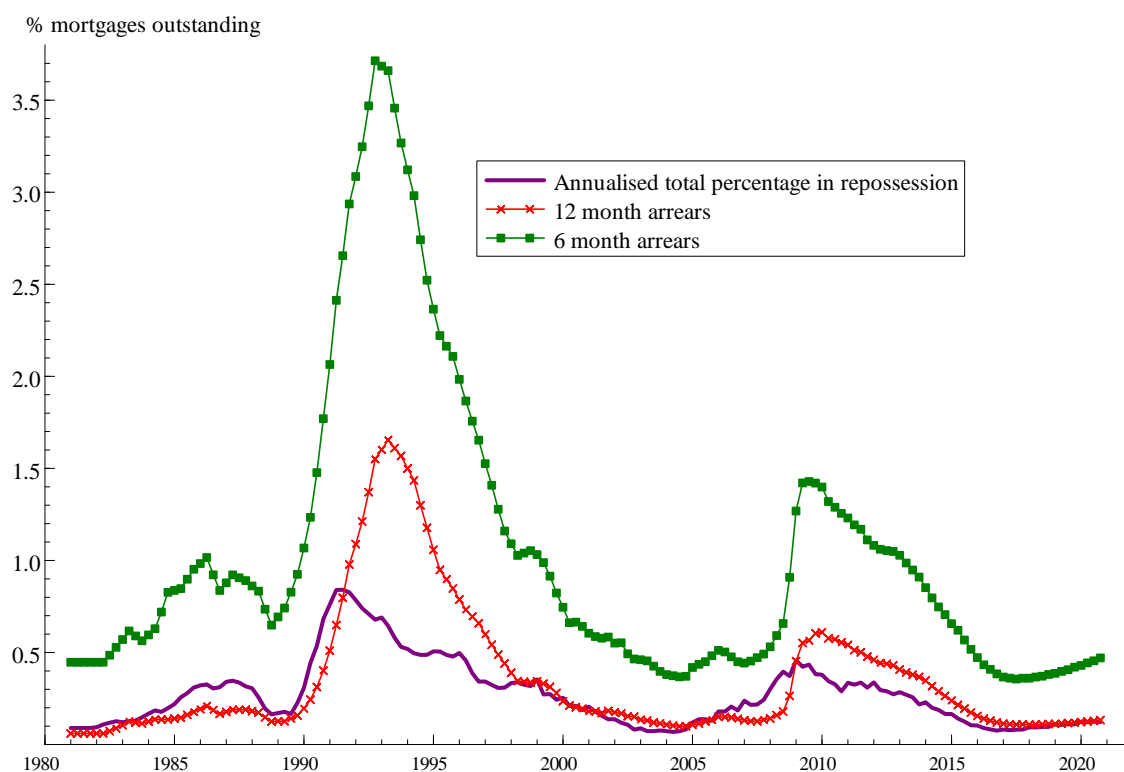
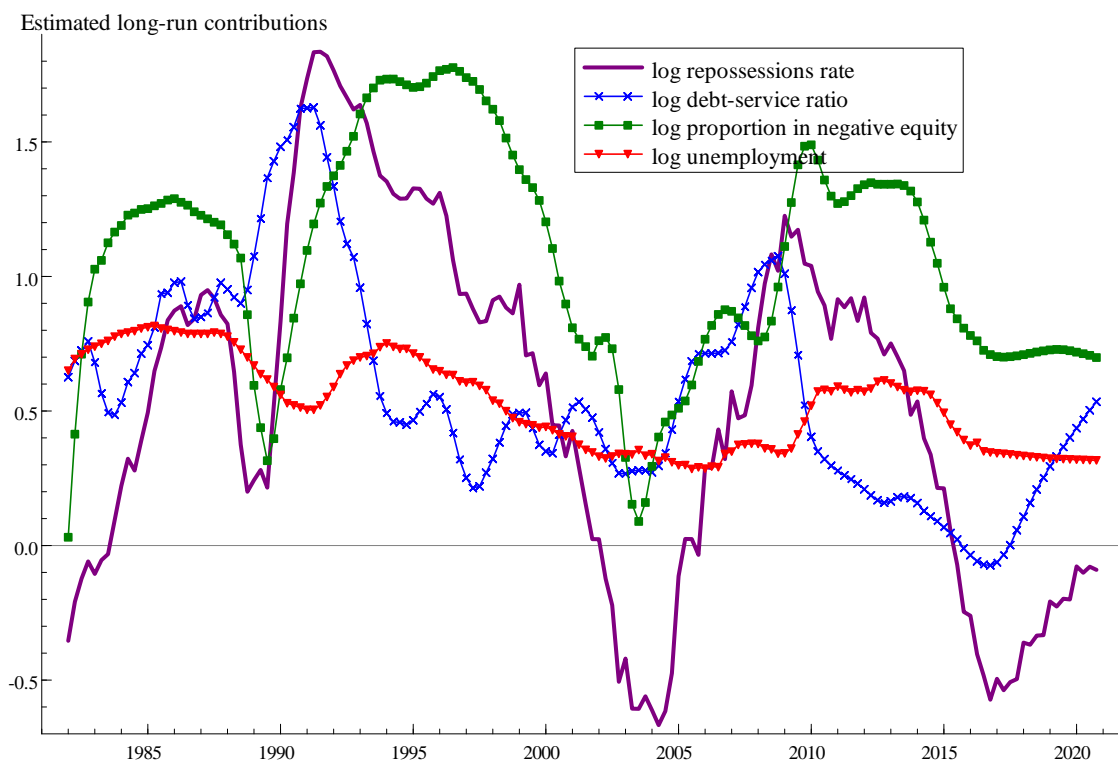
