Risk Heterogeneity and Credit Supply: Evidence from the Mortgage Market

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Abstract

This paper uses a unique data set on more than 600,000 mortgage contracts to estimate a credit supply function which allows for risk-heterogeneity. Non-linearity is modeled using quantile regressions. We propose an instrumental variable approach in which changes in the tax treatment of housing transactions are used as an instrument for loan demand. The results are suggestive of considerable risk heterogeneity with riskier borrowers penalized more for borrowing more.

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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. This is particularly true in the context of mortgage markets where different segments of the market face different prospects of repaying their loans. In spite of its manifest importance, there are few empirical studies that study this issue.

This paper investigates risk pricing of U.K. mortgage contracts over 30 years using a unique data set on more than 600,000 mortgage contracts. It is well-known that the law of one price does not hold in credit markets. To motivate this observation in the context of this paper, figure 1 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. We will pursue a quantile regression approach in which the non-linear relationship between the interest rate charged to borrowers and loan size is influenced by unobserved heterogeneity (controlling for observed borrower characteristics), which we interpret as risk.

As well as allowing for potential non-linearities, 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

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

exploit exogenous changes in the tax system on income to identify labour supply. To implement this, we employ the Instrumental Variable Quantile Regression estimator proposed by Chernozhukov and Hansen (2005).

The results demonstrate 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. 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.

The existing 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. (2009), 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.

We join a growing empirical literature that exploits an instrumental variable quantile regression approach to study heterogeneity in micro-data. Prominent examples are the analysis in Chernozhukov and Hansen (2004) to quantify the effects of retirement programs on saving, the work of Abadie et al. (2002) to estimate the returns on education and the study by Garcia, Hernandez and Lopez-Nicolas (2001) to investigate the sources of wage inequality. Risk heterogeneity in mortgage pricing is a very natural context in which to apply this approach.

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 empirical approach. Section five presents the empirical results, while section six concludes. The appendices report additional information on the data and the institutional background of the U.K. mortgage market together with a simple model of loan pricing.

2 Context and 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 includes characteristics of the loan at origination such as the loan size, purchase price, and the rate of interest charged. 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.

Most mortgage products in the U.K. are adjustable rate mortgages that move in line with the funding costs of the lender with the main trigger event for changes being movements in Bank Rate set by the Bank of England. Fixed rate mortgages, which have become more prevalent in recent years, are typically fixed for only two years and then revert to an adjustable rate. Almost all of the mortgages in our dataset are 'variable' rate products with 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

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

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 loan-to-income ratios.[4] However, over time such lending limits have been re-

[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.

[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.

laxed 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 2. Thus, there have been a number of changes in stamp duty over time and across sizes of housing transactions which we can exploit. Figure 3 gives a histogram of actual stamp duty rates paid. A significant proportion of the rates observed 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.

[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.

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 the proportion of housing wealth among those taking out new mortgage loans has generally kept pace with increases in house prices.

[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.

4 Conceptual Framework and Empirical Approach

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 risk premium being charged. Appendix C spells out a simple mortgage pricing model to motivate this.

More precisely, 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 us. This variable could represent the result of a credit scoring algorithm or the lender observing a variable like occupation or work 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:

$$R_{irt} = H\left(L_{irt}; D_{rt}, X_{irt}, U_{irt}\right) \tag{1}$$

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).

Our aim is to estimate the shape of (1) using quantile regression (QR). Above all, this will not assume that the relationship between the amount borrowed, characteristics and the interest rate is linear. We will, however, initially assume that L_{irt} is exogenous. 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:

$$Q_\tau\left(R_{irt} | L_{irt}, D_{rt}, X_{irt}\right) \quad \text{with } \tau \in (0,1). \tag{2}$$

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:

$$QTE_{\tau} = \frac{\partial Q_{\tau}\left(R_{irt}|L, D_{rt}, X_{irt}\right)}{\partial L} \tag{3}$$

