Risk Heterogeneity and Credit Supply: Evidence from the Mortgage Market*

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Abstract

This paper uses data on about 600,000 mortgage contracts to estimate a credit supply function that allows for heterogeneity in risk pricing. Changes in the tax system for housing transactions are used as instrument for loan demand. The results for the period 1975-2005 are suggestive of significant price heterogeneity with riskier borrowers increasingly penalized for borrowing more. A sub-sample analysis, however, reveals that the period before the financial crisis was characterized by a sharp fall in risk pricing and little evidence of heterogeneity, consistent with a relaxation of credit conditions.

JEL Classification: D10, E21, G21

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1 Introduction

The recent turbulence in global financial markets has brought into sharp relief the issue of how lenders price default risk on loans. And what should have been a local difficulty in the sub-prime segment of the U.S. mortgage market spawned a systemic crisis from which the world is still recovering. At the heart of the issue is a question of how credit contracts are structured and, in particular, the extent to which risk is properly priced and assessed by lenders. But despite its manifest importance, there are few empirical studies that study the micro-economics of risk pricing in mortgage markets empirically. Of particular interest is whether there is evidence in data on mortgage contracts issued that credit standards were being relaxed in observable ways.

In this paper, we approach the issue as follows. Lenders in mortgage markets should price loans to reflect default risk by borrowers. So larger loans, for example, should attract a higher interest rate creating an upward sloping interest-rate loan size locus, controlling for other borrower characteristics. Laxer credit conditions can be thought of as flattening the relationship between the loan size and interest rate. So we should expect to see evidence of this in the period prior to the financial crisis.

We will therefore use micro-data on credit contracts in the U.K. to investigate the empirical relationship between loan size and the interest. Despite some specific institutional features which we discuss below, the UK mortgage market is an interesting case study for understanding features of credit contracts. The market had been subject to a series of reforms aimed at widening availability of credit, particularly some forms of deregulation and greater competition. Greater use of securitized lending was also a feature of the period before the onset of the financial crisis. We are able to trace out how these led to changes in risk premia charged by lenders.

1.1 The Context

It is now recognized that the period leading up to the financial crisis was associated with an over extension credit. According to one influential account by Obstfeld and Rogoff (2009) the global financial crisis can be attributed to an interaction between the monetary stance of central banks (especially the Fed), global real interest rates, a series of credit market distortions coupled with financial innovation. Against this backdrop, global imbalances allowed a series of countries such as the U.S., U.K., Spain and Ireland to fund mortgage lending. Moreover, competition between lenders and the low cost of securitization created an incentive to increase financial sector balance sheets in what turned out to be an unsustainable process.

One way to look at the background macro factors and the idea that policy rates were kept low is to look at the deviation of the actual base rate set by the Bank of England from the prescription of a Taylor rule during this period, where the parameters are fixed to the values proposed by Taylor (1993) for the inflation and output gap terms and the interest rate smoothing is set to 0.7. This is shown in Figure 1 where each line is based on a different measure of inflation.

This relaxation of credit conditions enabled an increase in home ownership rates which was widely applauded at the time as a merit good, one notion being that home ownership created better citizens who behaved more responsibly in their local communities – see, for example, diPasquale and Glaeser (1999). Figure 2 gives rates of home ownership in the U.K. and U.S. between 1980 and the present. While both countries show an upward trend this was much more marked in the U.K. Unsurprisingly this was accompanied by some increase in household indebtedness in both countries as illustrated in Figure 3. And in the years leading up to the financial crisis this provoked some debates about the sustainability of such levels of indebtedness especially in view of the increases in house prices in both countries. From the point of view of lenders and the way that mortgages were priced, assumptions about the future path of house prices were key. And the period of prior to the crisis lead to significant increases as we see in Figure 4.

But in comparing the U.K. and the U.S. it is important to acknowledge a key institutional difference in the typical mortgage contracts between the U.K. and U.S. suggest a rather different calculus. In the U.K., unlike, the U.S. it would not be possible for debtors to walk away from their obligations in the event of defaulting. And the vast majority of U.K. households were dependent on adjustable rate mortgages, within any fixing typical on two to five year horizon. This is illustrated in Figure 5. Unlike the U.S., the tightness of the planning regime prevented any significant supply response to rising house prices limiting the stock of available new housing.

While there were some similarities, the post crisis experience in the two housing markets has been markedly different – the U.S. but not the U.K. has seen very significant increases in arrears and defaults – see Figures 6 and 7. The institutional features that we have outlined explain this. First, U.K. mortgage holders face higher penalties for default. Second, adjustable rate mortgages lead to a very significant part of the benefit from lowering policy rates being passed on to borrowers. In additional, unemployment rates rose much slower in the U.K. than in the U.S., in part because there was no significant construction sector boom.

While it is hard to know whether risk pricing in the U.K. mortgage market anticipated the relative robust performance of the housing market, the relatively softer landing looks to justify at least some of the severe features. It is interesting that the period of recovery from the housing boom in the late 1980s may have led to some greater experience with working out these issues. That said, we will present evidence that there was a change in the way that mortgage risk was priced in during the run-up to the financial crisis. This is most plausibly due to financial innovation creating opportunities for lenders to securitize mortgages on favorable terms. However, it could also be due to others factors such as lender's perceptions of default risk having changed.

1.2 Risk Pricing in the UK Mortgage Market

While the relaxation of credit conditions is a macro-economic phenomenon, it had micro-underpinnings in the specific credit contracts being agreed. Investigating these issues requires a country as well as market specific analysis. It is also important to control for individual risk characteristics as well as macro economic conditions. This paper investigates pricing of default risk in the U.K. mortgage contracts over thirty years using data set on more than 600,000 mortgage contracts. It is well-known that borrowers with similar characteristics (to the eye of the econometrician) may be treated differently in the credit market depending on specific circumstances that may be known to (or inferred by) the lender. To motivate this observation in the context of this paper, figure 8 gives the interest rate spread charged to mortgage borrowers from our data which we describe in details in the next section. The left panel illustrates the distribution of individual interest rate spreads which we have normalized to have mean zero. It is evident from this that there is considerable dispersion to explain in the way that borrowers are treated. But this is put into context by looking also at the right panel which gives the estimated density of a normalized loan size variable from our data. Not surprisingly, there is also a distribution of loan sizes. However, notice that there is considerably less dispersion in the latter distribution compared to interest rates suggesting that there is a potentially important source of heterogeneity which is driving interest rate dispersion that is not captured in loan size.[1]

Our primary focus in this paper is on understanding the relationship between the interest rate and loan size, namely the shape of the (inverse) credit supply function, as well as assessing its evolution over time. We will argue that the latter is mainly due to changes in funding conditions due to an increase in securitization. We will pursue a quantile regression approach in which the credit supply is allowed, but not required, to be (i) heterogeneous across borrowers and (ii) characterized by non-Gaussian disturbances. As observed borrower's characteristics such as demographics, income and initial down payment will be controlled for (alongside time fixed effects), we interpret the unobserved heterogeneity in mortgage pricing as individual risk.

As well as allowing for heterogeneous treatments, we also consider the possibility that the demand for credit responds endogenously to the terms offered by the lender. To disentangle supply and demand factors, we propose using variations in tax rates on housing transactions as an instrument for credit demand. This exploits the fact that these tax rates, which depend upon the value of the house purchased, vary over time and across borrowers. Our approach is therefore in the spirit of Blundell, Duncan and Meghir (1998) who exploit exogenous changes in the tax system on income to identify labour supply. To implement this, we employ Instrumental Variable Quantile Regressions (IVQR), which represent a flexible tool to handle simultaneously endogeneity and heterogeneity in the credit markets.

The results over the full sample 1975-2005 reveal that there is a good deal of heterogeneity in the pricing of risk and that a non-linear approach is essential to capture features of the data that would be missed by looking only at the average relationship between the loan size and interest rate implied by a linear specification. After treating loan size as endogenous, risk pricing is even more pronounced in the upper quantiles of the interest rate spread distribution conditional on covariates. A 1% increase in loan size triggers a 60 basis points rise in the interest rate charged to the riskiest borrowers in our sample, but it has small or insignificant impact on the interest rate charged to the safest borrowers. This should be contrasted with an average effect of 30 basis points estimated using least squares.

To investigate any possible time variation in credit conditions, we split our sample into three decades and apply the IVQR method to each of them.

[1] The dispersion of income and down payment are also far smaller than the dispersion of the interest rate.

The sub-sample analysis reveals that heterogeneity in risk pricing was very pronounced only during the 1980s, and to a lesser extent during part of the 1990s. Over the most recent period, in contrast, we find that lenders have charged similar interest rates to borrowers with very diverse risk propensity and almost irrespective of the loan size. These results appear consistent with the view that a relaxation of credit conditions took place in the 2000s before the financial crisis. The most likely source of such relaxed standards comes from the funding side of the credit market due to increased use of securitization.

1.3 Selected Literature Review on Risk Pricing

The literature on mortgage pricing has long been interested in risk heterogeneity. The contingent-claim approach, pursued for instance by Kau and Keenan (1995) and Deng et al. (2002), uses option pricing theory to explain default and prepayment behaviors while the intensity-form approach, taken by Chiang, Chow and Liu (2002) and Tsai, Liao and Chiang (2009) among others, investigates the link between termination probability, borrower's characteristics and mortgage risk premia. Our micro-data on mortgage contracts makes it possible to look at some of the basic facts on risk pricing while remaining agnostic about the exact underlying theoretical model. In light of recent issues, a recent strand of work, exemplified by Mian and Sufi (2009) and Keys et al. (2010), focuses on the role of securitization and credit expansion in the U.S. sub-prime crisis. While our data span a longer period of time, our focus on the extent of risk pricing clearly feeds into wider debates about the mortgage market.

Our paper is related to a series of important studies by Jimenez, Mian, Peydro and Saurina (2011) and Jimenez, Peydro, Ongena and Saurina (2011). Working with an extraordinarily rich supervisionary database from the Bank of Spain, the authors exploit firm balance sheet data to control for borrower's characteristics (including risk and net worth) and estimate a credit supply for corporate lending. While we share the same ends, our focus is on household lending and therefore our controls for borrower' characteristics are necessarily more limited in scope. In the same spirit of these studies, however, we complement our data with regional indicators and time fixed effects to absorb common variation in business cycle conditions.

1.4 Plan of the Paper

The remainder of the paper is organized as follows. In the next section, we set the scene for the empirical investigation by describing the data and key features of the U.K. mortgage market. In section three, we look at some empirical regularities in the raw data. Section four sets out the conceptual framework and section five develops this into an empirical approach. Section six presents the empirical results for the full sample, while section seven reports a sub-sample analysis over time. Interpretations are offered in section eight before conclusions. The appendices provide additional information on the data and the institutional background of the U.K. mortgage market.

2 Data

Our core data are a sample of more than 600,000 mortgage contracts issued in the U.K. between 1975 and 2005. The data come from the U.K. Survey of Mortgage Lenders (SML) and its predecessor, the 5% Sample Survey of Building Society Mortgages (SBSM).[2] This survey collects characteristics of the loan at origination such as the loan size, purchase price (i.e. house value), the rate of interest charged and down payment (which we refer to as housing wealth). It also includes borrower characteristics such as the age of the main borrower, total household income on which the mortgage advance is based, the previous tenure of the household, and the region in which the house is purchased. Previous tenure status includes information on whether a borrower is a "first time buyer", i.e. has any prior track record as a mortgage borrower. The data does not, however, contain any information credit scores nor do we know whether and how such scores are used by different lenders. One possible interpretation of the risk heterogeneity that we discuss below is therefore the risk assessment by the lender based on a credit score. The surveys that we use only covers mortgage contracts where the property is to be occupied by the borrower (so they exclude investment and buy-to-let properties). The sample that we use is further restricted to observations where the mortgage is defined as being for house purchase.

While within our dataset there are no identifiers that enable us to distinguish between variable and fixed rate contracts over the full sample, most

[2]The switch between the SBSM and the SML reflects the changing institutional nature of the UK mortgage market.

U.K. mortgage products are based on adjustable rates which move in line with the funding costs of the lender. The main trigger event for changes in the lending rate are movements in Bank Rate set by the Bank of England. Fixed rate mortgages, which have become relatively more prevalent in recent years, are typically fixed for only two years and then revert to an adjustable rate. 'Variable' rate products tend to have terms of approximately 25 years. Mortgages are secured on the property for the which the funds are advanced. In the U.K., the lender is able to possess the property in the event of default and can pursue the borrower for any shortfall in the amount recovered.

Mortgages in our data are issued by banks and specialist mortgage lenders called *Building Societies*. Prior to the 1980s, the UK mortgage market was dominated by a cartel structure of regional Building Societies protected from banking sector competition by legislation and deliberate policies that restricted Banks' involvement in the mortgage market. From that point on, financial liberalisation measures resulted in greater competition from the banking sector and other specialist lenders. It also resulted in market consolidation and the widening of the range of funding options available to all lenders.[3] Greater competition induced a proliferation of mortgage products (to over 13,000 by 2007) and greater variation in rates between lenders. For example, the Building Societies Association's recommended mortgage rate, which had been in existence since 1939, broke down in 1984. Lenders have also found ways of harnessing information on potential borrowers. Notable developments include the introduction (in 1982) and greater use (in the 1990s) of credit scoring techniques.