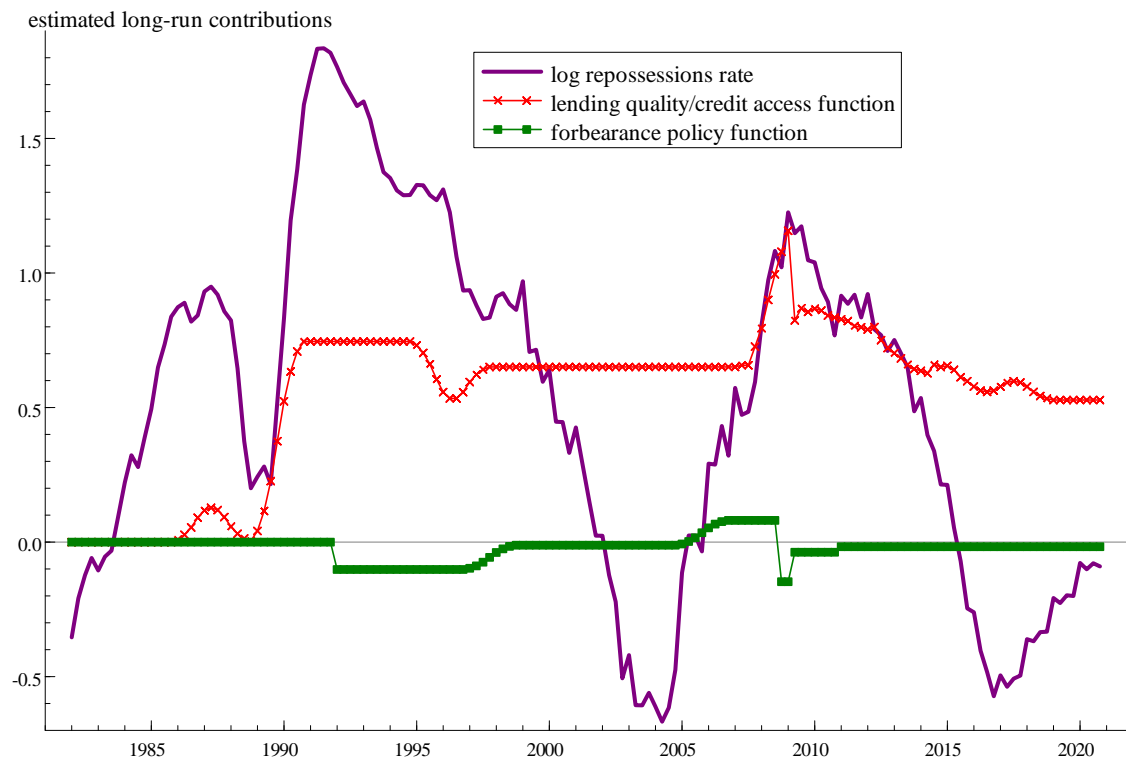


