Risk Heterogeneity and Credit Supply: Evidence from the Mortgage Market

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I. 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 subprime segment of the US 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 microeconomics 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 microdata on credit contracts in the United Kingdom to investigate the empirical relationship between loan size and the interest. Despite some specific institutional features, which we discuss later, 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, particu-
larly some forms of deregulation and introducing 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.

A. The Context

It is now recognized that the period leading up to the financial crisis was associated with an overextension 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, and a series of credit market distortions coupled with financial innovation. Against this backdrop, global imbalances allowed a series of countries such as the United States, United Kingdom, 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 United Kingdom and United States between 1980 and the present. While both countries show an upward trend, this was much more marked in the United Kingdom. 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 prior to the crisis led to significant increases, as we see in figure 4.
But in comparing the United Kingdom and the United States, it is important to acknowledge a key institutional difference in the typical mortgage contracts that suggests a rather different calculus. In the United Kingdom, unlike the United States, it would not be possible for debtors to walk away from their obligations in the event of defaulting. And the vast majority of UK households were dependent on adjustable-rate mortgages, fixing typically on a two- to five-year time horizon.

Fig. 1. Actual policy rate and prescriptions from a Taylor rule in the United Kingdom
Source: Authors’ calculations.

Fig. 2. Home ownership rates in the United States and the United Kingdom
Sources: Department for Communities and Local Government and the US Census Bureau.

But in comparing the United Kingdom and the United States, it is important to acknowledge a key institutional difference in the typical mortgage contracts that suggests a rather different calculus. In the United Kingdom, unlike the United States, it would not be possible for debtors to walk away from their obligations in the event of defaulting. And the vast majority of UK households were dependent on adjustable-rate mortgages, fixing typically on a two- to five-year time horizon.
Fig. 3. Household debt to disposable income ratios in the United States and the United Kingdom
Sources: Thomson Reuters DataStream and ONS.

Fig. 4. House prices in the United States and the United Kingdom
Notes: The US house price index captures the movement of single-family home prices based on repeated-sales or refinancings where mortgages have been purchased or securitized by Fannie Mae or Freddie Mac. The UK 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 US nominal index has been deflated by CPI-U and the UK index by RPIX.
This is illustrated in figure 5. Unlike the United States, the tightness of the planning regime prevented any significant supply response to rising house prices limiting the stock of available new housing. Thus, there was no significant construction boom in the United Kingdom.

While there were some similarities, the post-crisis experience in the two housing markets has been markedly different—the United States, but not the United Kingdom, has seen very significant increases in arrears and defaults—see figures 6 and 7. The institutional features that we have outlined explain this. First, UK 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 addition, unemployment rates rose more slowly in the United Kingdom than in the United States, in part due to the absence of a construction sector boom.

B. Risk Pricing in the UK Mortgage Market

While the relaxation of credit conditions is a macroeconomic phenomenon, it had micro-underpinnings in the specific credit contracts being agreed upon between lenders and borrowers. Investigating these issues requires a country-specific as well as market-specific analysis. It is also important to control for individual risk characteristics as well as macroeconomic conditions.

This paper investigates pricing of default risk in the UK 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.

Fig. 6. Mortgage arrears in the United States and the United Kingdom
Source: Thomson Reuters Datastream and Council of Mortgage Lenders.
Note: US Seriously delinquent and UK three months or more in arrears.

Fig. 7. Mortgage repossessions: New actions started
Source: Thomson Reuters Datastream and Council of Mortgage Lenders.
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 detail in the next section. The left panel illustrates the distribution of individual interest rate spreads that 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-hand 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 that is driving interest rate dispersion that is not captured in loan size.

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 (QR) approach in which the credit supply is allowed, but
not required, to be heterogeneous across borrowers. 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 riskiness.

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 assess the robustness of our conclusions to 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 labor supply.

The results over the full sample 1975 to 2005 reveal that there is significant heterogeneity in risk pricing and that a nonlinear approach is needed 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. More specifically, a 10 percent increase in loan size triggers an 80 basis point rise in the interest rate charged to the riskiest borrowers in our sample, but it has a significantly smaller impact—around 10 basis points—on the interest rate charged to the 70 percent of safest borrowers. This should be contrasted with an average effect of 60 basis points estimated using least squares. 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.