Quantities that institutions have been willing to lend have evolved over time in part in response to rule changes affecting mortgage lenders. For example, Building Societies were previously restricted in terms of the proportion of their loan book that could be constructed of larger loan advances (deemed 'special advances') in order to lower risk exposure of mortgage portfolios to relatively few large loans. Such restrictions and building societies mutual status resulted in relatively low loan-to-value ratios (or required single premium insurance indemnity to limit their risk to higher advances) and

[3]The Building Societies Act (1986) relaxed rules on Building Societies provision of services and sources of funds. Building Societies were allowed to access wholesale markets for up to 20% of their funding, a limit that has been steadily increased. Demutualisations and consolidations resulted in the number of Building Societies falling rapidly from 382 in 1975 to just 52 in 2009. Appendix A provides additional information on market liberalisation and demutualisations.

loan-to-income ratios.[4] However, over time such lending limits have been relaxed as we discuss further below. In our empirical analysis, we will treat these broad changes in the structure of mortgage markets as "macro-effects", which justify the use of year dummies in our empirical specification. As we discuss further in our concluding comments, an interesting focus for future research is to study time variation in mortgage pricing in a more flexible way.

We supplement the micro-data from our mortgage surveys with information on regional house price levels from the Nationwide house price index, and regional claimant count unemployment rates.[5] To benchmark individual borrowing rates against a funding rate, we compute the interest rate spread faced by borrowers over the Building Societies Associations' recommended deposit rate prior to 1985, and an average reported building society share (deposit) rate subsequently.[6]

We turn finally to the stamp duty rate which we will propose as an instrument for credit demand below. Stamp duty is the tax paid on housing transactions in the U.K.. It has a long history having originally been applied to transactions of vellum, parchment and paper in 1694 to pay for the war with France. Its success saw its extension (despite the role of the 1765 Stamp Act in the movement for U.S. Independence) with housing transactions incorporated by 1808. Today, stamp duty is levied on UK housing and land transactions at varying rates with a band and rate structure. The thresholds to these bands and the rates themselves have shown considerable variation over time, as demonstrated in table 1 and figure 9. Thus, there have been a number of changes in stamp duty over time and across sizes of housing transactions which we can exploit. Figure 10 gives a histogram of actual stamp duty rates paid. A significant proportion of the rates observed

[4]Mortgage indemnity insurance has been offered on U.K. mortgages, allowing lenders to insure against future collateral losses. When lenders take out this insurance it is typically passed onto borrowers through additional mortgage arrangement fees. Such mortgage indemnity insurance is not compulsory in the U.K., with no equivalent to U.S. public insurance funds, and the effect may be lessened by legislation ensuring that borrowers remain liable for mortgage shortfalls for up to 12 years. Over our sample period, both mortgage indemnity insurance and pursuit of mortgage shortfalls has had limited take-up.

[5]The Office for National Statistics report monthly rates for twelve geographical regions: Scotland, Wales, Northern Ireland and nine Government Office Regions within England. The English regions are: North East, North West, Yorkshire and the Humber, East Midlands, West Midlands, East of England, London, South East and South West.

[6]The use of building societies deposit rates as a benchmark reflects the fact that retail deposits remain the main source of funds for the building society sector.

in the sample are either in the 1% band or below the lowest stamp duty threshold. Over 60% of property transactions in our dataset are liable for the tax.

3 Empirical Regularities

Before we present regressions results, we explore some basic facts in the raw data. Table 2 begins with some key summary statistics from the micro-data on mortgage contracts. We report these for the full sample as well as ten year windows.[7] Given our interest in heterogeneity, we report, the mean, median, standard deviation, skewness and coefficient of variation. The latter offers a straightforward way of comparing dispersion in key variables.

The first panel looks at the interest rate spread; measured as the contract rate less the funding rate described in the last section. Two striking findings emerge. First, there has been a decline in this spread – it reaches its lowest value over the most recent past.[8] Second, the skew of the interest rate spread distribution has steadily increased over time moving from a negative value in the first period to a positive value in the second period, and then doubling over the latest ten year period. The coefficient of variation increases steadily over time.

The second panel looks at the loan size in real terms. In view of the reduction in the interest rate spread, the doubling in real loan size could be interpreted either as a demand or a supply effect. There is also an increase in dispersion, but this is less than the increase in the interest rate dispersion.

Two important background factors behind these changes are increases in real incomes and housing values. They are reported in panels three and four of table 2. The period of our data have seen increases in both the real incomes of house purchasers and house prices. Dispersion in the incomes of house purchases and house prices have also increased.

Finally in the fourth and fifth panels of Table 2, we report data on the loan to income and loan to value ratio. The loan to income ratio increases over time from 1.9 to 2.5 and the rise in the dispersion is modest. Looking at loan to value ratios, the increase is even less pronounced while dispersion actually falls. An implication of this is that down payments among those

[7]Appendix B provides additional information on the construction of the dataset.

[8]We note that comparing across funding rate definitions is difficult, providing additional justification for the use of year dummy variables.

taking out new mortgage loans has generally kept pace with increases in house prices.

4 Theoretical Framework

Our objective is to understand how the interest rate charged to borrowers depends on the amount that he/she borrows and his/her observed characteristics. We will interpret this as the inverse of a credit supply function which we expect to be an increasing function of the loan size, other things being equal: borrowing more means a lower probability of repayment and a higher default premium being charged. We will use the model to consider what happens to the inverse supply curve if the lender can securitize a larger fraction of the loan on favorable terms. In a competitive credit market, this will lead to relaxed credit conditions for mortgage borrowers.

4.1 Basic Model

Consider a mortgage contract of length T with regular repayment dates $t = 1, ..., T$. The lender makes an advance of L. The borrower makes a fixed repayment of m in each period of the mortgage contract. This mortgage contract is fully characterized by the triple: $\{m, L, T\}$.

The probability of continuing to pay in period t is $\beta(u, L)$ where u is an index of the riskiness of the borrower with $\beta_u(u, L) < 0$ and $\beta_L(u, L) < 0$. The latter says that, given u, a larger loan size is more likely to lead to default.

In the event of default, we assume that the lender is exposed to a loss with only a fraction α of the remaining mortgage payments being recoverable. The parameter $\alpha \in [0, 1]$ therefore captures the lender's exposure to default risk. An optimistic view of house prices would, for example, make α higher.[9] Let

$$\gamma(L, u, \alpha) = \beta(u, L) + (1 - \beta(u, L))\alpha \tag{1}$$

with $0 \leq \gamma \leq 1$ be the lender's expected recovery rate. This will be the key parameter affecting the pricing of mortgages.

[9]Obviously, we could allow α to depend on T. But in a more general model, we could allow α to depend on $T - t$, i.e. the remaining mortgage term.

On this basis, the expected revenues under the contract from time t forward are denoted by π_t whose evolution follows a difference equation:

$$\pi_t = \gamma \left[m + \pi_{t+1} \right]$$

Solving this and using the boundary condition $\pi_{T+1} = 0$ yields:

$$\pi_t = m \frac{\gamma}{1-\gamma} \left[1 - \frac{\gamma^{-t}}{\gamma^{-T-1}} \right]. \tag{2}$$

As we would expect, this is a decreasing function of t since the time remaining on the mortgage is smaller.

Now for $y \in \mathbb{R}^+$, define the function:

$$\psi(y;T) = \frac{y}{1-y} \left[\frac{y^{-T} - 1}{y^{-T}} \right]$$

This is an increasing function of y with $\psi(1;T) = T$ and $\psi(0;T) = 0$. When pricing the mortgage at inception, a lender cares about the expected revenues viewed from period one forward. Using (2), this is given by:

$$\pi_1 = \psi(\gamma;T)\, m \tag{3}$$

where $\psi(\gamma;T) \leq T$.

The lender compares the period one expected revenues with the opportunity cost of making a loan advance of L. Suppose that the lender's funding interest rate is ρ. Then this opportunity cost over T periods is $(1+\rho)^T L$. Using (3) and this observation, we conclude that, for a loan to be viable in a loan market with funding rate ρ, the fixed per-period repayment of a type γ borrower who borrows L must solve:

$$m(L,u,\alpha) = \frac{L(1+\rho)^T}{\psi(\gamma(L,u,\alpha);T)}. \tag{4}$$

using (1).[10] The left hand side of (4) is the fixed payment that must be paid

[10] We are implicitly assuming a competitive credit market. However, we could also introduce a mark-up factor $\Lambda > 1$ such that

$$m(L,u,\alpha) = \Lambda \frac{L(1+\rho)^T}{\psi(\gamma(L,u,\alpha);T)}$$

This could be time-varying in the empirical analysis to reflect changes in the mortgage market such as market liberalization. Its variation would then be absorbed in the yearly time effects used in the empirical specification below.

each period to borrow L given the default risk that the lender faces including his exposure to losses as represented by α.

Two things are immediate from (4). First, for $\gamma(u,\alpha)=1$, equation (4) collapses to:

$$m(L,u,\alpha)=\frac{L(1+\rho)^T}{T}$$

in which case the borrower faces a fixed payment based on the opportunity cost of funds paid by the lender and pays this over T years. If $\gamma(L,u,\alpha)<1$, then:

$$m(L,u,\alpha)>\frac{L(1+\rho)^T}{T}.$$

We can therefore interpret $1/\psi(\gamma(u,\alpha;L);T)\geq 1/T$ as a "markup" over funding costs which is increasing in L. This markup is higher if either α or $\beta(u,L)$ is lower (which is the case for higher u and higher loan size). Thus, borrowers with worse default probabilities and lower recovery rates will face a larger markup to compensate for default risk. This will also be true of borrowers with larger loans. The lender compensates for the risk of default by requiring a higher mortgage payment which shortens the effective term on the mortgage which the lender cares about. To get a "back-of-the-envelope" feel for this, consider a 25 year mortgage where β is 0.98, i.e. a 2% default probability and α is 0.8 (80%), then $\psi(\gamma;25)\approx 23.7$ so the lender sets a repayment rate "as if" the borrower was to repay the mortgage in 23.7 years as compensation for risk. It is also straightforward to see from (4) that $m(L,u,\alpha)/L$ is increasing in L for all (u,α).

4.2 Credit Supply and Demand

We now use the model to generate a prediction for the interest rate and loan size. For the interest rate $r(L,u,\alpha)$, observe that the interest rate implicit in the repayment function $m(L,u,\alpha)$ is defined by:

$$m(L,u,\alpha)=L\frac{(1+r(L,u,\alpha))^T}{T}, \tag{5}$$

i.e. as the interest rate that generates a stream of payments $m(L,u,\alpha)$ over the contract term in the absence of default. This will be the contractual interest rate in a T period mortgage and is what we observe in the data.

Equation (5) can be solved to yield:

$$r(L,u,\alpha) = \left(\frac{m(L,u,\alpha)T}{L}\right)^{\frac{1}{T}} - 1 = (1+\rho)\left[\psi(\gamma(L,u,\alpha);T)\right]^{-\frac{1}{T}} - 1 \geq \rho.$$

This equation makes clear why we expect the slope of the inverse credit supply function to be non-linear through its dependence of borrower characteristics as represented in the function $\gamma(L,u,\alpha)$. The variable u can be thought of the source of unobserved heterogeneity in our empirical model below. Expressing this as the difference from the funding rate, ρ, we have

$$R(L,u,\alpha) = r(L,u,\alpha) - \rho = (1+\rho)\left[\left[\psi(\gamma(L,u,\alpha);T)\right]^{-\frac{1}{T}} - 1\right] \tag{6}$$

To close the model and study credit demand, we suppose that borrowers have preferences over housing which generate demands for borrowing at different interest rates given the inverse supply curve, which depends on the borrower's riskiness index. Let preferences over loan size and interest rate be summarized by $W(L,R;\theta)$ given borrower characteristics θ and policy/economic factors that influence housing demand. Then:

$$L^*(u,\alpha,\theta) = \arg\max\left\{W(L,R(L,u,\alpha);\theta)\right\}. \tag{7}$$

To identify supply and demand, we need to identify factors that represent θ. We will return to this below.

4.3 Relaxing Credit Conditions via Securitization

We now consider how increased use of securitization in the mortgage market could change the terms offered to borrowers by extending the model to include the possibility that a lender can "sell" the expected financial flows from a mortgage. Since such sales take place only when the valuation of the buyer of such securities exceeds that of the mortgage lender from holding the mortgage, this will lead to more favorable terms being offered to borrowers in a competitive credit market.[11] For the U.K. as we have seen, there was a significant increase in issuance of mortgage backed securities in the period

[11] This will happen even if we do not explicitly invoke a screening decision by borrowers as in Keys et al (2010). The effect that we identify would be amplified by such considerations.

leading up to the financial crisis which, at the time, was heralded as an important financial innovation which increased access to mortgage finance on favorable terms. Thus securitization was part of the transition over the period leading to the financial crisis towards viewing routine funding operations by mortgage lenders as profit centers in their own right as has been argued, for example, by Kay (2010).

For simplicity, we assume that the lender has an option to securitize a fraction σ of the revenue stream from the loan. Trade in the securities market will be based on purchasers of securities having different beliefs about γ. Specifically, we denote these beliefs by $(\hat{u}, \hat{\alpha})$ with $\gamma(L, \hat{u}, \hat{\alpha}) > \gamma(L, u, \alpha)$. (The latter is needed for there to be gains from trade in the securities market.) These differences in beliefs about effective recovery rates from mortgage loans could be based, for example, on different views about the evolution of house prices captured in $\hat{\alpha}$ or the use of different risk assessment models which affect $\hat{u}$ conditional on borrower characteristics. We will focus here on the case where all of the trading surplus accrues to the lender.[12] We are agnostic about whether the gains from trade in the securities market are due to "genuine" financial innovation leading to the use of better risk pricing models or over-optimism. All that matters for this story is lenders are able to generate higher value revenue streams in the secondary market. Our assumption that there is competition for borrowers ensures that these gains are passed on in the form of relaxed credit conditions in the mortgage market.