The quantile treatment model can then be written as:

$$R_{irt} = q\left(L_{irt}, D_{rt}, X_{irt}, U_{irt}\right) \quad \text{where } U_{irt}|L_{irt} \sim U\left(0,1\right). \tag{4}$$

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 (1). The empirical specification of the conditional τ-*th* quantile distribution takes the following form:

$$Q_{\tau}(R_{irt}|\cdot) = a_L\left(\tau\right)L_{irt} + a_x\left(\tau\right)X_{irt} + a_D\left(\tau\right)D_{rt}. \tag{5}$$

The variable L_{irt} is the log of the *real* loan size. The vector X_{irt} includes log of household real income, initial real housing wealth, 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 regional and year dummy variables as well as a regional house price index and the regional unemployment rate measured by the claimant count in the quarter before the mortgage contract was agreed.

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. Let $W(L, R, \cdot)$ 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.

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:

$$R_{irt} = q(L_{irt}, X_{irt}, D_{rt}, U_{irt}) \quad \text{where } U_{irt}|Z_{irt} \sim U(0,1) \tag{6}$$

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 initial housing wealth and the size of the loan, i.e.

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

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}.[9] Thus we are confident that variations in (ξ_t, V_{irt}) are inducing variation in Z_{irt}.

Further credence is given to this view by observing that variation in stamp duty rates paid depends significantly on region 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 covariates in our empirical specification. Furthermore, we also condition on regional dummies in an effort to control for other regional features unrelated to loan pricing. Figure 4 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:

$$L_{irt} = b_S Z_{irt} + b_X X_{irt} + b_D D_{rt} + \eta_{irt} \tag{7}$$

where X_{rit} is the same vector of observed household characteristics as above and D_{rt} are the same regional and time-varying regional variables as in equation (5).

Results from estimating (7) are presented in Table 3. The first column uses the baseline sample which drops observations which are within +/-5%

[9]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.

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. 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.[10]

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.

5 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.

5.1 The interest rate and loan size

In Figure 5, we present the estimates (and the 95% confidence intervals) of the coefficient on loan in a QR equation of the form (5).[11] To emphasise the

[10] 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.

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

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 6 as the red line with asterisks. For the sake of comparison, we also report estimates and confidence intervals for the QR method of figure 5 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 5. 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 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.[12] 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.

5.2 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 7, we report results for housing wealth, 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 7 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 part of the conditional distribution. However, for housing wealth 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 housing wealth on the interest rate spread is intuitive. There is essentially no effect from having a higher level of initial wealth for lower quantiles. However, for the higher "riskier" quantiles higher housing wealth yields a lower interest rate. This makes sense if greater wealth provides 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

[12]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.

household. This makes sense if higher incomes matter most when borrowers are riskier.

A comparison between figures 6 and 7 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 7 reflects the fact that the estimates of $a_L(\tau)$ based on (5) 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.

5.3 Regional features

Turning to the effects of regional characteristics on mortgage conditions, figure 8 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, on average, better price conditions. The QR estimates do not seem to indicate a clear pattern across household whereas the IVQR estimates suggest the effect is significantly larger for mortgagors charged higher interest rates conditional on covariates. Regional unemployment in contrast appears of little economic and statistical significance, and no systematic differences emerge between estimates using the QR and IVQR methods.

6 Conclusions

The issue of how far lenders price in risk has become more salient during the recent turbulence in financial markets. And there has been much discussion of risk pricing models and their adequacy. While this paper cannot say whether lenders have been sufficiently prudent in their risk pricing, it is informative in documenting the historic practices in the U.K. mortgage market. To do so, we have exploited a sizeable micro-data set on mortgage contracts. It is natural to approach this issue using a framework which takes risk heterogeneity seriously. However, it is also important to consider the implications of loan being endogenous. We proposed using taxation of housing transactions as an instrument for loan size.

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 more housing wealth are by and large better treated, although this has most bite in the higher risk groups.

Taken together, the empirical results confirm the importance of taking seriously concerns about heterogeneity and endogeneity in this context. The results underline the importance of looking at non-linearities in a customer market like mortgages where individual characteristics matter.