To investigate any possible time variation in credit conditions, we split our sample into three decades and apply the QR method to each of them. The subsample analysis reveals that heterogeneity in risk pricing was pronounced mostly 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 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.
C. Related Literature on Risk Pricing

The literature on mortgage pricing has long been interested in risk heterogeneity. The contingent-claim approach, pursued by Kau and Keenan (1995) and Deng, Quigley, and Van Order (2000), 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 microdata 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 US subprime 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, et al. (2011) and Jimenez, Peydro, et al. (2012). Working with a 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 relationship for corporate lending. While we share the same ends, our focus is on household lending and therefore our controls for borrower’s characteristics are necessarily more limited in scope. In common with these studies, we use regional indicators and time fixed-effects to absorb common sources of regional variation and business cycle conditions.

D. 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 UK mortgage market. In section III, we look at some empirical regularities in the raw data. Section IV sets out the conceptual framework and section V develops this into an empirical approach. Section VI presents the empirical results for the full sample, while section VII reports a subsample analysis over time. Interpretations of the patterns found are offered in section VIII. Section IX discusses results from a strategy aimed at dealing with endogeneity.
of loan size. Concluding comments are in section X. The appendices provide additional information on the data, more on the institutional background of the UK mortgage market and discussion of instrumental variables approach used in section IX.

II. Data

Our main data set comes from a sample of more than 600,000 mortgage contracts issued in the United Kingdom between 1975 and 2005. These data are from the UK Survey of Mortgage Lenders (SML) and its predecessor, the 5 percent Sample Survey of Building Society Mortgages (SBSM). 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”; that is, has any prior track record as a mortgage borrower. The data do not, however, contain information on credit scores. Nor do we know whether and how such scores might be used by different lenders. One possible interpretation of the unobserved risk heterogeneity that we discuss in the following is therefore the risk assessment by the lender based on a credit score. The surveys that we use only cover 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 data set there are no identifiers that enable us to distinguish between variable and fixed-rate contracts over the full sample, most UK mortgage products are based on adjustable rates that 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 twenty-five years. Mortgages are secured on the property for which the funds are advanced. In the United Kingdom, 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 liberalization 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. 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. However, over time such lending limits have been relaxed, as we discuss further later. 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 microdata from our mortgage surveys with information on regional house price levels from the Nationwide house price index, and regional claimant count unemployment rates (Figure 9). To benchmark individual borrowing rates against a funding rate, we compute the interest rate spread faced by borrowers over the Building Societies Association’s recommended deposit rate prior to 1985, and an average reported building society share (deposit) rate subsequently.

We turn finally to the stamp duty rate, which we will propose as
an instrument for credit demand later. Stamp duty is the tax paid on housing transactions in the United Kingdom. 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 US 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 10. Thus, there have been a number of changes in stamp duty over time and across sizes of housing transactions that we can exploit. Figure 11 gives a histogram of actual stamp duty rates paid. A significant proportion of the rates observed in the sample are either in the 1 percent band or below the lowest stamp duty threshold. Over 60 percent of property transactions in our data set are liable for the tax.

III. 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 microdata 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 skewness 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 parts 3 and 4 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 parts 5 and 6 of table 2, we report data on the loan to income and loan to value ratio. The loan to income ratio increases over
Table 1
Rates of Stamp Duty and Thresholds