Formally, observe that if a fraction σ of loans is securitized, i.e. sold on day one of the mortgage, then the period one expected return from lending to a borrower becomes:

$$\begin{aligned} \hat{\pi}_1 &= \left[(1-\sigma)\,\psi\left(\gamma\left(L,u,\alpha\right);T\right) + \sigma\psi\left(\gamma\left(L,\hat{u},\hat{\alpha}\right);T\right)\right] m \\ &\equiv \hat{\psi}\left(\sigma\right) m > \psi\left(\gamma\left(L,u,\alpha\right);T\right) m. \end{aligned}$$

And (6) becomes

$$R\left(L,u,\alpha\right) = (1+\rho)\left[\left[\hat{\psi}\left(\sigma\right)\right]^{-\frac{1}{T}} - 1\right].$$

Since $\hat{\psi}(\sigma)$ is increasing in σ, we can see that our model of securitization predicts that the inverse supply function for credit is shifted down by secu-

[12] Our results rely on at least a share of the surplus accruing to the lender.

ritization, i.e.:

$$\frac{\partial R(L,u,\alpha)}{\partial\sigma} = -\frac{(1+\rho)}{T}\left[\hat{\psi}(\sigma)\right]^{-\left(\frac{T+1}{T}\right)}\left[\psi\left(\gamma\left(L,\hat{u},\hat{\alpha}\right);T\right)-\psi\left(\gamma\left(L,u,\alpha\right);T\right)\right]<0$$

For given σ, a similar effect would be found if there were a shift in the beliefs of purchasers of securities represented by $\gamma(L,\hat{u},\hat{\alpha})$ increasing. It is also clear that more relaxed mortgage credit conditions could be obtained in the model by supposing that lenders themselves changed their views about recovery rates through either an increase in perceived α or a shift up in the function $\beta(u,L)$.[13]

To the extent that conditions in the securities market are changing over time, the model predicts that there will a shift in credit supply. This shift can be heterogeneous depending on differences in beliefs between lenders and purchasers of securities. However, we would not expect much of a shift for sub-classes of very low risk borrowers where $\gamma(L,\hat{u},\hat{\alpha}) \simeq \gamma(L,u,\alpha) \simeq 1$. Thus, we would expect shifts in the supply curve to be most pronounced for riskier sub-classes of borrowers, particularly those where purchasers of securities have more favorable views of recovery rates than mortgage lenders.

5 Empirical Approach

The empirical approach is based on the theoretical framework from the last section. Suppose that borrower i in region r at date t is characterized by observable characteristics X_{irt} and a scalar index of riskiness, U_{irt}, which we assume to be observed by the lender but not by the econometrician. This variable could represent the result of a credit scoring algorithm or the lender observing a variable like occupation or employment history which we do not have in our data. We will treat U_{irt} as the key source of unobserved heterogeneity. The (inverse) credit supply function is denoted by, the empirical counterpart of (6), is:

$$R_{irt} = H\left(L_{irt}; D_{rt}, X_{irt}, U_{irt}\right) \tag{8}$$

where R_{irt} is the interest rate relative to the funding rate, D_{rt} are macro covariates which shift the supply function around and L_{irt} is the amount borrowed. This gives the interest rate spread faced by an individual who chooses to borrow L given a vector of characteristics (D,X,U).

[13] If we were to add a markup factor $\Lambda > 1$ as discussed in footnote 9 , then a similar effect would also follow from reducing lender margins in mortgage markets.

5.1 Quantile regressions: a primer

Several statistical approaches can be taken to estimate equation (8). One of the most popular would be to specify a linear relationship between interest rate and loan, and then use a Least Square (LS) method to estimate the average effect of an exogenous movement in loan demand on lending rate. This strategy implicitly relies on two presumptions. First, the disturbances are Gaussian. Second, the average effect provides a 'complete' picture of the entire distribution of interest rate responses to loan demand across borrowers conditional on covariates.

In the context of the present study, however, theoretical and empirical considerations suggest that both presumptions are unlikely to hold. First, different borrowers face (and are likely to be priced for) different risks in a way that depends on (i) characteristics observed by both the lender and the econometrician (such as demographics, income, property value and location, down payment, etc.) and (ii) information available only to the lender (credit score, employment history, family circumstances, etc.). Second, the descriptive statistics in Figure 8 and Table 2 as well as the econometric analysis below reveal that our data, which cover about $600,000$ housing transactions, feature a large extent of heterogeneity and significant departures from normality.

The considerations above suggest that there is a wealth of information that could be lost by focussing exclusively on average effects and therefore motivates our emphasis on distributional considerations. Accordingly, we propose to estimate the shape of (8) using quantile regression (QR). Above all, this will not assume that the relationship between the amount borrowed, characteristics and the interest rate is globally linear.

To develop intuition for the way quantile regressions work and what they can deliver, note that LS estimators are the solution to the problem of minimizing a sum of squared residuals. It is well-know, however, that LS estimates are not robust to outliers, leading econometricians to focus on Least Absolute Deviation (LAD) whenever, for instance, fat tails are a concern. As much as the solution to the problem of minimizing a sum of *squared* residuals yields an estimate of the mean of a distribution, the solution to the problem of minimizing a sum of *absolute* residuals yields an estimate of the median. This is an estimate of the median because the symmetry of the piecewise linear absolute penalty function ensures that there are the same number of positive and negative residuals.

Quantile regressions generalize the principle behind LAD to *asymmetric* piecewise linear absolute penalty function. The asymmetry is introduced by a tilting term which weights differently the absolute residuals associated with different parts of the distribution of interest. As much as the estimate of the median is defined as the solution to the minimization problem that leaves 50% of the observations either side of the regressions slope, the estimate of the q^{th} percentile is defined as the solution to the minimization problem that leaves q% of the observations on one side of the q^{th} regressions slope. By varying the tilting term, and therefore the weights in the penalty function, quantile regressions yield a family of slopes across the conditional distribution of the interest rate spread, which can be used to assess the extent of heterogeneous responses of credit supply to changes in loan demand.

5.2 A non-instrumental variable benchmark

The QR approach treats the interest rate spread as a potential latent outcome. It is latent because, given a loan size, L_{irt}, other observable individual characteristics, X_{irt}, and macro covariates D_{rt}, the observed outcome for each unit of observation i is only one of the possible realizations in the admissible space of outcomes. The quantiles, Q_τ, of the potential outcome distributions conditional on covariates are denoted by:

$$Q_\tau \left(R_{irt}|L_{irt}, D_{rt}, X_{irt}\right) \quad \text{with } \tau \in (0,1). \tag{9}$$

We will initially assume that L_{irt} is exogenous. The effect of a change in loan size, L_{irt} (the “treatment”), on different points of the marginal distribution of the potential outcome is given by:

$$QTE_\tau = \frac{\partial Q_\tau \left(R_{irt}|L, D_{rt}, X_{irt}\right)}{\partial L} \tag{10}$$

The quantile treatment model can then be written as:

$$R_{irt} = q\left(L_{irt}, D_{rt}, X_{irt}, U_{irt}\right) \quad \text{where } U_{irt}|L_{irt} \sim U\left(0,1\right). \tag{11}$$

In this notation, $q\left(L_{irt}, D_{rt}, X_{irt}, U_{irt}\right) = Q_\tau \left(R_{irt}|L_{irt}, D_{rt}, X_{irt}\right)$. In effect, we can always work with a suitable monotonic transformation of the underlying measure of riskiness such that U_{irt} is a rank variable, i.e. it measures the relative ranking of individuals in terms of potential outcomes. According to this interpretation, QTE_τ measures the causal effect of loan size on the interest rate spread, holding the degree of riskiness fixed at $U_{irt} = \tau$.

Since we are treating loan size, L_{irt}, as exogenous, the methods outlined in Koenker and Bassett (1968) can be used to estimate quantile effects on the basis of the conditional moment restrictions:

$$Prob[R \leq q\left(L, D, X, \tau\right)|L, x] = Prob[U \leq \tau|L, D, X] = \tau \quad \text{for each } \tau \in (0,1).$$

This permits us to explore the shape of the relationship between loan size and interest rate spread using (8). The empirical specification of the conditional τ-th quantile distribution takes the following form:

$$Q_\tau(R_{irt}|\cdot) = a_L\left(\tau\right)L_{irt} + a_x\left(\tau\right)X_{irt} + a_D\left(\tau\right)D_{rt}. \tag{12}$$

The variable L_{irt} is the log of the *real* loan size. The vector X_{irt} includes log of household real income, initial down payment (i.e. the difference between house value and loan, age of the household head and a dummy variable that takes the value one if the household head is a first time buyer and zero otherwise. The vector D_{rt} includes a full set of regional and year dummies as well as a regional house price index, which given the high persistence of the series reported in figure 4 may also capture house price expectations, and regional unemployment rate measured as the claimant count in the quarter before the mortgage contract was agreed.

Before proceeding, it is useful to draw attention on a specific assumption behind quantile regression methods: monotonicity. This says that the conditional quantile function is monotone in τ. In the context of our analysis, we require that variation in unobserved characteristics that make a borrower riskier are associated with larger interest rate spreads conditional on covariates. The linearity assumption embedded in the specification of the quantile functions (12) implies that $q(\cdot)$ is monotone in the ranking variable U_{irt}.

5.3 Identification

As we discussed in our theoretical discussion leading up to (7), supposing that L_{irt} is exogenous is not satisfactory. Perhaps the most plausible justification would be to suppose that it varies solely with tastes for housing which are uncorrelated with the vector (D, X, U). But to the extent that households know that a lender is treating them more or less favorably, they may change the amount that they choose to borrow creating an endogeneity problem.

We can close the model by supposing that the borrower picks a loan size given the credit supply function that he faces and his taste for housing. As above, let $W(L, R, \theta)$ be the expected life time payoff from borrowing an amount L at interest spread R. Then the optimal choice of loan is:

$$\begin{aligned} L_{irt} &= \hat{L}(D_{rt}, X_{irt}, U_{irt}, Z_{irt}, V_{irt}) \\ &= \arg\max \{W(L, R(L, D_{rt}, X_{irt}, U_{irt}), D_{rt}, X_{irt}, Z_{irt}, V_{irt})\}. \end{aligned}$$

The variable Z_{irt} denotes an additional observable that affects loan choice – the instrument in our approach. The variable V_{irt} is an unobserved component which we interpret as the taste for housing.[14]

We will discuss below the particular instrument that we have in mind. Given this, we can exploit the IVQR model of Chernozhukov and Hansen (2005). Our observables are now $(R_{irt}, L_{irt}, X_{irt}, Z_{irt})$. For the IVQR model:

$$R_{irt} = q(L_{irt}, X_{irt}, D_{rt}, U_{irt}) \quad \text{where } U_{irt}|Z_{irt} \sim U(0, 1) \tag{13}$$

where

$$Prob[R \leq q(L, D, X, \tau)|Z, X] = Prob[U \leq \tau|Z, D, X] = \tau \quad \text{for each } \tau \in (0, 1).$$

In particular, we require that, given (D_{rt}, X_{irt}), then $\{U_{irt}\}$ is distributed independently of Z_{irt}. For some random vector, Σ, we also require that:

$$L_{irt} = \hat{L}(X_{irt}, D_{rt}, Z_{irt}, \Sigma_{irt})$$

where $\Sigma_{irt} = (V_{irt}, U_{irt})$ in our context.

An important and non-standard requirement relative to standard instrumental variables is the rank similarity condition which says that given $(X_{irt}, D_{rt}, Z_{irt}, \Sigma_{irt})$, the distribution of U_{irt} does not vary systematically with L_{irt}. This will hold as long as the direct dependence of L_{irt} on U_{irt} is sufficiently weak. We will now argue that this is plausible given the approach that we propose.

The instrument we use is the stamp duty rate which depends on the house price paid by a borrower which we denoted by P. We denote the rules governing stamp duty as $S(P; \xi_t)$ – a piecewise linear function which depends on a set of time-varying policy rules denoted by ξ_t. The price paid for a house is the sum of the down payment and the size of the loan:

$$P_{irt} = W_{irt} + L_{irt}.$$

[14] So $\theta_{irt} = (D_{rt}, X_{irt}, Z_{irt}, V_{irt})$.

Our proposed instrument is therefore implicitly defined from:

$$Z_{irt} = S\left(W_{irt} + \hat{L}\left(D_{rt}, X_{irt}, U_{irt}, Z_{irt}, V_{irt}\right); \xi_t\right).$$

As we have already noted, the validity of Z_{irt} as instrument hinges on variation in Z_{irt} being driven by underlying variation in (ξ_t, V_{irt}) conditional on (D_{rt}, X_{irt}), recalling that W_{irt} is part of the vector X_{irt}. This requires that changes in tax rules and unobserved preferences for housing should be responsible for variations in tax rates across individuals and over time rather than variation in U_{irt}. In fact, we adopt a conservative approach by dropping households who are within +/-5% (by value) of the stamp duty thresholds. It is only amongst individuals who are close to the threshold where we would expect variations in U_{irt} to be correlated with Z_{irt}.[15] Thus we are confident that variations in (ξ_t, V_{irt}) are inducing variation in Z_{irt}.

In the language of simultaneous equation models, we regard variation in stamp duty rates as likely to shift credit demand rather than supply. This is especially true at the high end of the riskness distribution where lenders are likely to have more market power. Another way to exemplify the logic behind our identification strategy is to abstract from heterogeneity and say that if two borrowers, with similar demographics, similar income and similar down payments, are observed to pay two different stamp duty tax rates over a property in the same region, then we assume that the borrower paying the highest stamp duty rate is more likely to have a stronger preference for housing and therefore demand a larger loan. Furthermore and related to heterogeneity, because she has a relatively stronger housing preference for given observed characteristics, the lender is charging her relatively more than an otherwise identical borrower demanding a smaller loan.