Endogeneity bias also appears to be important but in a somewhat subtle way. It appears to be rather unimportant for safer borrowers. However, the results suggests a more exaggerated response of lenders to high risk borrowers demanding higher loans when loan size is treated as endogenous. Our results suggest that the U.K. mortgage market has actively priced risk for high loan borrowers through the period in question, which explains why we see a pronounced dispersion in the rates paid by borrowers.

A number of issues for further research suggest themselves. One particularly interesting issue is to focus more on the time-varying nature of the relationships that we have studied. A concern prior to the current financial crisis was that lenders lost control of risk pricing due to either failure to perceive risk or a changing in pricing methods. They have since responded by increasing spreads once again. Accounting for the dynamic factors, particularly the impact of competition and market liberalization, is an interesting topic for further research.

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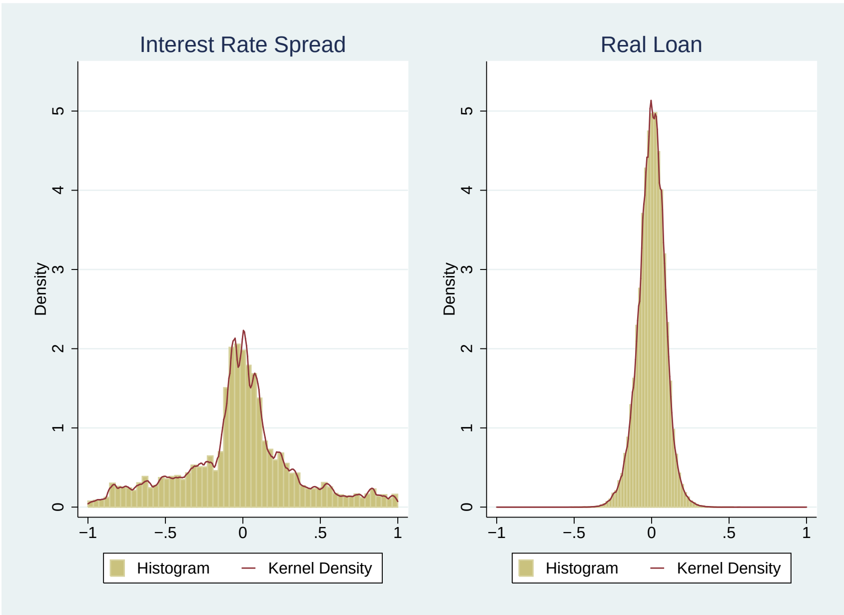

Figure 1: **Data Statistics: Kernel Density Functions**

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

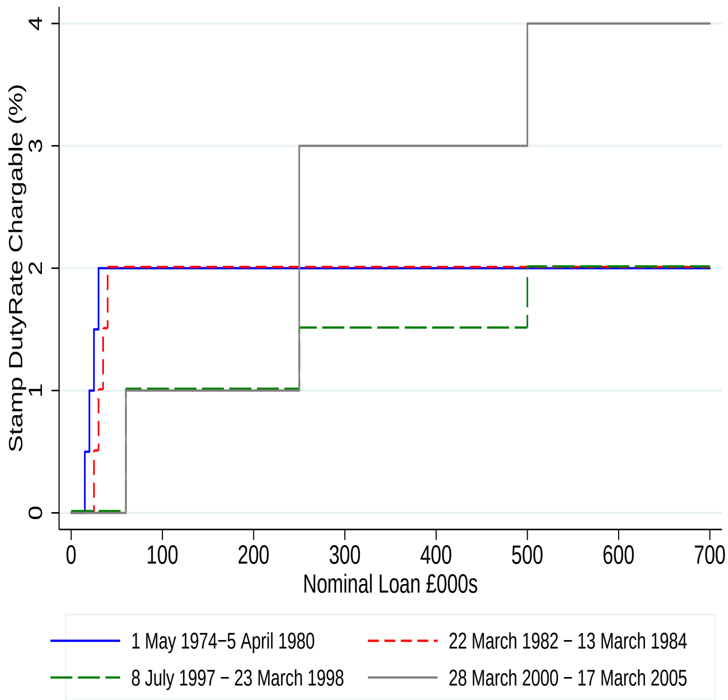

Figure 2: **Piece-wise Linear Structure of Stamp Duty Tax Rates**

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.