Figure 2: Estimated long-run contributions of key explanatory variables to the log repossessions rate.



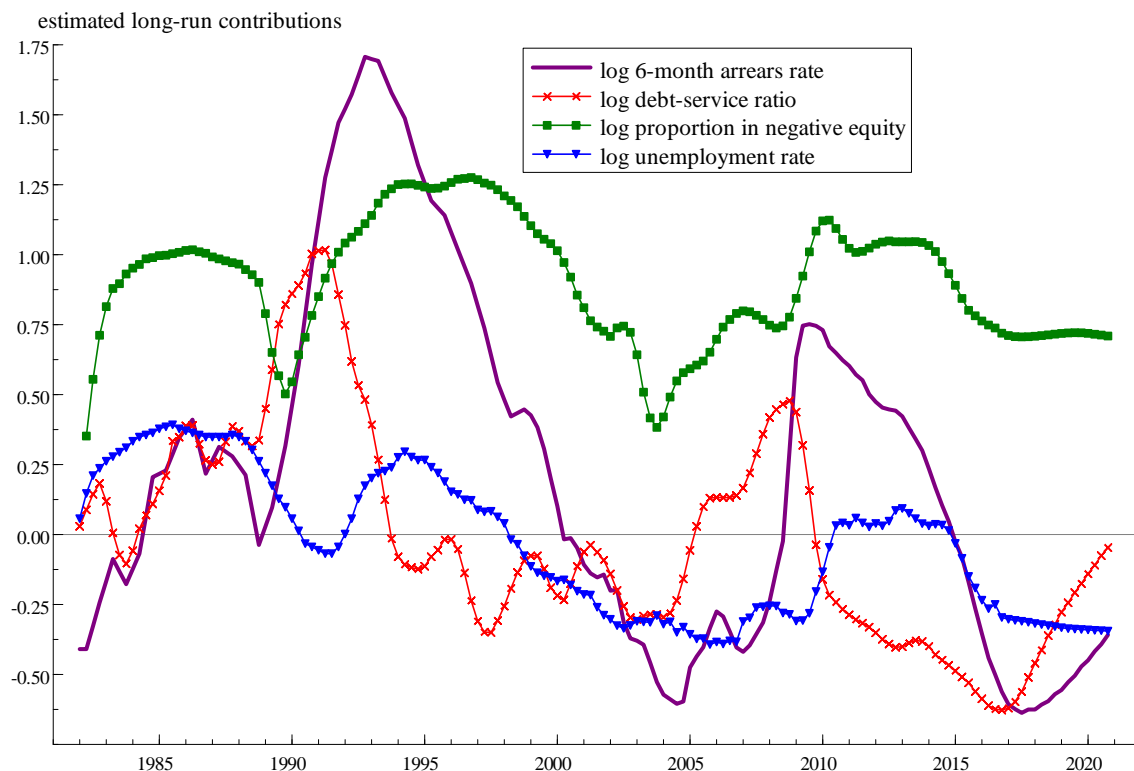
Note 1: Variables are level-adjusted for visual purposes. The Base Scenario is assumed for 2015q4 to 2020q4.

Figure 3: Estimated long-run contribution of lending standards and policy shift proxies to the log reposessions rate.



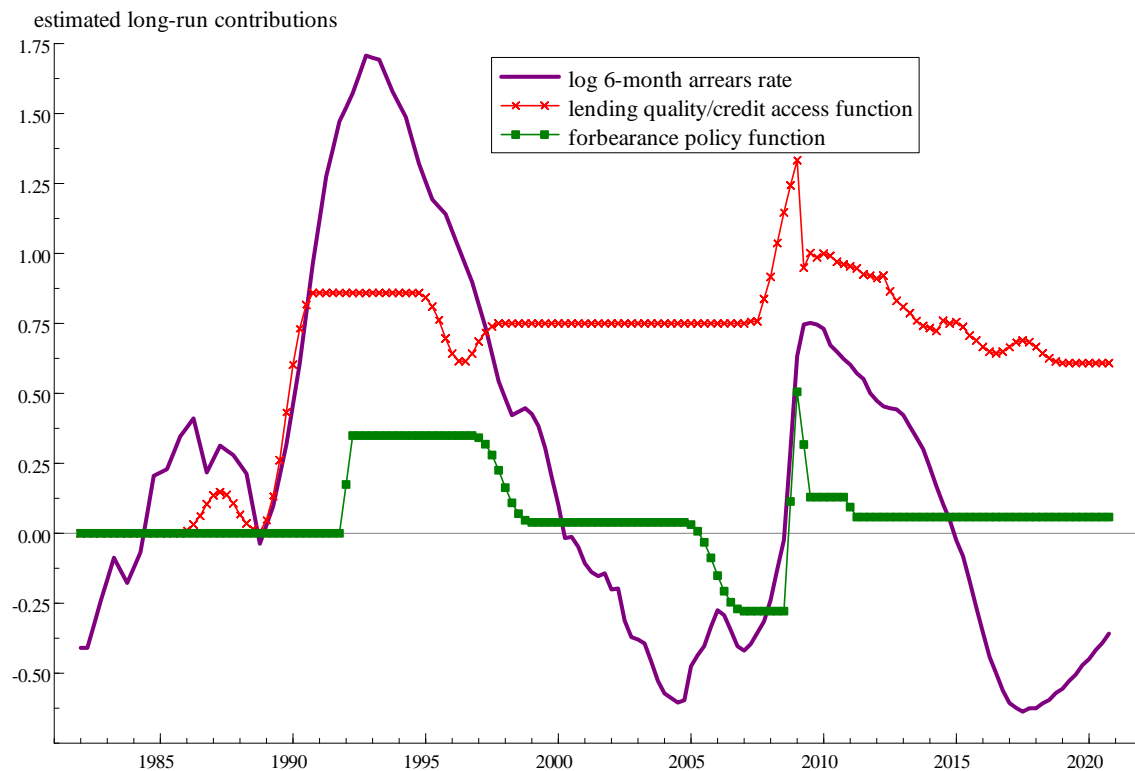
Note 1: Variables are level-adjusted for visual purposes. The Base Scenario is assumed for 2015q4 to 2020q4.