<table>
<thead>
<tr>
<th>Commencing Date</th>
<th>Nil rate</th>
<th>Up to 0.5%</th>
<th>1%</th>
<th>1.5%</th>
<th>2%</th>
<th>2.5%</th>
<th>3%</th>
<th>3.5%</th>
<th>4%</th>
</tr>
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<tr>
<td>1 May 1974</td>
<td>15,000</td>
<td>15,000</td>
<td>20,000</td>
<td>25,000</td>
<td>30,000</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>6 April 1980</td>
<td>20,000</td>
<td>20,000</td>
<td>25,000</td>
<td>30,000</td>
<td>35,000</td>
<td>—</td>
<td>—</td>
<td>—</td>
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</tr>
<tr>
<td>22 March 1982</td>
<td>25,000</td>
<td>25,000</td>
<td>30,000</td>
<td>35,000</td>
<td>40,000</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>13 March 1984</td>
<td>30,000</td>
<td>—</td>
<td>30,000</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>20 December 1991</td>
<td>250,000</td>
<td>—</td>
<td>250,000</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>19 August 1992</td>
<td>30,000</td>
<td>—</td>
<td>30,000</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>16 March 1993</td>
<td>60,000</td>
<td>—</td>
<td>60,000</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>8 July 1997</td>
<td>60,000</td>
<td>—</td>
<td>60,000</td>
<td>250,000</td>
<td>500,000</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
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<tr>
<td>24 March 1998</td>
<td>60,000</td>
<td>—</td>
<td>60,000</td>
<td>250,000</td>
<td>500,000</td>
<td>—</td>
<td>—</td>
<td>—</td>
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<tr>
<td>16 March 1999</td>
<td>60,000</td>
<td>—</td>
<td>60,000</td>
<td>—</td>
<td>250,000</td>
<td>—</td>
<td>500,000</td>
<td>—</td>
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<td>28 March 2000</td>
<td>60,000</td>
<td>—</td>
<td>60,000</td>
<td>—</td>
<td>—</td>
<td>250,000</td>
<td>—</td>
<td>500,000</td>
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<tr>
<td>1 December 2003 (nondisadvantaged areas)</td>
<td>60,000</td>
<td>—</td>
<td>60,000</td>
<td>—</td>
<td>—</td>
<td>250,000</td>
<td>—</td>
<td>500,000</td>
<td>—</td>
</tr>
<tr>
<td>1 December 2003 (disadvantaged areas)</td>
<td>150,000</td>
<td>—</td>
<td>150,000</td>
<td>—</td>
<td>—</td>
<td>250,000</td>
<td>—</td>
<td>500,000</td>
<td>—</td>
</tr>
<tr>
<td>17 March 2005 (nondisadvantaged areas)</td>
<td>120,000</td>
<td>—</td>
<td>120,000</td>
<td>—</td>
<td>—</td>
<td>250,000</td>
<td>—</td>
<td>500,000</td>
<td>—</td>
</tr>
<tr>
<td>17 March 2005 (disadvantaged areas)</td>
<td>150,000</td>
<td>—</td>
<td>150,000</td>
<td>—</td>
<td>—</td>
<td>250,000</td>
<td>—</td>
<td>500,000</td>
<td>—</td>
</tr>
<tr>
<td>23 March 2006 (nondisadvantaged areas)</td>
<td>125,000</td>
<td>—</td>
<td>125,000</td>
<td>—</td>
<td>—</td>
<td>250,000</td>
<td>—</td>
<td>500,000</td>
<td>—</td>
</tr>
<tr>
<td>23 March 2006 (disadvantaged areas)</td>
<td>150,000</td>
<td>—</td>
<td>150,000</td>
<td>—</td>
<td>—</td>
<td>250,000</td>
<td>—</td>
<td>500,000</td>
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</tr>
<tr>
<td>3 September 2008</td>
<td>175,000</td>
<td>—</td>
<td>175,000</td>
<td>—</td>
<td>—</td>
<td>250,000</td>
<td>—</td>
<td>500,000</td>
<td>—</td>
</tr>
</tbody>
</table>

Source: HM Revenue and Customs.

Notes: 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 twenty-one years and properties bought in disadvantaged areas.
Fig. 10. Piecewise linear structure of stamp duty tax rates
Note: The figure shows the piecewise linear structure of stamp duty tax for housing transactions in the United Kingdom across four time periods selected from table 1.