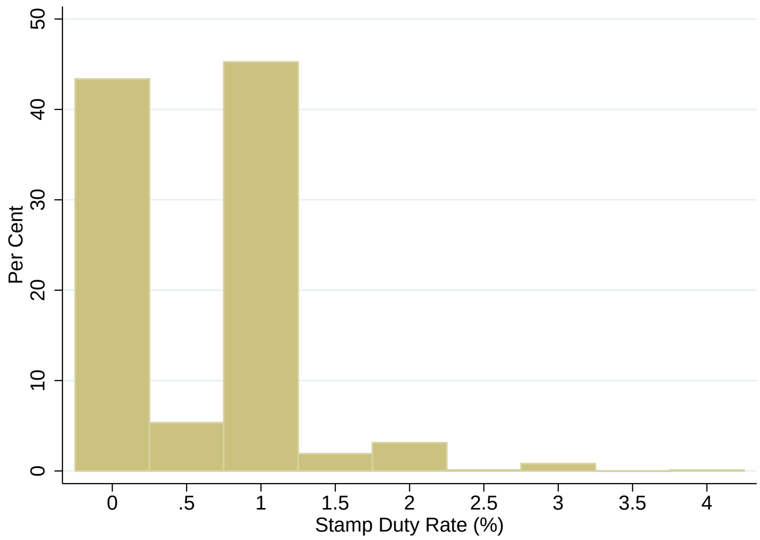

Figure 3: **Histogram of Stamp Duty Tax Rates**

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.