Figure 4: Estimated long-run contributions of key explanatory variables to the log 6 month arrears rate.



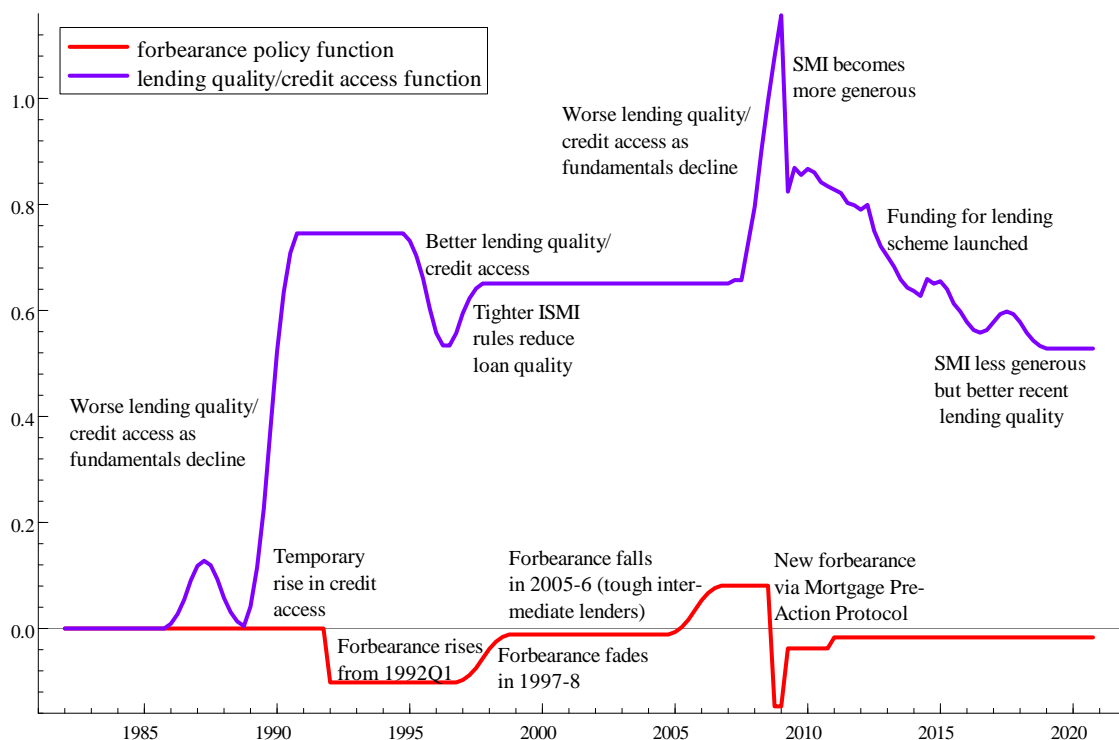
Note 1: Variables are level-adjusted for visual purposes. The Base Scenario is assumed for 2015q4 to 2020q4.

Figure 5: Estimated long-run contribution of lending standards and policy shift proxies to the log 6 month arrears rate.



Note 1: Variables are level-adjusted for visual purposes. The Base Scenario is assumed for 2015q4 to 2020q4.

Figure 6: An annotated version of forbearance and 'loan quality/credit access' functions



Note 1: The Base Scenario is assumed for 2015q4 to 2020q4. Abbreviations: Financial Services Authority (FSA); Income Support for Mortgage Interest (ISMI)/ Support for Mortgage Interest (SMI).

APPENDIX A – A Brief Overview of the US Literature on Mortgage Default and Delinquency

The evolution of mortgage default studies in the US is characterised by Quercia and Stegman (1992) in a typology of three generations or sets of studies. The earliest work on default and delinquency risk rates from the 1960s onwards focused from a *lender's* perspective on simple correlations or empirical regression models capturing, at loan origination, the characteristics of the mortgages (e.g. loan-to-value ratio, interest rate and mortgage term) and of borrowers (e.g. family size, location, marital status, junior financing and characteristics of employment) that might be correlated with later default.