Further credence to this view is given by observing that variation in stamp duty rates paid depends significantly on regions, reflecting disparities in regional house prices: average London house prices in our sample are over 1.7 times higher than those in Northern Ireland, and London has a greater proportion of observations in our dataset. This motivates the addition of regional house price, as well as regional unemployment claimant count rate, as

[15] Nearly 13% of our sample lies within +/-5% of the stamp duty thresholds. As a robustness check we also tested a sample where only observations within the 5% below stamp duty thresholds were dropped without materially altering our results. Results from a sensitivity analysis where we do not trim the data around the stamp duty thresholds are discussed at the end of section 4.

covariates in our empirical specification. Furthermore, we also condition on time and region fixed-effects in an effort to control for unobserved common features unrelated to individual loan pricing. Figure 11 illustrates the extent of geographical dispersions as captured by real house prices and claimant count unemployment rate for each region.

This gives a "first stage" equation explaining the amount borrowed:

$$L_{irt} = b_S Z_{irt} + b_X X_{irt} + b_D D_{rt} + \eta_{irt} \tag{14}$$

where X_{rit} is the same vector of observed household characteristics as above and D_{rt} are the same regional and time-varying variables as in equation (12).

Results from estimating (14) are presented in Table 3. The first column uses the baseline sample which drops observations which are within +/-5% of any of the stamp duty thresholds. This will be the sample which we use when we present results for the credit supply relation below and hence it is our actual first stage regression. After controlling for observed individual characteristics, regional features and year dummies, the rate of stamp duty is positively correlated with loan size. This reflects the fact that the stamp duty is larger for higher house values all else equal. A 1% increase in stamp duty rate is associated with a significant change in the (log) level of real loan of around 0.229. This coefficient corresponds to a change in nominal loan demand of £2,332 in 2005.[16]

The second column presents the same regression results where we exploit only the variation in stamp duty rates across regions and years (but not across individuals). This is important as it tells us how much of the identification is coming from ξ_t, the changes in stamp duty rules. Again, the stamp duty rate is positive and significant which reassures us that stamp duty rules are giving us an important source of exogenous variation. Finally, for the sake of comparison only, we give the results from estimating the regression in column 1 on the full sample, i.e. without trimming the data around stamp duty thresholds. As can be seen the results are broadly similar to those in the first column.

[16]The first stage F-statistics, which Stock, Wright and Yogo (2002) advocate as a useful rule of thumb to assess an instrument strength, largely exceeds the value of 10, implying that when we move to the second stage inference in the IV approach below, this appears reliable under both the relative bias and the size criteria defined in Stock and Yogo (2001). We note that the first stage F-statistics exceed the value of 10 even when we assess the instrument strength in each quantile separately.

6 Results

In this section, we present our main results in two parts. First, we contrast the estimated average effects for the whole sample with the estimated effects for each quantile. Second, we assess the extent to which treating loan size as endogenous affects the results.

6.1 The interest rate and loan size

In Figure 12, we present the estimates (and the 95% confidence intervals) of the coefficient on loan in a QR equation of the form (12).[17] To emphasise the importance of risk heterogeneity, we compare these results with the estimates (and the 95% confidence intervals) from using OLS which are given by the dotted line.

The results show strong evidence of heterogeneity in the conditional interest rate spread distribution with respect to real loan size. The semi-elasticity of spread with respect loan size for borrowers below the 70^{th} percentile is around 0.01. By contrast, borrowers in the upper tail of the conditional distribution face a significantly steeper curve with a slopes of up to 0.08 in the top quantiles. This pattern makes economic sense with those taking out comparatively smaller loans paying a small interest rate premium compared to a much steeper relationship for higher quantiles.

It is clear in particular how the OLS gives a misleading picture. According to the OLS results, a 1% increase in the size of the real loan is associated with an interest rate spread which is 6 basis points higher irrespective of the borrower's position in the conditional distribution. This, understates the effect at higher quantiles and overstates it at lower quantiles.

We turn next to the IVQR results which are reported in figure 13 as the red line with asterisks. For the sake of comparison, we also report estimates and confidence intervals for the QR method of figure 12 and a standard two-stage least squares (TSLS) estimator (the dotted blue line).

The comparison between the IVQR and the TSLS estimates echo the results from Figure 12. There is strong evidence of heterogeneity with the least squares approach failing to account for different slopes along the credit supply relationship. The point estimate for the average effect of around

[17] Confidence bands are estimated using the method for heteroskedasticity consistent standard errors described in Chernozhukov and Hansen (2005).

30 basis point response following a 1% increase in the loan size should be compared with a response which is small or not significantly different from zero in the lower quantiles while it is larger than 50 basis points at the upper quantiles.

The comparison between the IVQR and the QR estimators gives a sense of the potential importance of endogeneity bias across households. In this respect, two features of the comparison between the solid and the asterisked lines are worth emphasizing. First, the IV and non-IV methods deliver estimates quantitatively similar up to the 30^{th} percentile. Above that, however, a borrower who is ranked higher in the riskiness distribution (as measured by higher conditional interest rate spreads) seems to exhibit a greater endogeneity bias. There is little evidence of bias in the QR estimates for the safest borrowers. This is plausible since loan size is unlikely to be influenced by the lender's risk pricing when the risk of default is small. The bias for the riskiest borrowers appears, however, to be sizeable. The latter is precisely where we would expect a non-trivial interaction between loan demand and the lender's risk pricing behavior.[18] Thus, the results in this section make theoretical sense. Second, according to the IVQR estimates, the borrowers with the highest conditional interest rate spread are charged an additional 60 basis points for every 1% increase in their loan demand. This number is only 8 basis points according to the standard QR method.

6.2 Individual characteristics

Our empirical methods also allow us to look at how other elements of X_{irt} affect the mortgage spread charged conditional on L_{irt}. In figure 14, we report results for down payment, income, age and whether the borrower is a first-time-buyer. In each case, the solid line and grey area (the asterisked line and the shaded pink area) represent IVQR (QR) estimates. The results from TSLS are reported as dotted lines.

For income and age, figure 14 finds, in line with the previous charts, that there is heterogeneity in the endogeneity bias. This is seen by observing that the divergence between the solid and asterisked lines becomes larger and is significant at the upper tail of the conditional distribution. The estimates based on least square miss the significant differences across borrowers in this

[18] In a similar class of models, Chesher (2005) shows that when instruments are only effective over a limited quantile range, then average effects are likely not to be identified.

part of the conditional distribution. However, for down payment and first time buyer status, the effects are fairly similar whether or not we use an instrumental variable method.

The pattern for the effect of down payment size on the interest rate spread is intuitive. There is essentially no effect from having a higher level of down payment for lower quantiles. However, for the higher "riskier" quantiles higher down payments yield a lower interest rate. This makes sense if larger down payments provide a collateral cushion which the lender prices into his risk assessment.

According to the QR method, income is of little relevance for loan pricing over the entire conditional distribution. The IV estimator, however, reveals a quite different picture for households above the 30^{th} percentile where a higher real income contributes significantly to lower the borrowing rate conditional on covariates. The slope associated with mortgagors in the 0.9 quantile, for instance, is three times larger (in absolute value) than the slope of the median household. This makes sense if higher incomes matter most when borrowers are riskier.

A comparison between figures 13 and 14 highlights that the endogeneity of loan size generates an appreciable downward bias in the coefficient on loan size and a noticeable upward bias on the coefficient on income at the upper end of the conditional interest rate distribution. Interpreting the downward bias on loan, we should expect the fact that a higher interest rate will discourage borrowing to imply less sensitivity of the interest rate to loan size when the latter is treated as exogenous. The finding on income reflects the fact that income is an important driver of loan size as well as important in assessing default risk. The effect that we document in figure 14 reflects the fact that the estimates of $a_L(\tau)$ based on (12) when loan size is treated as exogenous are contaminated by the effects of the demand-driven component of loan.

For age, the QR estimates appear to be downward biased. According to both the QR and IVQR methods, the age of an individual paying a higher conditional interest rate spread is significantly more important for her/his borrowing rate than the age of an individual paying a lower spread. Thus, lenders do appear to penalize higher risk older borrowers, controlling for other observable characteristics.

For first time buyers there is little evidence of heterogeneity. While there is a downward slope at the highest quantiles, the results are imprecisely estimated. Even at the 90^{th} percentile, however, the magnitude of the coefficient seems too small for the first time buyer status to be of great economic significance.

6.3 Regional features

Turning to the effects of regional characteristics on mortgage conditions, figure 15 reports the coefficient on real house price and claimant count rate across quantiles for the different methods of estimation. Borrowers in regions characterized by higher house prices enjoy better price conditions, consistent with the view that lenders factor in expectations of future price increases. The QR estimates do not seem to indicate a clear pattern across household whereas the IVQR estimates suggest the effect is significantly larger for riskier mortgagors. Regional unemployment in contrast appears of little economic and statistical significance, and no systematic differences emerge between estimates using the QR and IVQR methods.

7 Changes over time

The approach that we have taken can be used to assess how credit conditions have changed over time in response to changes in competition, financial liberalization and the use of new funding methods such as securitization. The latter was a focus of our empirical approach and is especially important in the latter part of our data period. We are interested to assess the extent to which the slope of the credit supply function may have changed over time. This will give some insight into how mortgage pricing changed and whether there was a noticeable reduction in the pricing of default risk.

To investigate this, we repeat the IVQR analysis for three different subperiods spanning the decades 1975-1985, 1986-1995 and 1996-2005. While this specific division is somewhat arbitrary, it represents an even split of the thirty years spanned by the data. Furthermore, the sub-sample selection lines up well with some of the main institutional regimes in the U.K. mortgage that we discussed in section 2 and in Appendix A.

The estimated effects of loan size on borrowing rates are reported in figure 16 and they reveal significant time variation across sub-samples. During the period 1975-85, for instance, only 30% of borrowers were offered contracts for which the interest rate is independent of the loan size. The remaining 70% of households face an upward sloping credit supply function which becomes steeper at a higher level of the conditional distribution of interest rate which we interpret as risk. Furthermore, the riskiest borrowers are charged an additional 130 basis points for every 1% increase in their loan demand. This contrasts with only 60 basis points using both IVQR over the full-sample and TSLS over the period 1975-1985.

The central panel of figure 16 reports estimates for the years between 1986 and 1995. In contrast to the previous decade, now 80% of borrowers are offered very similar interest rates despite different loan size. At the upper tail of the conditional interest rate distribution, a 1% rise in loan demand is associated with a 60 basis points increase in the borrowing rate, which is significantly higher than the estimated average effect of 0.35.

The most striking change, however, occurs in the final decade of the sample. The bottom panel of figure 16 reveals that the 1996-2005 period is characterized by a lack of both risk pricing and heterogeneity. In particular, the IVQR estimates are statistically different from the TSLS estimates only at the tails of the distribution but the size of the coefficients in both specifications appears too small to be of any economic significance.

8 Interpretations

The finding that risk pricing in the U.K. mortgage market has changed over time and that the curve relating the interest rate to loan size has flattened could be interpreted as evidence of slacker credit conditions. And our evidence parallels that found elsewhere by, for example, Dynan, Elmendorf and Sichel, 2006, and Den Haan and Sterk, 2011. Since the onset of the financial crisis, debates have raged about the causes of the crisis and policy measures that might have been implemented to avoid it. Our micro-based approach does provide a window on this and invites speculation about the link to the macro-economic discussion.

One benign interpretation of the results is that they reflect better information flows in the mortgage market due to more effective credit scoring allowing lenders to separate borrowers of different risk groups and hence to lower the risk premia charged on larger mortgage loans. And there is an air of plausibility to this given the institutional changes in train over this period. Moreover, the so-far relatively modest increases in mortgage market defaults post crisis are perhaps indicative of some justification for the belief that much lending was indeed to credit worthy clients who were correctly scored. This would certainly set the U.K. housing market apart from that in many other countries, especially the U.S..

At the other extreme from this benign view is the animal spirits interpretation of Akerlof and Shiller (2009) which applies ideas from psychology to explain the kind of phenomenon shown in our data. This would see the reduction in the risk premium charged on larger loans as the product of a misplaced extrapolation of trends in house prices which could have been thought to protect lenders from potential losses in the event of default. Related, lenders could have failed to take account of significant tail risks in their over-exuberant approach to risk pricing. It is difficult to find any evidence for this view in our findings. But it could explain the flattening of the curve that we document.

The third explanation would be to point to some significant structural changes in the mortgage market in the latter period of our data, particularly increased competition and the growth of securitized lending. This would doubtless have changed the risk assessment model since lenders needed to hold fewer risky loans on their balance sheets. And this was a singular development in the post Millennium world as Figure 17 shows. This, after all, is one of the familiar tails of the period leading to the financial crisis which saw the search for yield leading to the acquisition of mortgage backed securities. On this view, the risk preference of lenders, particularly concerns about default on their mortgage book, would have relaxed in a way that is not inconsistent with our findings. And there would be pressure also on the extensive margin, attracting some borrowers who would not have previously be deemed credit worthy. The latter was, of course, the story of the U.S. sub-prime market and is consistent with the animal spirits view to the extent that the mortgage backed securities where incorrectly priced.

Securitization could also have fueled aggressive competitive behavior by some lenders whose mortgage funding was no longer dependent on raising domestic savings. However, as shown in Figure 18, increases in competition tend to predate the period in which we are suggesting that credit conditions relaxed. It seems more likely therefore that securitization was the principal driving force.

9 Conclusions

This paper explores empirically how credit standards were relaxed in the U.K. housing market in the period before the financial crisis. We use a detailed analysis of risk pricing in the mortgage market to look at this issue. Our results suggest that the credit supply function that individuals face is upward sloping – larger loans mean larger interest rates. However, the supply function is highly heterogeneous and depends on borrower characteristics and macro conditions. Higher income individuals and those with larger down payments are by and large better treated, although this has most bite in the higher risk groups.

More significantly in view of recent debates, we show that the slope of the credit supply function became flatter and less heterogeneous over time. In particular, the evidence for risk-pricing heterogeneity over the 1980s is stronger than the evidence over the full sample. The most recent period, in contrast, has been associated with little sensitivity of borrowing rates to both loan size and the risks perceived by the lenders. This evidence offers specific window on the relaxation of credit conditions in the period prior to the financial crisis of 2008.