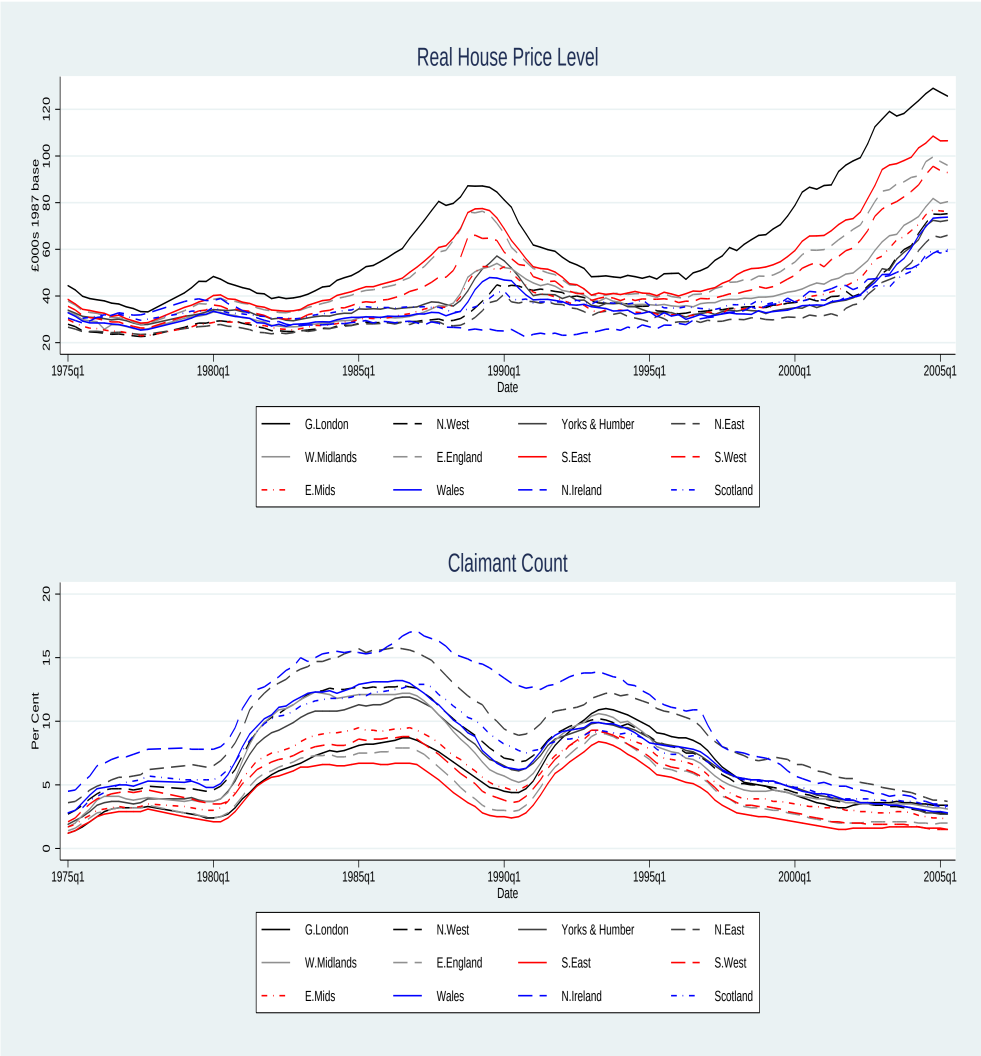

Figure 4: **Regional real house prices and claimant count**

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

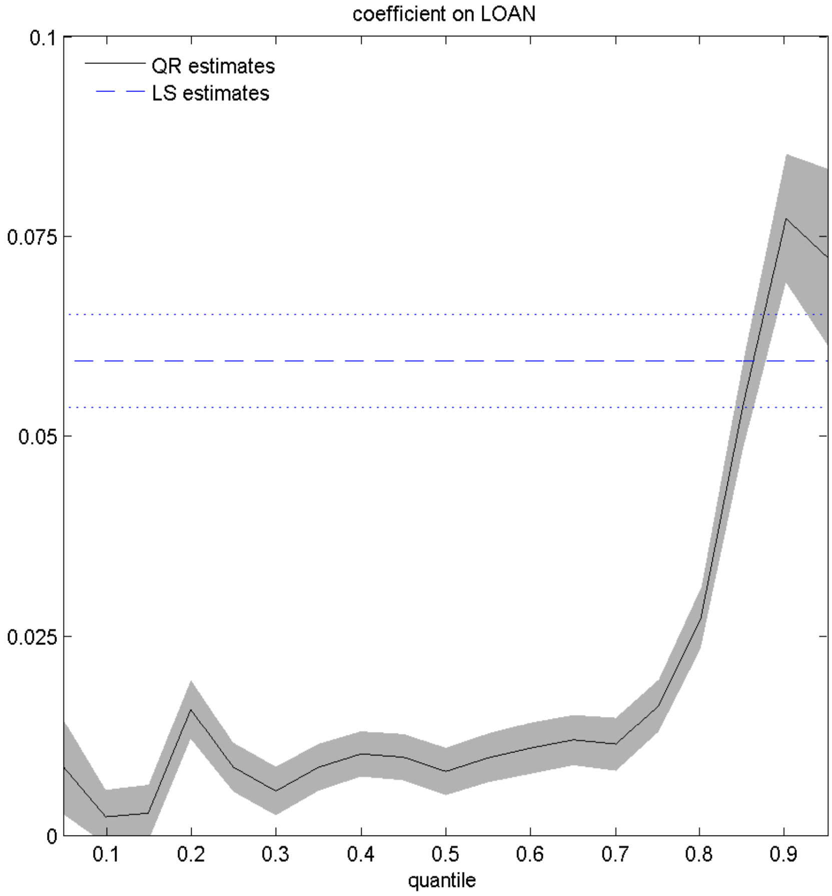

Figure 5: **Estimates of the Effect of Loan Size on Individuals' Interest Rate Spread conditional on Covariates - by quantile**

The figure shows the coefficient on real loan from regressions of individual interest rate spread on real loan, real income, initial real wealth, 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.