Fig. 11. Histogram of stamp duty tax rates
Note: The figure shows the proportion of borrowers in our data set that are liable for each rate band of stamp duty taxation as reported in table 2.
Table 2
Disaggregated Data on Key Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Median</th>
<th>St. dev.</th>
<th>Skew</th>
<th>Coeff. of var.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Interest Rate Spread</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1975–1985</td>
<td>4.13</td>
<td>4.25</td>
<td>1.27</td>
<td>-0.74</td>
<td>0.31</td>
</tr>
<tr>
<td>1986–1995</td>
<td>1.34</td>
<td>1.37</td>
<td>0.70</td>
<td>0.36</td>
<td>0.52</td>
</tr>
<tr>
<td>1996–2005</td>
<td>1.20</td>
<td>1.01</td>
<td>0.84</td>
<td>0.60</td>
<td>0.70</td>
</tr>
<tr>
<td>Full sample</td>
<td>2.41</td>
<td>1.70</td>
<td>1.71</td>
<td>0.55</td>
<td>0.71</td>
</tr>
<tr>
<td>2. Real Loan (£, in thousands)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1975–1985</td>
<td>21.81</td>
<td>20.93</td>
<td>8.67</td>
<td>1.14</td>
<td>0.40</td>
</tr>
<tr>
<td>1986–1995</td>
<td>32.63</td>
<td>29.01</td>
<td>18.09</td>
<td>3.30</td>
<td>0.55</td>
</tr>
<tr>
<td>1996–2005</td>
<td>44.71</td>
<td>36.74</td>
<td>30.67</td>
<td>2.91</td>
<td>0.69</td>
</tr>
<tr>
<td>Full sample</td>
<td>31.02</td>
<td>26.05</td>
<td>20.97</td>
<td>3.79</td>
<td>0.68</td>
</tr>
<tr>
<td>3. Real Income (£, in thousands)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1975–1985</td>
<td>11.98</td>
<td>10.92</td>
<td>5.40</td>
<td>2.49</td>
<td>0.45</td>
</tr>
<tr>
<td>1986–1995</td>
<td>15.13</td>
<td>13.25</td>
<td>8.79</td>
<td>4.31</td>
<td>0.58</td>
</tr>
<tr>
<td>1996–2005</td>
<td>19.06</td>
<td>15.58</td>
<td>14.05</td>
<td>4.67</td>
<td>0.74</td>
</tr>
<tr>
<td>Full sample</td>
<td>14.76</td>
<td>12.50</td>
<td>9.60</td>
<td>5.28</td>
<td>0.65</td>
</tr>
<tr>
<td>4. Real House Value (£, in thousands)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1975–1985</td>
<td>33.19</td>
<td>29.05</td>
<td>17.42</td>
<td>2.20</td>
<td>0.52</td>
</tr>
<tr>
<td>1986–1995</td>
<td>45.40</td>
<td>38.29</td>
<td>29.55</td>
<td>3.48</td>
<td>0.65</td>
</tr>
<tr>
<td>1996–2005</td>
<td>62.45</td>
<td>49.15</td>
<td>46.27</td>
<td>2.78</td>
<td>0.74</td>
</tr>
<tr>
<td>Full sample</td>
<td>44.35</td>
<td>35.44</td>
<td>32.42</td>
<td>3.63</td>
<td>0.73</td>
</tr>
<tr>
<td>5. Loan-to-income ratio</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1975–1985</td>
<td>1.92</td>
<td>1.91</td>
<td>0.57</td>
<td>0.32</td>
<td>0.30</td>
</tr>
<tr>
<td>1986–1995</td>
<td>2.27</td>
<td>2.26</td>
<td>0.71</td>
<td>0.94</td>
<td>0.31</td>
</tr>
<tr>
<td>1996–2005</td>
<td>2.50</td>
<td>2.47</td>
<td>0.90</td>
<td>1.03</td>
<td>0.36</td>
</tr>
<tr>
<td>Full sample</td>
<td>2.18</td>
<td>2.14</td>
<td>0.75</td>
<td>1.06</td>
<td>0.34</td>
</tr>
<tr>
<td>6. Loan-to-Value Ratio</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1975–1985</td>
<td>0.72</td>
<td>0.77</td>
<td>0.21</td>
<td>-0.57</td>
<td>0.30</td>
</tr>
<tr>
<td>1986–1995</td>
<td>0.78</td>
<td>0.86</td>
<td>0.21</td>
<td>-0.93</td>
<td>0.27</td>
</tr>
<tr>
<td>1996–2005</td>
<td>0.77</td>
<td>0.85</td>
<td>0.21</td>
<td>-1.01</td>
<td>0.27</td>
</tr>
<tr>
<td>Full sample</td>
<td>0.75</td>
<td>0.82</td>
<td>0.21</td>
<td>-0.78</td>
<td>0.28</td>
</tr>
</tbody>
</table>

Notes: Individual housing contract data are from the 1975 to 2005 (excluding 1978) waves of the Survey of Mortgage Lenders (SML) and its predecessors. The selected subsample 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 St. dev./Mean. Sample sizes: 1975–1985 = 256,154; 1986–1995 = 246,444; 1996–2005 = 143,472.
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 disper-
sion actually falls. An implication of this is that down payments among
those taking out new mortgage loans has generally kept pace with in-
creases in house prices.