All this said, the U.K. housing market has so far had a somewhat soft landing with only modest falls in prices and increases in mortgage arrears and defaults. However, this appears to be mainly due to some institutional features (such as variable rate mortgages) and the reasonably modest increases in unemployment among householders who hold mortgages. This may have helped to shield the market from the consequences of the laxer lending standards that have been identified here. In future, it will be interesting to see how risk pricing changes as the mortgage market goes forward since it seems reasonable to expect that larger risk premia will be charged in future. Indeed, the current debate is about a backlash which is maker lenders extremely cautious. Volumes of lending in the U.K. have certainly fallen and spreads over funding rates appear to have widened on average. It will be interesting to look at this in more detail using the methods detailed here once the data for the post-crisis period become available.

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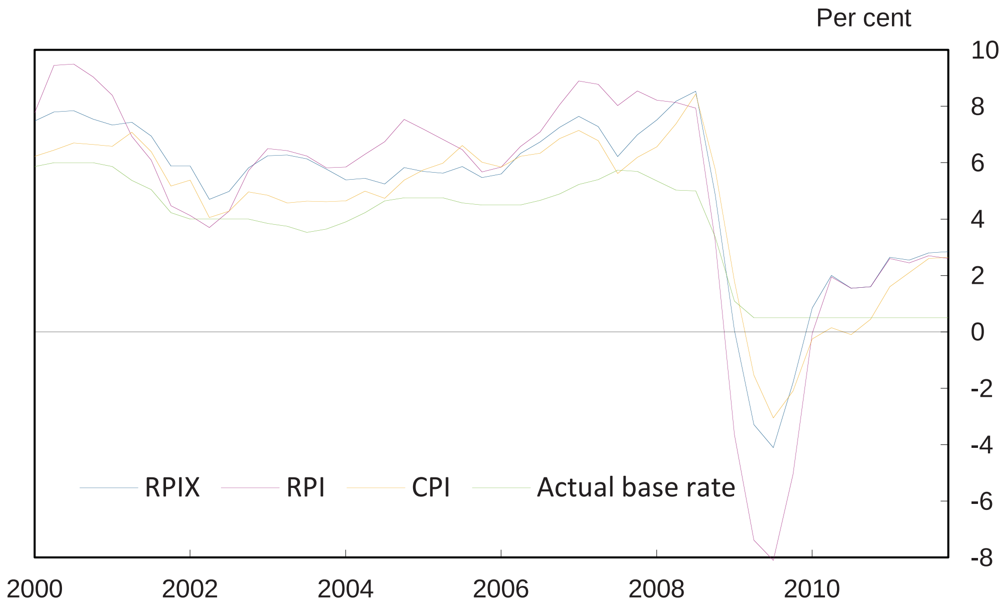

Figure 1: **Actual Policy Rate and Prescriptions from a Taylor rule in the U.K.**

Sources: Authors' calculations.

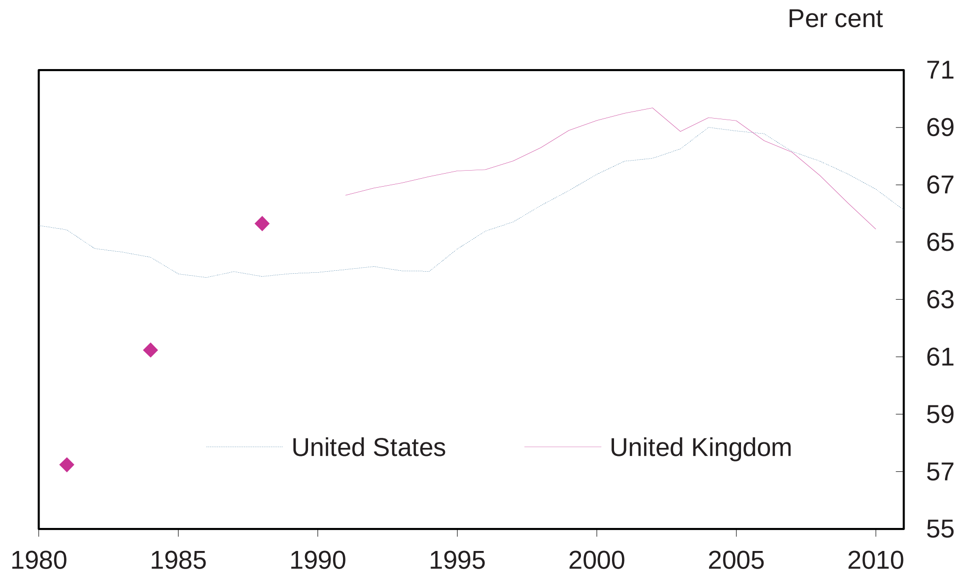

Figure 2: **Home Ownership Rates in the U.S. and the U.K.**

Sources: Department for Communities and Local Government and U.S. Census Bureau.

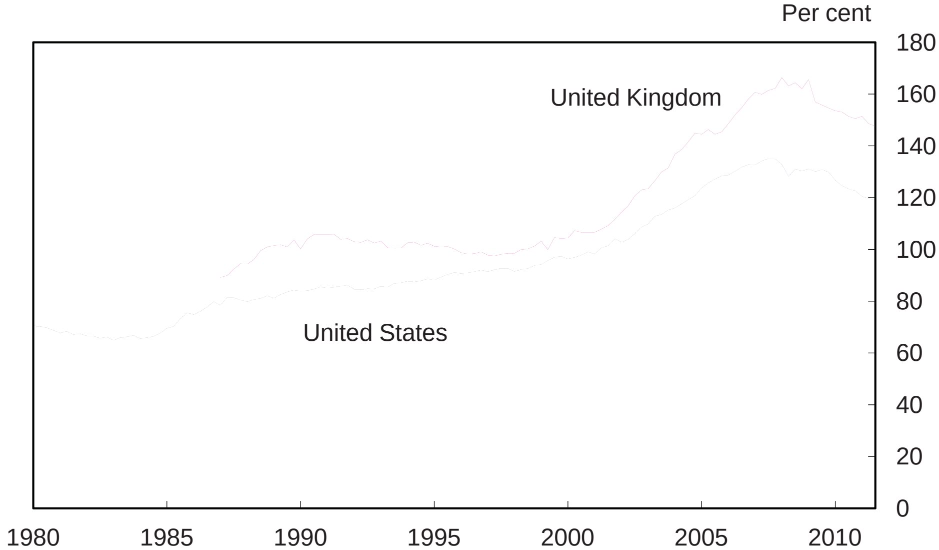

Figure 3: **Household Debt to Disposable Income Ratios in the U.S. and the U.K.**

Sources: Thomson Reuters DataStream and ONS.

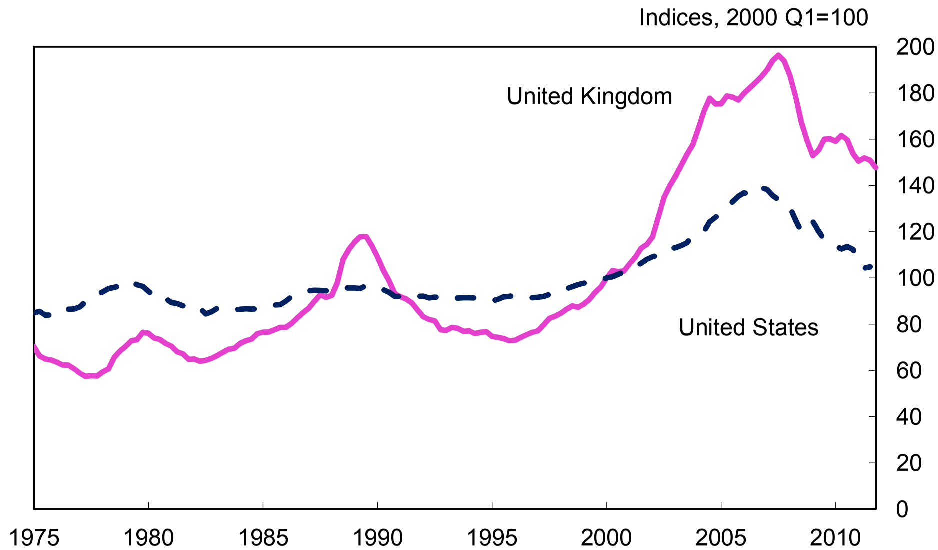

Figure 4: **House Prices in the U.S. and the U.K.**

Sources: Federal Housing Finance Agency, Bureau of Labor Statistics, Nationwide and the Office for National Statistics. The U.S. house price index captures the movement of single-family home prices based on repeated-sales or refinancings where mortgages have been purchased or securitised by Fannie Mae or Freddie Mac. The U.K. Nationwide house price index is based on lending data for properties by the Nationwide building society that are mix-adjusted to track a representative house price over time. The Nationwide data are seasonally adjusted. The U.S. nominal index has been deflated by CPI-U and the U.K. index by RPI-X.

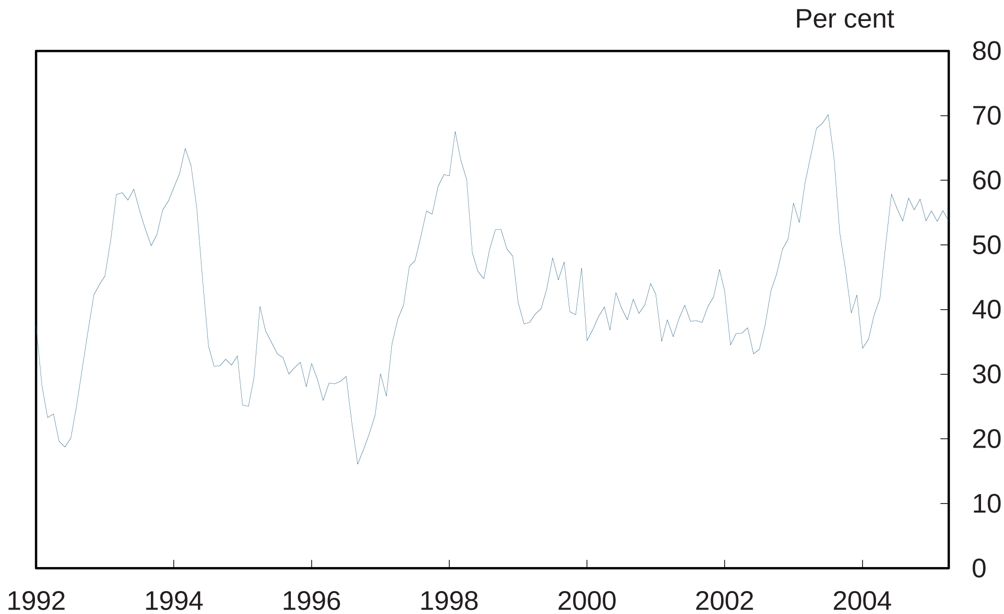

Figure 5: **Share of Fixed Rate Mortgages on New Loans in the U.K.**

Source: Survey of Mortgage Lenders.

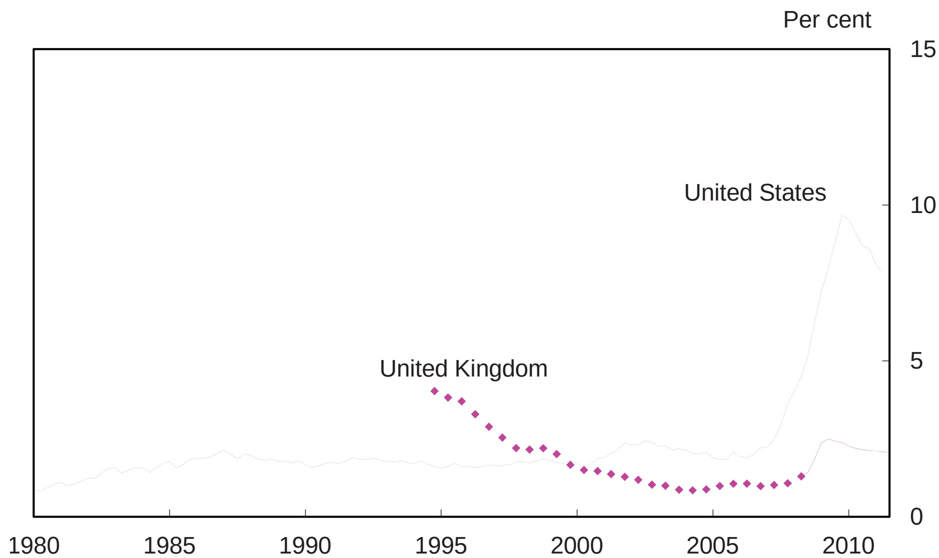

Figure 6: **Mortgage Arrears in the U.S. and the U.K.**

Source: Thomson Reuters Datastream and Council of Mortgage Lenders. Note: US Seriously delinquent and U.K. 3 months or more in arrears.