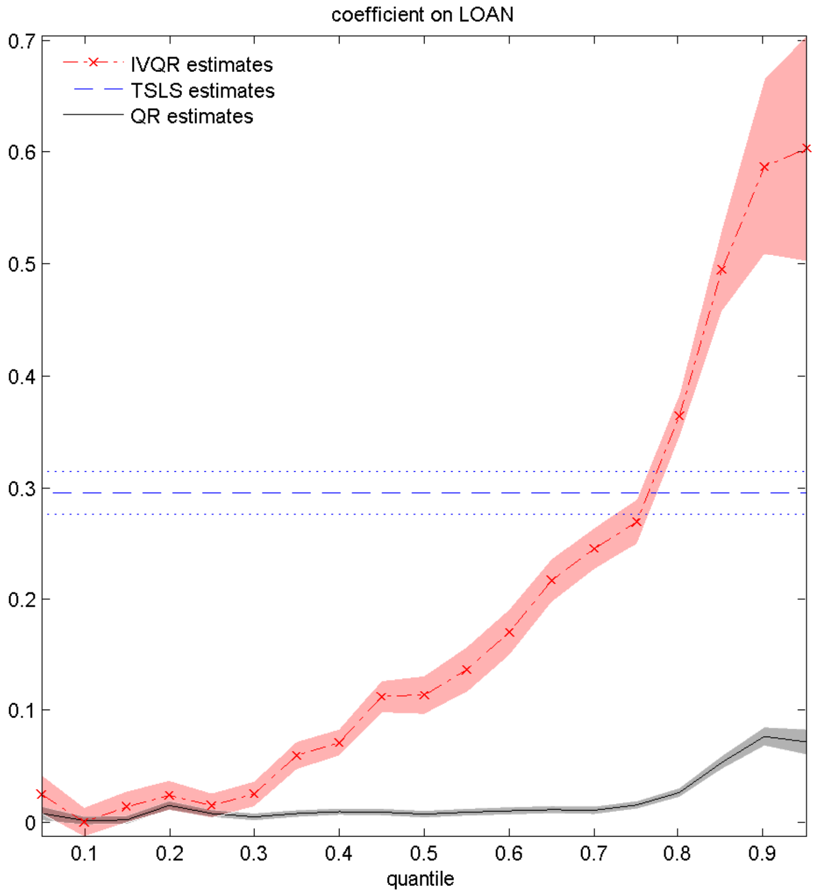

Figure 6: **Estimates of the Effect of Loan Size (Instrumented) on Individuals' Interest Rate Spread conditional on Covariates - by quantile**

Coefficients on loan size from instrumental variable regressions of individual interest rate spread on real loan, real income, initial real wealth, 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.