A second generation of empirical models derived from theoretical models that instead emphasised factors influencing the *borrowers'* decisions on payment, prepayment, delinquency or default. Couched in a utility maximising framework, such models allow four alternative choices at each payment period, where the chosen outcome maximises utility over time, given the borrower's circumstances. A special case is the large literature on option theoretic models from the mid-1980s, in its simplest form abstracting from transactions costs ("frictionless" models), where prepayment is treated as a call option and default as a put option in a competitive market. Such models predict immediate default if a property's value drops to the level of the mortgage value minus a small margin depending on house price volatility ("ruthless default", Vandell, 1995).³⁹ These models emphasise the *financial* aspects of the decision via negative equity, and borrower characteristics are excluded. Thus, such frictionless models predict identical default behaviour for borrowers with similar mortgages and houses. Much of the empirical literature, however, has explored the evidence for "default under-exercise" rather than "ruthless default", whereby the default decision is delayed on reaching sufficiently negative equity. Some studies rationalise such evidence by transactions costs, such as from moving house, and by future credit restrictions (e.g. Kau et al., 1993). Others suggest a role for "trigger events" (Riddiough, 1991), or crises affecting income, such as divorce or loss of employment, that when intersecting with marginal equity, may precipitate the move from a delinquent state with negative equity, to default. This introduces a role for ability to pay factors in addition to equity. The evidence on both sides of the "ruthless default" was summarized by Vandell (1995), who recommended, *inter alia*, a better empirical understanding of the role of trigger events through improved micro-data sets and analyses of mortgage case studies, of credit constraints and solvency, of the functional forms of various transactions costs, and of lender influences on default and delinquency.

The so-called third generation of models mainly represent a technological improvement on the second generation models in applying proportional hazard models to estimate default probabilities, and utilizing a measure of mortgage risk that better reflects lenders' concerns: expected mortgage loss⁴⁰ rather than default rates, as in most second generation studies. The predominant empirical model in the literature stems from the second and third generational research. It finds an important role for net equity in default risk, but also some evidence for borrower effects and transactions costs, though these effects are less well understood (examples focused on the sub-prime crisis are Foote et al. (2008), Gerardi et al. (2008), Bajari et al. (2009), Haughwout et al. (2009) and Bhutta et al. (2010)). However, as Bajari et al. makes clear, the neglected factors of lending quality or credit constraints do not find an obvious place in the utility-maximising framework underlying second generational and option theoretical models. These require an extension to such models, see section 2.1 for discussion.

³⁹ Even within the option theoretic model, however, it is not optimal to default immediately that negative equity is reached if there are possibilities to default in the future which could be more valuable, given volatile prices.

⁴⁰ Mortgage loss varies with the size of the loan, and this is not picked up when using default rates.

Studies on delinquency are far fewer, mainly due to the difficulty in modelling the delinquency decision, not easily set within the option theoretic model unless a competing risk model is contemplated (Quercia and Stegman, 1992).

APPENDIX B – Addressing measurement bias in the “months-in-arrears” data measure

This appendix discusses correcting the bias from the “months-in-arrears” measure, never previously addressed by an empirical study on UK data.

It is unfortunate that a long history of arrears data is available only for a count of arrears measured as “months in arrears” (those with an accumulated level of arrears in excess of an equivalent number of months of normal payments). When mortgage rates fall, normal payments fall and the “months-in-arrears” count *rises*.

We illustrate this with an example. With a 25 year conventional repayment mortgage, at a 7.5 percent mortgage rate, being 2.5 percent in arrears (e.g. with arrears of £2500 on a £100,000 loan) translates into being 3.3 months in arrears (see CML information notes on release of arrears data, e.g. February 20, 2009). For a similar interest-only mortgage, the number of months in arrears is higher at 4 months, as monthly payments do not incorporate a repayment element. If the current interest rate falls and so the regular monthly payments, the accumulated arrears translate into a higher monthly payment equivalent at the new lower interest rate, and months in arrears *rises*. With a lower 4.5 percent interest rate, being 2.5 percent in arrears translates into 4.4 months for a conventional mortgage, and 6.7 months for an interest only mortgage. This pushes more existing cases into the 3-6 months and the 6-12 months in arrears categories.

A bias correction based on the log debt-service ratio is used to formulate a relationship for a more satisfactory measure, arr^* (a count of arrears by the ratio of arrears to mortgage debt) from one for the biased measure, arm (a count by months). We approximate the relationship between the two measures as follows:

$$\log arr^*_i = \text{constant} + \log arm_i + \theta^a \log dsr_i \quad (\text{B.1})$$

where arm is the month in arrears count which best matches the percentage in arrears count represented by arr^* , and $\theta^a \log dsr$ proxies the measurement bias.

APPENDIX C– Introducing regional heterogeneity into the measure of the proportion of mortgages in negative equity.

The Bank of England estimates of negative equity, explained in Bank of England (1992) and subsequent Quarterly Bulletins, and in Cutler (1995), use data from the 5 percent sample of mortgages, to count high loan-to-value loans in regions where average house prices fell sufficiently to put those loans into negative equity. The peak number estimated was 1.8m mortgages in 1993Q1. This count excludes the contribution that mortgage arrears make to outstanding mortgage debts. It is unclear whether the cases of negative equity going into repossession are subtracted. The Bank of England estimates the decline implausibly rapidly in 1993, despite an only very modest recovery in house prices in London and other Southern regions from 1993Q2, and even weaker recoveries in the rest of the country.