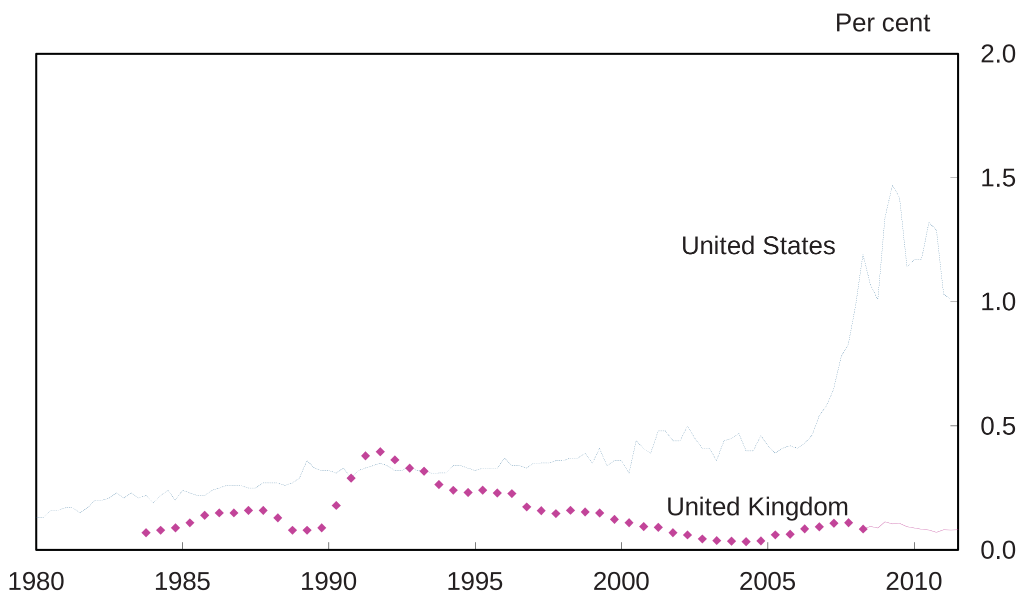

Figure 7: **Mortgage Repossessions: New Actions Started**

Source: Thomson Reuters Datastream and Council of Mortgage Lenders.

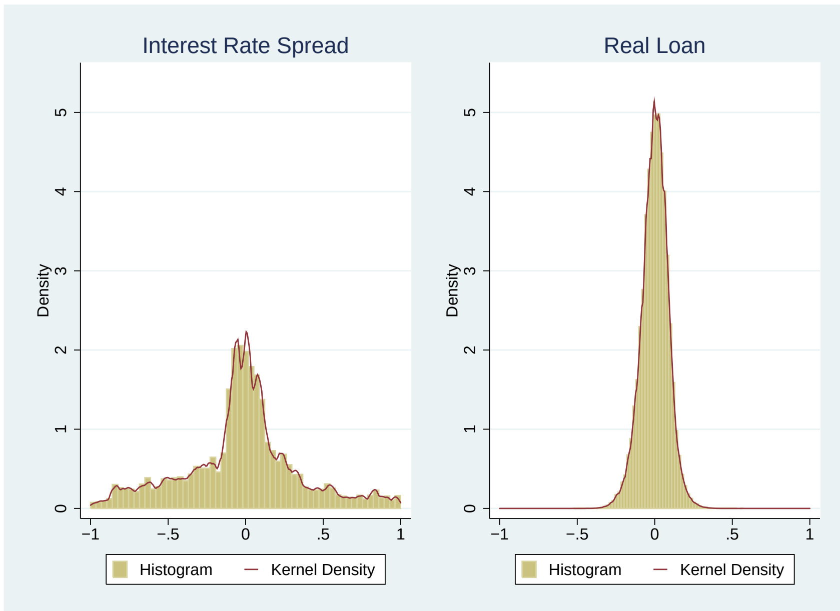

Figure 8: **Data Statistics: Kernel Density Functions**

Kernel density based on epanechnikov kernel function using the width which would minimize the mean integrated squared error under Gaussian data. For each variable, the figure reports the deviations from the annual average over the annual average

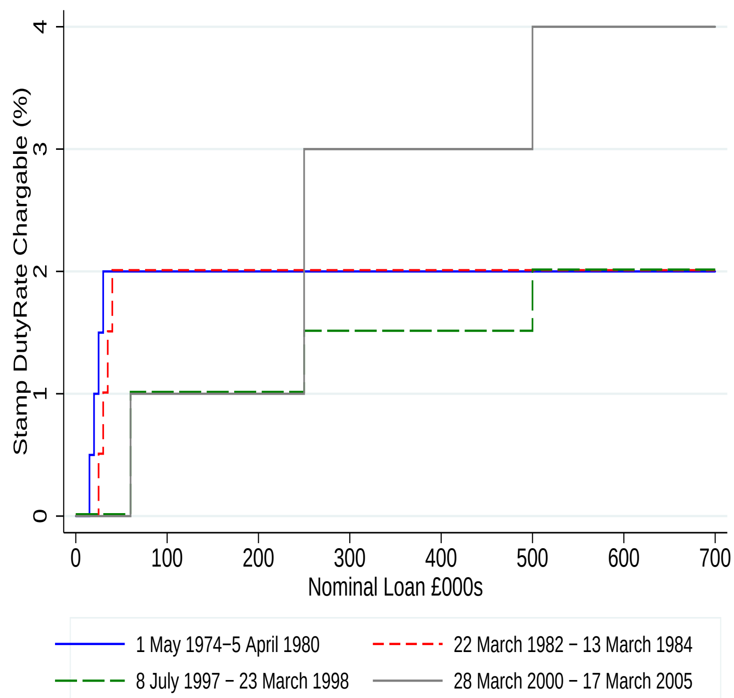

Figure 9: **Piece-wise Linear Structure of Stamp Duty Tax Rates**

The figure shows the piece-wise linear structure of stamp duty tax for housing transactions in the U.K. across four time periods selected from Table 1.

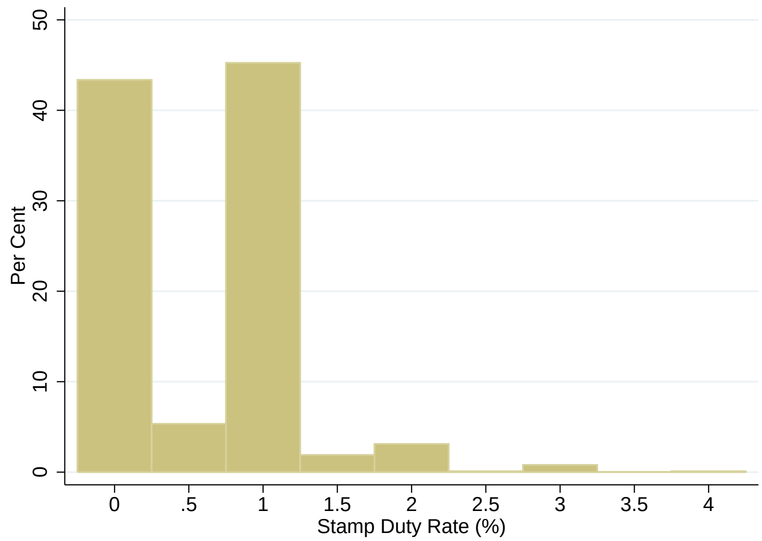

Figure 10: **Histogram of Stamp Duty Tax Rates**

The figure shows the proportion of borrowers in our dataset that are liable for each rate band of stamp duty taxation as reported in Table 2.

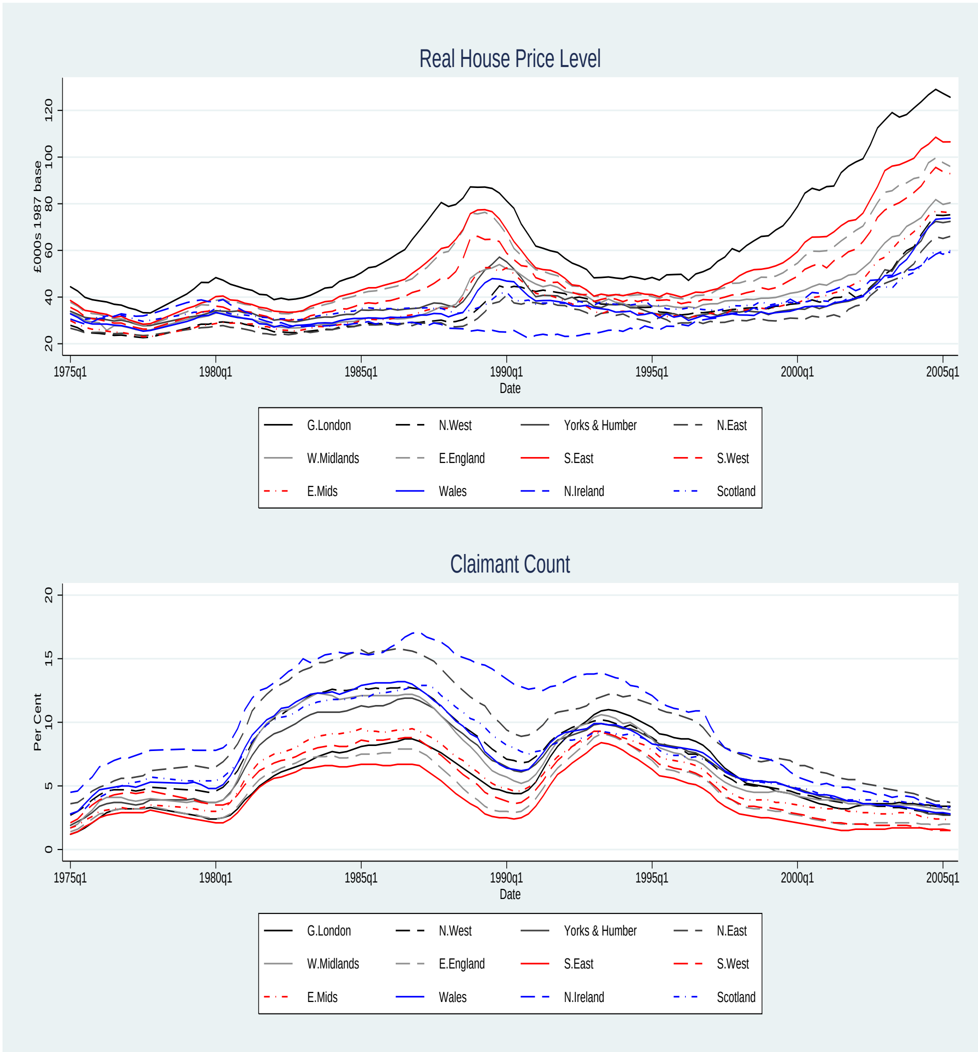

Figure 11: **Regional real house prices and claimant count**

The figure shows time series for real house prices and the claimant count unemployment rate for each region within our dataset.

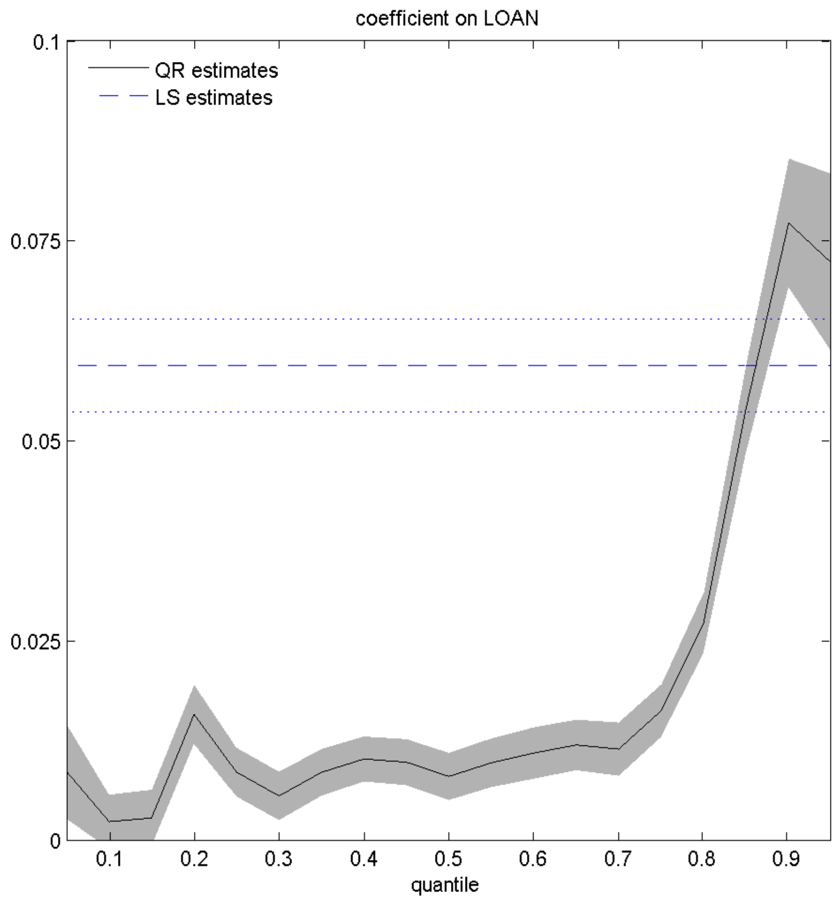

Figure 12: **Estimates of the Effect of Loan Size on Individuals' Interest Rate Spread conditional on Covariates - by quantile**

The figure shows the coefficient on real loan from regressions of individual interest rate spread on real loan, real income, real down payment, age, first time buyer dummy, regional house price, regional claimant count, year and region-specific dummies. Regional house price and claimant count data are lagged one quarter. QR (LS) estimates in black (blue) refer to quantile (least squares) regressions. Shaded areas (dotted lines) are 95% confidence intervals estimated using robust standard errors. Estimates are reported for $\tau \in [0.05, 0.95]$ at 0.05 unit intervals.