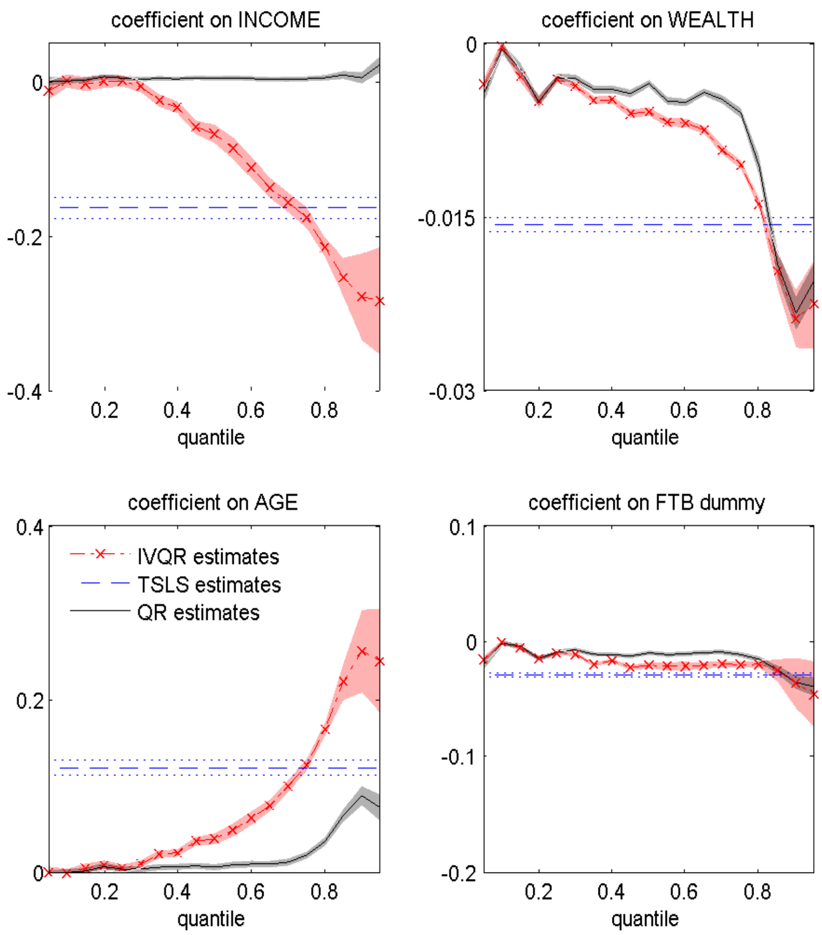

Figure 7: **Estimates of the Effect of Borrowers' Specific Variables on Individuals' Interest Rate Spread conditional on Covariates - by quantile**

Coefficients on borrower-specific variables (real income, initial real wealth, age, and first time buyer status) from instrumental variable regressions of individual interest rate spread on real loan, real income, initial real wealth, 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.

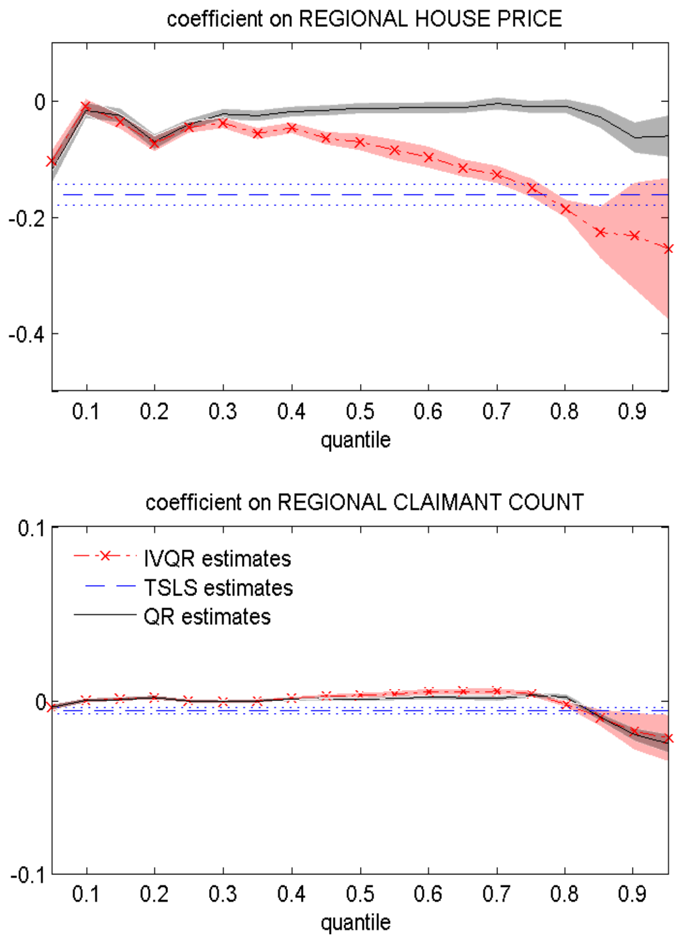

Figure 8: **Estimates of the Effect of Region Specific Variables on Individuals' Interest Rate Spread conditional on Covariates - by quantile**

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, initial real wealth, 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.