In the more recent mortgage crisis of 2009 similar methods were used based on loan-to-value data from the Survey of Regulated Mortgages, see Hellebrandt et al. (2009) and Financial Services Authority (2012). These suggest peak estimates of around 1.1m mortgages for owner-occupiers, and

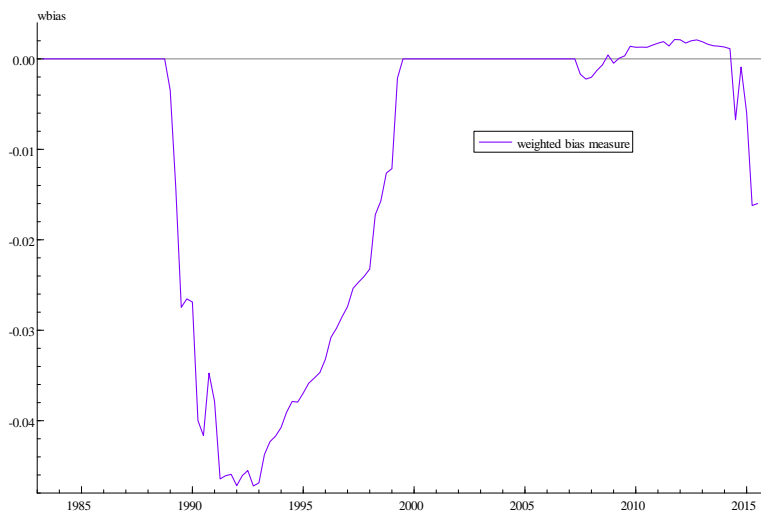
perhaps 0.2m for buy-to-let mortgages. Similar methods were used by Tatch (2009) at the Council of Mortgage Lenders with comparable results. Such estimates are necessarily approximate as they depend on which house price indices are employed.

We adapt our own method for measuring negative equity by incorporating a measure of regional house price heterogeneity. The main regional divide is between London and other Southern regions (South West, South East and East) and the rest of the country, including Wales, Scotland, Northern Ireland, Midlands, North and North West. House prices, from the Halifax source used by the Bank of England, peaked in the Greater South in 1988Q4, then fell, began to recover in 1993Q2, and first exceeded their previous peak in 1999Q3. House prices in the Greater North peaked far later in 1991Q2, hovered in a range between 1993Q1 and 1995Q4, and first exceeded their previous peak in 1998Q2, having fallen rather less than house prices in the Greater South. The UK house price index from the same source peaked in 1989Q2, hovered in a range between 1993Q2 and 1995Q4, and then recovered systematically.

For the Greater North, we can construct a proxy for the degree of negative equity, which is zero up to the peak quarter 1991Q2, equals the deviation between the log house price index at t and its peak value at 1991Q2, and becomes zero again in 1998Q2, when house prices in the Greater North first exceeded their previous peak. However, since most borrowers will be repaying some of their debt, though some will suffer repossession, we need to apply a decay factor to this indicator or negative equity. Grid search with different values suggested a decay factor of 0.975, implying a decay rate of around 10 percent per annum. To illustrate, we define $DEVGN$ for 1991Q3 to 1998Q1 to be the deviation between the log of house prices in the Greater North and its peak value in 1991Q2, and for 2009Q1 to 2014Q1, to be the deviation from the peak value in 2008Q4. $DEVGN$ is zero outside these time intervals. The weighted deviation is defined as $WDEVGN_t = 0.975^{t-(peak\ t)} DEVGN_t$, where peak t is 1991Q2 between 1991Q3 and 1998Q1, and 2008Q4 for 2009Q1 to 2014Q1.

We construct analogous measures for the Greater South and for the UK as a whole. The weighted bias measure, $wbias$, is then defined as the difference between the UK indicator and the average of the two regional indicators. It is negative in the 1989Q1 to 1999Q3 period, suggesting that negative equity rose more strongly from 1989Q1 than a proxy based on the UK house price index, see Figure C.1. In the later mortgage crisis from 2009, $wbias$ is rather smaller for there was little difference in the timing of house price peaks and troughs between the regions, though recovery in the Greater North was slower.

Figure C.1: Estimated weighted bias measure of regional differences in incidence of negative equity.



APPENDIX D – Details of estimated equations

Parsimonious versions of the estimated equations are presented below, with the variables defined in Table 3. Equation estimates are given in Tables 4a- 4b.