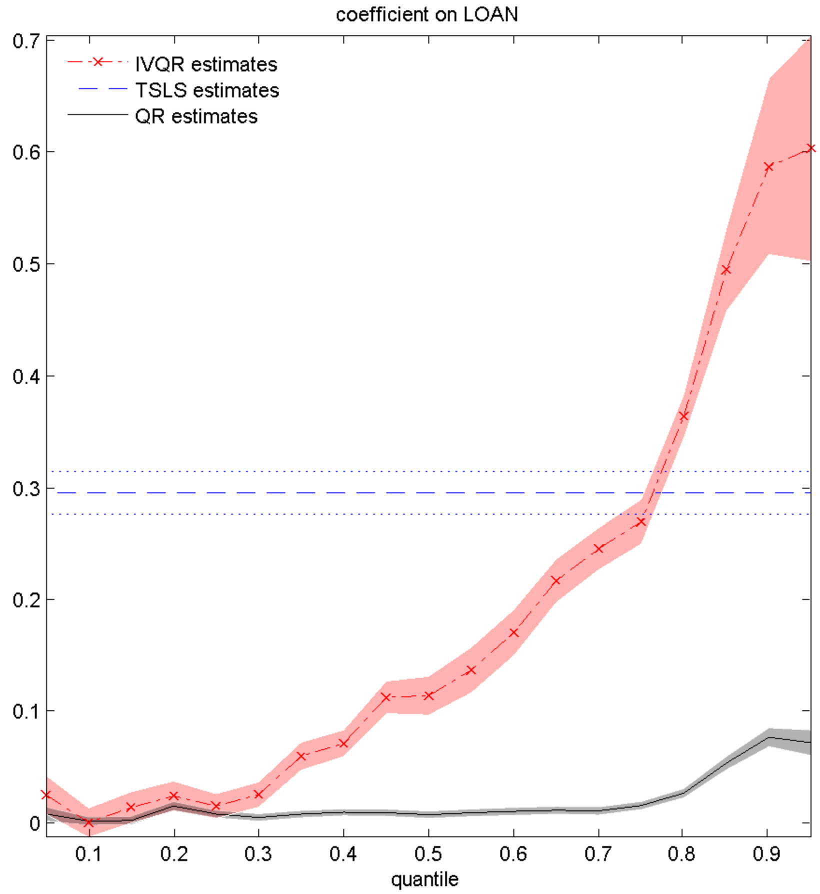

Figure 13: **Estimates of the Effect of Loan Size (Instrumented) on Individuals' Interest Rate Spread conditional on Covariates - by quantile**

Coefficients on loan size from instrumental variable regressions of individual interest rate spread on real loan, real income, real down payment, age, first time buyer dummy, regional real house price, regional claimant count, year and region-specific dummies. The instrument for individual loan is individual stamp duty rate. IVQR (TSLS) estimates in black (blue) refer to quantile (two stage least squares) regressions. Shaded areas (dotted lines) are 95% confidence intervals estimated using robust standard errors. QR estimates from Figure 1 are reported as red line with asterisks. Estimates are reported for $\tau \epsilon$ [0.05, 0.95] at 0.05 unit intervals.

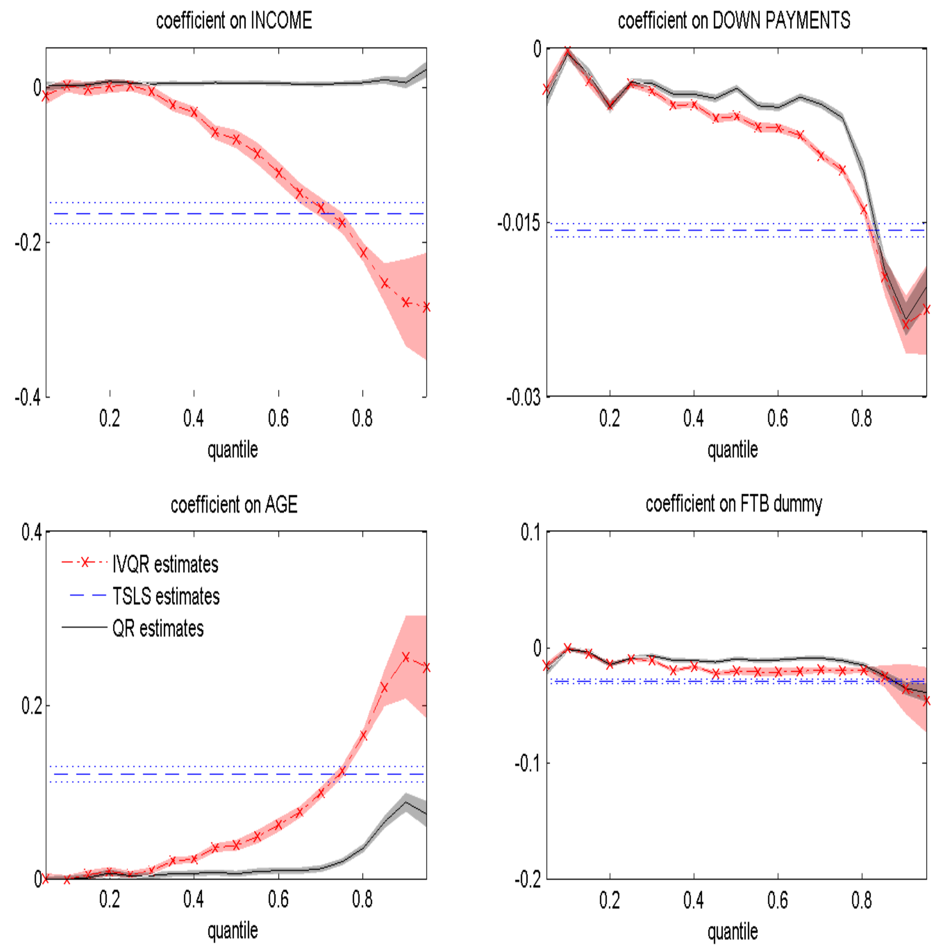

Figure 14: **Estimates of the Effect of Borrowers' Specific Variables on Individuals' Interest Rate Spread conditional on Covariates - by quantile**

Coefficients on borrower-specific variables (real income, real down payment, age, and first time buyer status) from instrumental variable regressions of individual interest rate spread on real loan, real income, real down payment, age, first time buyer dummy, regional real house price, regional claimant count, year and region-specific dummies. The instrument for individual loan is individual stamp duty rate. IVQR (TSLS) estimates in black (blue) refer to quantile (two stage least squares) regressions. Shaded areas (dotted lines) are 95% confidence intervals estimated using robust standard errors. QR estimates are reported as red line with asterisks. Estimates are reported for $\tau \in [0.05, 0.95]$ at 0.05 unit intervals.

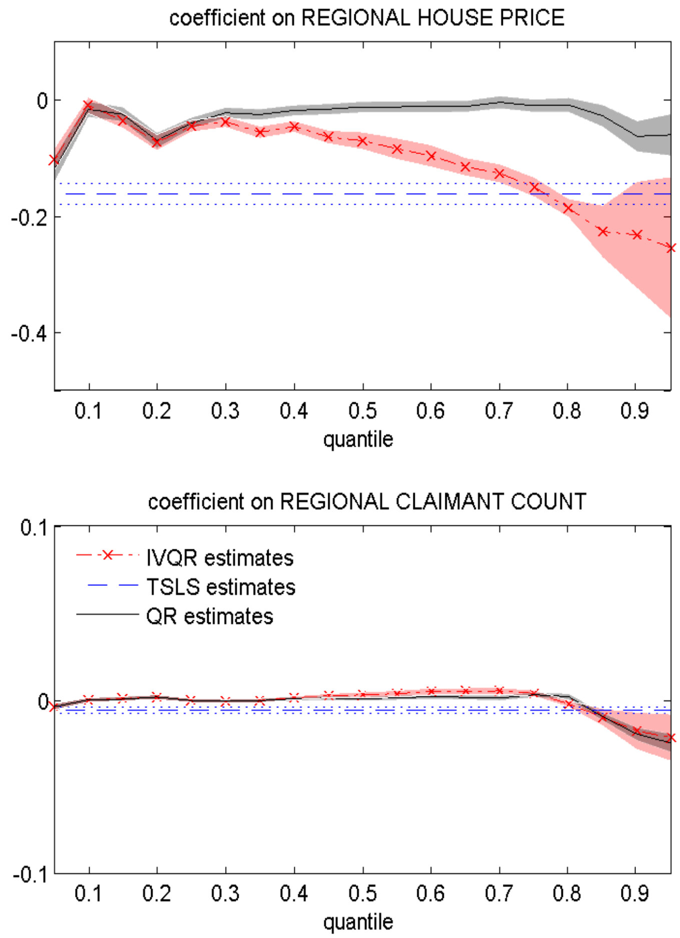

Figure 15: **Estimates of the Effect of Region Specific Variables on Individuals' Interest Rate Spread conditional on Covariates - by quantile**

Coefficients on region-specific variables of house prices and claimant count rate from instrumental variable regressions of individual interest rate spread on real loan, real income, real down payment, age, first time buyer dummy, regional real house price, regional claimant count, year and region-specific dummies. The instrument for individual loan is individual stamp duty rate. IVQR (TSLS) estimates in black (blue) refer to quantile (two stage least squares) regressions. Shaded areas (dotted lines) are 95% confidence intervals estimated using robust standard errors. QR estimates are reported as red line with asterisks. Estimates are reported for $\tau \in [0.05, 0.95]$ at 0.05 unit intervals.

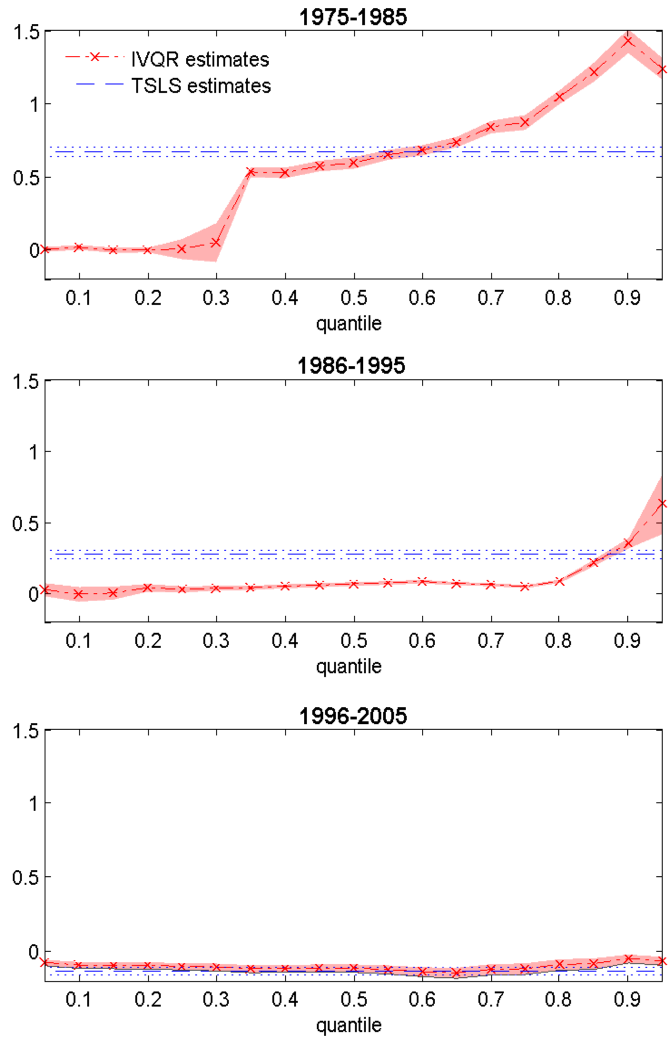

Figure 16: **Sub-sample Estimates of the Effect of Loan Size (Instrumented) on Individuals' Interest Rate Spread conditional on Covariates - by quantile**

Coefficients on loan size from instrumental variable regressions of individual interest rate spread on real loan, real income, real down payment, age, first time buyer dummy, regional real house price, regional claimant count, year and region-specific dummies. The instrument for individual loan is individual stamp duty rate. IVQR (TSLS) estimates in black (blue) refer to quantile (two stage least squares) regressions. Shaded areas (dotted lines) are 95% confidence intervals estimated using robust standard errors. QR estimates from Figure 1 are reported as red line with asterisks. Estimates are reported for $\tau \epsilon$ [0.05, 0.95] at 0.05 unit intervals.

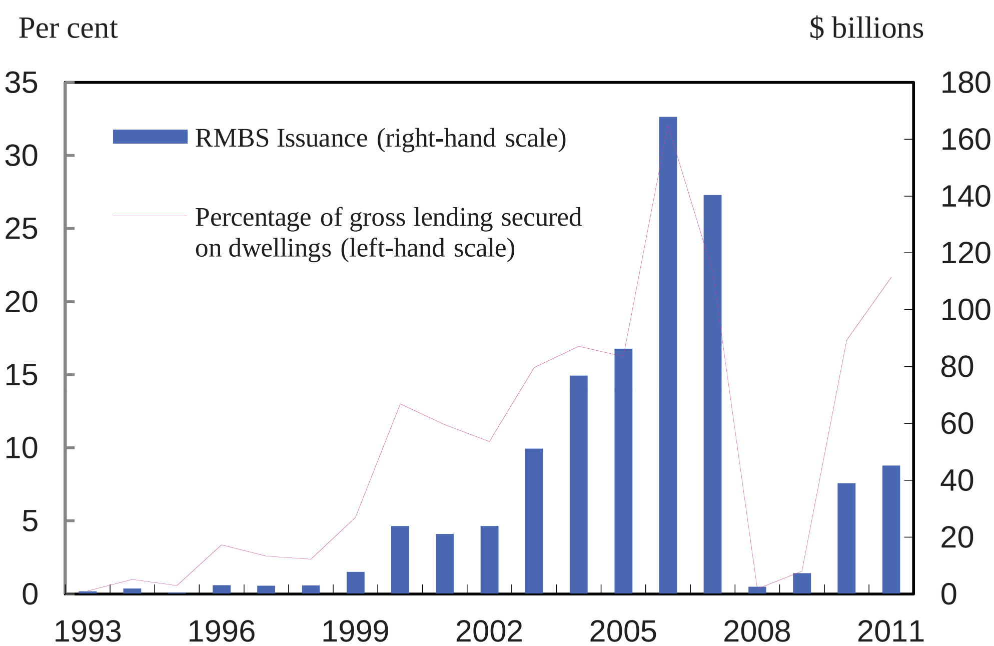

Figure 17: **Residential Mortgage Backed Security (RMBS) Issuance in the U.K.**

Sources: Dealogic and Bank calculations. Note: Non-retained issuance only. Data to January 2012.