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

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.

Appendix C: A micro-foundation for the mortgage pricing equation

We seek the simplest model of mortgage pricing which allows for the possibility of default. 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, which we assume to depend on m, is $\beta(m, u)$ where u is index of riskiness. We assume that $\beta_m(m, u) < 0$, so that a higher repayment increases the chances that a borrower will default. We also assume that $\beta_u(m, u) < 0$. In the event of default, we assume that the lender recovers a fraction α of the remaining payments due under the contract. This reflects the extent of any lien on future earnings and/or the recovery of losses through collateral.

Let

$$\gamma = \Gamma(m, u) = \beta(m, u) + (1 - \beta(m, u))\alpha \tag{8}$$

with $0 \leq \gamma \leq 1$ be the lender's expected recovery rate. We can think of γ as encapsulating the borrower's type in terms of riskiness.

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

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

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

$$\pi_t = m\frac{\gamma}{1-\gamma}\left[1 - \frac{\gamma^{-t}}{\gamma^{-T-1}}\right]. \tag{9}$$

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 (9), this is given by:

$$\pi_1 = \psi(\gamma; T)\, m \tag{10}$$

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 (10) 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:

$$\frac{m(L,u)}{L} = \frac{(1+\rho)^T}{\psi(\Gamma(m(L,u),u);T)}. \tag{11}$$

using (8).[13] The left hand side of (11) is the proportion of the loan that must be paid off during each period.

Two things are immediate from (11). First, for $\Gamma(m,u) = 1$, equation (11) collapses to:

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

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 $\Gamma(m,u) < 1$, then:

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

We can interpret $1/\psi(\Gamma(m(L,u),u);T) \geq 1/T$ as a "markup" over funding costs which is increasing in L. This markup is higher if either α or $\beta(m,u)$ is lower (which is the case for higher u). Thus, borrowers with worse default probabilities and lower recovery rates will face a larger markup to compensate for risk. It is "as if" the lender compensates for the risk of default by charging a payment as there is a shorter term of the mortgage. To get a "back-of-the-envelope" feel for this, suppose that 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

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

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

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 year dummy variables.

as if the borrower was to repay the mortgage in 23.7 years as compensation for risk.

Second, it is also straightforward to see from (11) that $m(L,u)/L$ is increasing in L for all u. To see this, observe that if L increases and the ratio on the right hand side of (11) remains fixed, then $m(L,u)$ must rise proportionately. However, since m is now higher, the right hand side of (11) is higher. This is because the markup has to rise to compensate for the increased risk (since $\beta(m,u)$ is lower). Thus $m(L,u)/L$ must be higher.

To generate a prediction for the interest rate $r(L,u)$, observe that the interest rate implicit in the repayment function $m(L;x,u)$ is defined by:

$$m(L,u) = L\frac{(1+r(L,u))^T}{T}, \tag{12}$$

i.e. as the interest rate that generates a stream of payments $m(L,u)$ over the contract term without default. This will be the contractual interest rate in a T period mortgage and is what we observe in the data. Equation (12) can be solved to yield:

$$\begin{aligned} r(L,u) &= \left(\frac{m(L,u)\,T}{L}\right)^{\frac{1}{T}} - 1 = (1+\rho)\left[\frac{T}{\psi(\Gamma(m(L,u),u);T)\,T}\right]^{\frac{1}{T}} - 1 \\ &= (1+\rho)\,\lambda(L,u) - 1 \geq \rho \end{aligned} \tag{13}$$

where $\lambda(L,u) \geq 1$ is increasing in L and u.

Equation (13) makes clear why we expect the slope of the inverse credit supply function to be non-linear. Thus we have

$$R(L,u) = r(L,u) - \rho = (1+\rho)\left[\lambda(L,u) - 1\right] \tag{14}$$

where, as in the empirical model that we proposed, the variable u can be thought of the source of unobserved heterogeneity.