The selected repossession equation

$$\begin{aligned}\Delta \log poss_t = & \kappa^p \times (a_0 + a_1 \log dsrma_{t-1} + a_2 \log negeqma_{t-1} + a_3 \log ur_{t-5} \\ & + LQ_t + FP_{t-1} - \log poss_{t-1}) + \Delta FP_t + \alpha_{1,1} \Delta \log dsr_{t-1} + \alpha_{2,0} \Delta_2 \log negeq_t \\ & + \alpha_{2,1} \Delta_8 \log negeq_{t-1} + \phi_1 (1 - SD1999_t) \Delta \log poss_{t-1} + \phi_2 \Delta \log poss_{t-2} \\ & + \alpha_1 Q1_t + \alpha_2 (1 - SD1999_t) Q1_t + \alpha_3 \Delta ID1989 Q3_t \\ & + \alpha_4 \Delta ID1999 Q2_t + \alpha_5 \Delta ID2003 Q4_t + \alpha_6 \Delta ID2005 Q4_t\end{aligned}\quad (D.1)$$

The selected arrears equations: arrears > 12 months

$$\begin{aligned}\Delta \log arr12_t = & \kappa^{a12} \times (b_0 + b_1 \log dsrma_{t-1} + b_2 \log negeqma_{t-1} + b_3 \log ur_{t-5} \\ & + b_4 LQ_t - b_5 (0.5FP_t + 0.5FP_{t-1}) - (\log arr12_{t-1} - \theta^{a12} \log dsr_{t-1})) \\ & + \theta^{a12} \Delta \log dsr_t - 0.3 poss_t / arr12_{t-1} + \beta_{2,0} \Delta_2 \log negeq_t \\ & + \beta_{3,1} \Delta_4 \log ur_{t-1} + \chi_1 (1 - SD1999_t) (\Delta \log arr12_{t-1} - \theta^{a12} \log \Delta dsr_{t-1}) + \beta_1 ID1987 Q1_t\end{aligned}\quad (D.2)$$

The selected arrears equations: arrears > 6 months

$$\begin{aligned}\Delta \log arr6_t = & \kappa^{a6} \times (c_0 + c_1 \log dsrma_{t-1} + c_2 \log negeqma_{t-2} + c_3 \log ur_{t-5} \\ & + c_4 LQ_t - c_5 (0.5FP_t + 0.5FP_{t-1}) - (\log arr6_{t-1} - \theta^{a6} \log dsr_{t-1})) \\ & + \theta^{a6} \Delta \log dsr_t - 0.9 poss_t / arr6_{t-1} \\ & + \gamma_{1,1} \Delta \log dsr_{t-1} + \gamma_{2,0} \Delta_2 \log negeq_t + \gamma_{3,0} \Delta_4 \log ur_t \\ & + \psi_1 (1 - SD1999_t) (\Delta \log arr6_{t-1} - \theta^{a6} \log \Delta dsr_{t-1}) \\ & + \gamma_1 ID1984 Q3_t + \gamma_2 ID1987 Q1_t\end{aligned}\quad (D.3)$$

The selected 'loan quality/credit access' equation

$$\begin{aligned}LQ_t = & l86 \times OD1986_t + l87 \times OD1987_t + l89 \times OD1989_t \\ & + l95 \times OD1995_t + l96 \times OD1996_t + l08 \times OD2008 Q2_t \\ & + l09 \times SD2009 Q2_t + l11 \times SD2011 Q1_t + lcred \times mcred_t^{adj}\end{aligned}\quad (D.4)$$

The selected forbearance policy equation

$$\begin{aligned}FP_t = & p92 \times SD1992_t + p97 \times OD1997_t + p05 \times OD2005_t + p08 \times SD2008 Q4_t \\ & + p09 \times SD2009 Q2_t + p11 \times SD2011 Q1_t\end{aligned}\quad (D.5)$$

APPENDIX E – Estimation results

Table E.1 Estimation results: arrears and reposessions equations.