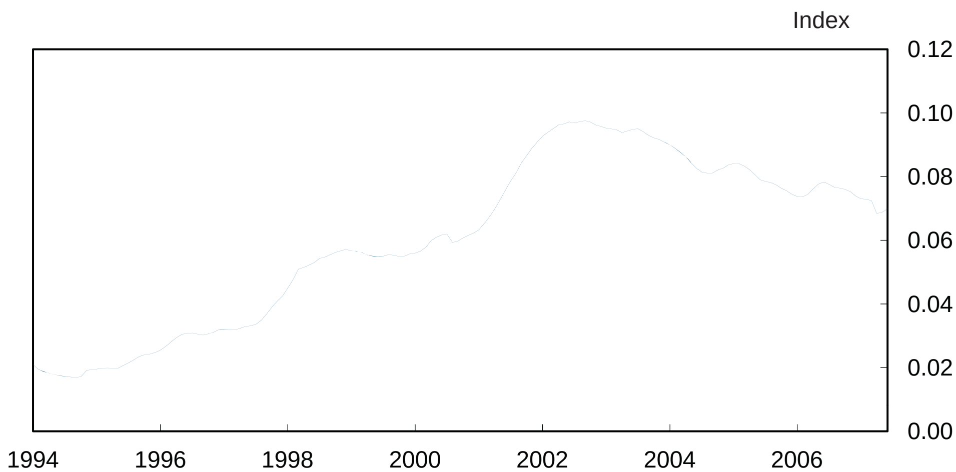

Figure 18: **Herfindahl Index of Mortgage Market Concentration in the U.K.**

Source: Bank of England and Bank calculations. Note: lower figures for the index mean more competition

Table 1: RATES OF STAMP DUTY AND THRESHOLDS

Commencing Date:	**Nil rate**	**0.5%**	**1%**	**1.5%**	**2%**	**2.5%**	**3%**	**3.5%**	**4%**
	Up to				*Exceeding*				
					£				
1 May 1974	15,000	15,000	20,000	25,000	30,000	–	–	–	–
6 April 1980	20,000	20,000	25,000	30,000	35,000	–	–	–	–
22 March 1982	25,000	25,000	30,000	35,000	40,000	–	–	–	–
13 March 1984	30,000	–	30,000	–	–	–	–	–	–
20 December 1991	250,000	–	250,000	–	–	–	–	–	–
19 August 1992	30,000	–	30,000	–	–	–	–	–	–
16 March 1993	60,000	–	60,000	–	–	–	–	–	–
8 July 1997	60,000	–	60,000	250,000	500,000	–	–	–	–
24 March 1998	60,000	–	60,000	–	250,000	–	500,000	–	–
16 March 1999	60,000	–	60,000	–	–	250,000	–	500,000	–
28 March 2000	60,000	–	60,000	–	–	–	250,000	–	500,000
1 December 2003 (non-disadvantaged areas)	60,000	–	60,000	–	–	–	250,000	–	500,000
1 December 2003 (disadvantaged areas)	150,000	–	150,000	–	–	–	250,000	–	500,000
17 March 2005 (non-disadvantaged areas)	120,000	–	120,000	–	–	–	250,000	–	500,000
17 March 2005 (disadvantaged areas)	150,000	–	150,000	–	–	–	250,000	–	500,000
23 March 2006 (non-disadvantaged areas)	125,000	–	125,000	–	–	–	250,000	–	500,000
23 March 2006 (disadvantaged areas)	150,000	–	150,000	–	–	–	250,000	–	500,000
3 September 2008	175,000	–	175,000	–	–	–	250,000	–	500,000

Source: HM Revenue and Customs.

If the value of a property is above a specified threshold, Stamp Duty is liable at the appropriate rate on the whole amount paid. Special rules exist for residential leases of less than 21 years and properties bought in disadvantaged areas.

Table 2: Disaggregated Data on Key Variables

VARIABLE	Mean	Median	St.dev.	Skew.	Coeff. of var.
INTEREST RATE SPREAD					
1975-1985	4.13	4.25	1.27	-0.74	0.31
1986-1995	1.34	1.37	0.70	0.36	0.52
1996-2005	1.20	1.01	0.84	0.60	0.70
Full Sample	2.41	1.70	1.71	0.55	0.71
REAL LOAN £000s					
1975-1985	21.81	20.93	8.67	1.14	0.40
1986-1995	32.63	29.01	18.09	3.30	0.55
1996-2005	44.71	36.74	30.67	2.91	0.69
Full Sample	31.02	26.05	20.97	3.79	0.68
REAL INCOME £000s					
1975-1985	11.98	10.92	5.40	2.49	0.45
1986-1995	15.13	13.25	8.79	4.31	0.58
1996-2005	19.06	15.58	14.05	4.67	0.74
Full Sample	14.76	12.50	9.60	5.28	0.65
REAL HOUSE VALUE £000s					
1975-1985	33.19	29.05	17.42	2.20	0.52
1986-1995	45.40	38.29	29.55	3.48	0.65
1996-2005	62.45	49.15	46.27	2.78	0.74
Full Sample	44.35	35.44	32.42	3.63	0.73
LOAN TO INCOME RATIO					
1975-1985	1.92	1.91	0.57	0.32	0.30
1986-1995	2.27	2.26	0.71	0.94	0.31
1996-2005	2.50	2.47	0.90	1.03	0.36
Full Sample	2.18	2.14	0.75	1.06	0.34
LOAN TO VALUE RATIO					
1975-1985	0.72	0.77	0.21	-0.57	0.30
1986-1995	0.78	0.86	0.21	-0.93	0.27
1996-2005	0.77	0.85	0.21	-1.01	0.27
Full Sample	0.75	0.82	0.21	-0.78	0.28

Notes: Individual housing contract data are from the 1975-2005 (excluding 1978) waves of the Survey of Mortgage Lenders (SML) and its predecessors. The selected sub-sample includes all households within each wave whose observation is identified as being for house purchase. The interest rate spread reflects the spread between individuals contracted rate of interest and benchmark funding rates (the average deposit rate reported by Building Societies). Age reflects the age of the first named (main) borrower on the mortgage contract. Stamp duty is imputed for each individual from the prevailing regulations given recorded nominal transaction prices. Real values are computed through deflating nominal values by monthly observations of the Retail Price Index excluding mortgage interest payments (RPIX) with all amounts reported in January 1987 £. Coefficient of variation represents $\frac{\textbf{St.dev}}{\textbf{Mean}}$. Sample sizes: 1975-1985=256,154, 1986-1995=246,444, 1996-2005=143,472.

Table 3: FIRST STAGE REGRESSION

VARIABLES	Baseline	Collapsed	Full Sample
STAMP DUTY RATE	0.229***	0.065***	0.207***
	(0.001)	(0.023)	(0.001)
AGE	-0.009***	-0.016***	-0.009***
	(0.000)	(0.003)	(0.000)
REAL INCOME	0.600***	0.804***	0.602***
	(0.001)	(0.063)	(0.001)
REAL DOWNPAYMENT	-0.009***	0.019***	-0.009***
	(0.000)	(0.008)	(0.000)
FTB DUMMY	0.015***	0.135***	0.013***
	(0.001)	(0.048)	(0.001)
REAL REGIONAL HOUSE PRICE	0.276***	0.205***	0.289***
	(0.004)	(0.037)	(0.003)
REGIONAL CLAIMANT COUNT	0.002***	-0.007***	0.002***
	(0.000)	(0.002)	(0.000)
Observations	564551	360	646070
R^2	0.749	0.996	0.737
F-test for the insignificance of stamp duty rate			
	F(1,564403)=62823	F(1, 312) =8.05	F(1,646022)=65444
	Prob>F = 0.00	Prob>F =0.005	Prob>F =0.00
F-test for the null of joint insignificance of the regional dummies			
	F(11,564403)=384	F(12, 312)=13.3	F(11,646022)=437
	Prob>F = 0.00	Prob>F=0.00	Prob>F =0.00
F-test for the null of joint insignificance of the year dummies			
	F(29,564403)=2241	F(28, 312)=37.6	F(29,646022)=2546
	Prob>F = 0.00	Prob>F=0.00	Prob>F =0.00

Notes: see section 2 and Table 2 for sample and data description. The table reports the estimates from a regression of the log of real loan size on the reported variables and controls for years and regions. Real values are in 000s of January 1987 pounds. The Baseline column refers to the sample which excludes house buyers within +/-5% (by value) around the stamp duty thresholds. The Collapsed column refers to the sample which collapses the data by regions and years. The Full Sample column refers to the sample which places no restrictions on the distance from the stamp duty threshold values. Standard errors are reported in parenthesis. *** = p-value <0.01, ** = p-value <0.05, * = p-value <0.1,

Appendix A: Institutions

In this appendix, we briefly set out some of the measures of financial and mortgage market developments since the late 1970s. In table A1 we highlight liberalisation measures affecting the U.K. mortgage market. For example, in 1979 exchange controls were removed exposing the U.K. banking sector to greater foreign competition but also providing them with access to Eurodollar funding markets. In 1980, the Supplementary Special Deposit Scheme (the 'Corset') was removed. The Corset had introduced penalties (the requirement to hold non-interest bearing deposits) to limit the rate of growth of banks' balance sheets and so inflationary pressures. With the removal of exchange controls, domestic controls on banks balance sheet growth was rendered obsolete as customers could now borrow from abroad and banks were able to develop new areas of business, such as mortgage lending, and were able to compete for retail funds.

Table A1: MARKET LIBERALISATION

Date	Liberalisation Measure
1979	Removal of Exchange Controls
1980	Removal of Supplementary Deposit Scheme
1981	BSA Recommended Rate becomes advisory
1983	Changes to Building Society Tax Position
1984	BSA Recommended Rate removed
1986	The Building Societies Act (1986)
1988	Raising of Building Societies Wholesale Funding Limit to 40%
	Basel I Accords on capital adequacy give mortgage loans lower
1991	Building Society Commission Increased Prudential Advice
1994	Raising of Building Societies Wholesale Funding Limit to 50%
1997	Amendment of the Building Societies Act (1986) takes permissive approach
2007	Building Societies (Funding) and Mutual Societies (Transfers) Act 2007
	increases wholesale funding limit to 75

Table A1 indicates some of the major market legislative changes that have impacted upon the workings of the UK mortgage market.

A provision of the Building Societies Act (1986) was to allow Building Societies to convert to p.l.c. status, and so escape limits that remained preventing commercial lending or unsecured lending above limits, and give access to other forms of capital that would allow more rapid expansion/diversification. In the period since, there have been a range of major demutualisations; from

Abbey National in 1989, to Northern Rock, Alliance and Leicester, Woolwich, Bradford and Bingley during the 1990s (table A2).

Table A2: DEMUTUALISATIONS

Institution	Date	Current Status	Latest Change
Abbey National	1989	Subsidiary of Santander	2004
Converted to plc			
Cheltenham and Gloucester	1994	Subsidary of Lloyds Banking Group	1994
Takeover by Lloyds TSB			
National and Provincial	1995	Name not in use	
Takeover by Abbey National			
Alliance and Leicester	1997	Subsidary of Santander	2008
Converted to plc			
Bristol and West	1997	Subsidary of Bank of Ireland	1997
Takeover by Bank of Ireland			
Halifax	1997	Subsidary of Lloyds Banking Group	2009
Converted to plc			
Northern Rock	1997	Nationalised	2008
Converted to plc			
The Woolwich	1997	Subsidary of Barclays	2000
Converted to plc			
Birmingham Midshires	1999	Subsidary of Lloyds Banking Group	1999
Takeover by Halifax			
Bradford and Bingley	2000	Nationalised	2008
Converted to plc			

One of the impacts of The Building Societies Act (1986) was to permit Building Societies to demutualise. Information in Table A2 indicates major demutualisations and the current status of these institutions.

One of the new sources of funding that would be heavily exploited by several of these former Building Societies was the issuance of Mortgage Backed Securities (MBS). Mortgage securitisation emerged in the UK during the late 1980s with the first centralised mortgage lenders. However, it was not until the late 1990s the UK residential mortgage backed securities (MBS) market experienced rapid growth with the participation of many major banks and building societies.

Appendix B: Dataset Restrictions

In this appendix, we report restrictions placed upon the raw data from which we obtain our results. Our mortgage origination data covers the period 1975 to 2005, and comes from the Survey of Mortgage Lenders and its predecessor, the 5% Sample Survey of Mortgages (SBSM). These surveys are available in electronic format for the years 1975-2001 from the Data Archive at the University of Essex. Unfortunately, the year 1978 is missing. Data covering the period 2002 to 2005 was obtained by the Bank of England from the Council of Mortgage Lenders (CML). To obtain our dataset we supplement data from the SBSM/SML on loan size, property value, gross interest rate, age, income and first time buyer status with regional house price data from the Nationwide house price index, and regional claimant count unemployment rate data from the Office for National Statistics (ONS). Further, we include the Building Societies Associations' recommended deposit rate as our funding cost prior to 1985, and the average building society gross deposit rate from the ONS subsequently.
The following restrictions were also placed upon the data to construct our dataset:

1. discard individuals over the age of 75 and under 21.
2. omit individuals buying a house with a price discount and who were previously local authority or housing association tenants.
3. exclude sitting tenants not covered by restriction 2.
4. omit observations for individuals with outlying loan-to-value(LTV) and loan-to-income (LTI) ratios. The threshold levels chosen were LTI>=10, and LTV<0.2 or LTV>1.1
5. discard observations where lending is not for house purchase (further advances and remortgaging activity).
6. discard observations with a gross interest rate below 0.5.
7. omit observations where relevant data are missing.