<i>Variable</i>	<i>Para- meter</i>	<i>Reposessions equation</i>	<i>Reposessions equation</i>	<i>Para- meter</i>	<i>12-month arrears equation</i>	<i>12-month arrears equation</i>	<i>Para- meter</i>	<i>6-month arrears equation</i>	<i>6-month arrears Equation</i>
		1983Q2- 2014Q1	1983Q2- 2005Q4		1983Q2- 2014Q1	1983Q2- 2005Q4		1983Q2- 2014Q1	1983Q2- 2005Q4
Speed of adjustment	κ^p	0.39** (0.040)	0.37** (0.048)	κ^{a12}	0.28** (.026)	0.30** (0.039)	κ^{a6}	0.28** (0.028)	0.27** (0.041)
<i>Long-run terms</i>									
Constant	a_0	3.66** (0.77)	3.98** (0.87)	b_0	2.91 (1.73)	0.76 (1.96)	c_0	4.96** (1.18)	4.01** (1.47)
log dsrma(-1)	a_1	1.62** (0.099)	1.71** (0.097)	b_1	1.80** (0.214)	1.73** (0.223)	c_1	1.72** (0.152)	1.71** (0.175)
log negeqma(-1)	a_2	0.287** (0.025)	0.272** (0.027)	-		-	c_2	0.152** (0.022)	0.129** (0.024)
log negeqma(-2)	-			b_2	0.174** (0.032)	0.133** (0.032)			
log ur(-5)	a_3	0.57** (0.146)	0.67** (0.191)	b_3	0.99** (0.252)	1.56** (0.337)	c_3	0.84** (0.17)	1.16** (0.24)
<i>LQ</i> (loan quality)	a_4	1	1	b_4	1.75** (0.17)	2.05** (0.25)	c_4	1.15** (0.12)	1.30** (0.17)
<i>FP</i> (forbearance policy)	a_5	1	1	b_5	4.11** (0.76)	3.38* (1.37)	c_5	3.43** (0.63)	3.06* (1.21)
Correction factor	-	-	-	θ^{a12}	-0.285** (0.062)	-0.303** (0.071)	θ^{a6}	-0.162** (0.043)	-0.160** (0.047)
<i>Dynamic terms</i>									
Δ_2 log negeq	$\alpha_{1,1}$	0.045** (0.009)	0.040** (0.009)	$\beta_{2,0}$	0.013* (0.006)	0.009 (0.006)	$\gamma_{1,1}$	0.021** (0.006)	0.018** (0.006)
Δ_8 log negeq(-1)	$\alpha_{2,0}$	-0.011** (0.004)	-0.005 (0.0039)						
Δ log dsr(-1)	$\alpha_{2,1}$	0.20** (0.070)	0.28** (0.076)				$\gamma_{2,0}$	0.150** (0.046)	0.162** (0.051)
Δ_4 log ur				$\beta_{3,1}$	0.213** (0.063)	0.323** (0.090)	$\gamma_{3,0}$	0.160** (0.041)	0.196** (0.054)
Δ log poss(-2)	φ_1	0.20** (0.052)	0.22** (0.058)						
Dynamic shift adjustment	φ_2	0.14 (0.070)	0.18* (0.080)	χ_1	0.274** (0.096)	0.237* (0.103)	ψ_2	0.381** (0.109)	0.413** (0.120)
<i>Diagnostics</i>									
Eq. standard error		0.0410	0.0402		0.0341	0.0353		0.0244	0.0260
R squared		0.9951	0.9964		0.9982	0.9984		0.9984	0.9985
LM Het test P-val		0.000	0.002		0.212	0.264		0.350	0.217
Durbin-Watson		2.02	1.89		1.95	1.99		2.05	2.25

1. The selected repossessions equation and selected arrears equations for 12-month arrears and 6-month arrears are given in Appendix D. Variables are defined in Table 3. ** indicates significant at the 1% level; * indicates significant at the 5% level. Parameter estimates for seasonals and impulse dummies are not shown.
2. The forbearance policy shift function enters as: $0.5FP_t + 0.5FP_{t-1}$.
3. The dynamic shift adjustment for the repossessions equation is $(1 - SD1999_t)(\Delta_2 \log poss_{t-1})$ and for the 12-month and 6-month arrears, respectively, $(1 - SD1999_t)(\Delta \log arr12_{t-1} - \theta^{a12} \Delta \log dsr_{t-1})$ and $(1 - SD1999_t)(\Delta \log arr6_{t-1} - \theta^{a6} \Delta \log dsr_{t-1})$ where SD1999 is a step dummy beginning in 1999 when data frequency shifted to quarterly.

Table E.2: Estimation results: forbearance policy and ‘loan quality/credit access’ equations.

<i>Variable</i>	<i>Parameter</i>	1983Q2-2014Q1	1983Q2-2005Q4
<i>SD1992</i>	<i>p92</i>	-0.104** (0.022)	-0.096** (0.020)
<i>OD1997</i>	<i>p97</i>	0.092** (0.025)	0.087* (0.034)
<i>OD2005</i>	<i>p05</i>	0.093** (0.019)	0.015 (0.058)
<i>SD2008Q4</i>	<i>p08</i>	-0.230** (0.030)	-
<i>SD2009Q2</i>	<i>p09</i>	0.122** (0.025)	-
<i>SD2010Q4</i>	<i>p10</i>	-0.024* (0.0117)	-
<i>SD2011Q1</i>	<i>p11</i>	0.026** (0.0082)	-
<i>OD1986</i>	<i>l86</i>	0.180** (0.062)	0.154** (0.055)
<i>OD1987</i>	<i>l87</i>	-0.170* (0.085)	-0.118 (0.083)
<i>OD1989</i>	<i>l89</i>	0.760** (0.075)	0.738** (0.100)
<i>OD1995</i>	<i>l95</i>	-0.281** (0.048)	-0.203** (0.047)
<i>OD1996</i>	<i>l96</i>	0.189** (0.044)	0.177** (0.039)
<i>OD2008Q2</i>	<i>l08</i>	0.238** (0.085)	-
<i>SD2009Q2</i>	<i>l09</i>	-0.361** (0.070)	-
<i>mcred^{adj}</i>	<i>lcred</i>	-0.207** (0.028)	-

1. The equations that generated these results are shown in Appendix D; variables are defined in Table 3. ** indicates significant at the 1 percent level; * indicates significant at the 5 percent level.