IV. Theoretical Framework

Our objective is to understand how the interest rate charged to bor-
rowers depends on the amount that he or she borrows and his or 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 fa-
vorable terms. In a competitive credit market, this will lead to relaxed
credit conditions for mortgage borrowers.

A. Basic Model

Consider a mortgage contract of length $T$ with regular repayment dates
$t = 1, \ldots, T$. 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 $\alpha$ of the remaining mortgage payments being re-
coverable. The parameter $\alpha \in [0, 1]$ therefore captures the lender’s expo-
sure to default risk. An optimistic view of house prices would, for ex-
ample, make $\alpha$ higher. Let $\gamma(L, u, \alpha) = \beta(u, L) + (1 - \beta(u, L))\alpha$,

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

On this basis, the expected revenues under the contract from time $t$ for-
ward are denoted by $\pi$, 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:

\[ \pi_t = m \frac{\gamma}{1 - \gamma} \left[ 1 - \frac{\gamma^t}{\gamma^{T-1}} \right]. \] (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:

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

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:

\[ \pi_1 = \psi(y; T) m \] (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 \( \rho \). 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 \( \rho \), the fixed per-period repayment of a type \( \gamma \) borrower who borrows \( L \) must solve:

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

using (1). The left-hand side of (4) is the fixed payment that must be paid each period to borrow \( L \) given the default risk that the lender faces including his exposure to losses as represented by \( \alpha \).

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 $\alpha$ 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 that the lender cares about. To get a “back-of-the-envelope” feel for this, consider a twenty-five year mortgage where $\beta$ is 0.98 (i.e., a 2 percent default probability) and $\alpha$ is 0.8 (80 percent), 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 $(u,\alpha)$.

B. 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:

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

that is, 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:

$$r(L, u, \alpha) = \left( \frac{m(L, u, \alpha)T}{L} \right)^{1/T} - 1 = (1 + \rho) \left[ \frac{\psi(\gamma(L, u, \alpha); T)}{T} \right]^{-1/T} - 1 \geq \rho. \quad (6)$$

This equation makes clear why we expect the slope of the inverse credit supply function to be nonlinear 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 following. Expressing this as the difference from the funding rate, $\rho$, we have

$$R(L, u, \alpha) = r(L, u, \alpha) - \rho = (1 + \rho) \left[ \frac{\psi(\gamma(L, u, \alpha); T)}{T} \right]^{-1/T} - 1. \quad (6)$$
To close the model and study credit demand, we suppose that borrowers have preferences over housing that 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 $\theta$ and policy/economic factors that influence housing demand. Then:

$$L^*(u, \alpha, \theta) = \arg \max \{W(L, R(L, u, \alpha); \theta)\}.$$  \hspace{1cm} (7)

To identify supply and demand, we need to identify factors that represent $\theta$. We will return to this issue in section IX, with further discussion in appendix C.

C. Relaxing Credit Conditions via Securitization

We now consider how increased use of securitization in the mortgage market could change the terms offered to borrowers in theory 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 United Kingdom, as we have seen, there was a significant increase in issuance of mortgage-backed securities in the period leading up to the financial crisis which, at the time, was heralded as an important financial innovation that increased access to mortgage finance on favorable terms. Thus securitization was part of the transition over the period leading to the financial crisis toward viewing routine funding operations by mortgage lenders as profit centers in their own right, as it has been argued, for example, by Kay (2010).

For simplicity, we assume that the lender has an option to securitize a fraction $\sigma$ of the revenue stream from the loan. Trade in the securities market will be based on purchasers of securities having different beliefs about $\gamma$. 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.\textsuperscript{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 that 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 $\sigma$ of loans is securitized; that is, sold on day one of the mortgage, then the period one expected return from lending to a borrower becomes:

$$\hat{\pi}_1 = [(1 - \sigma)\psi(\gamma(L, u, \alpha); T) + \sigma\psi(\gamma(L, \hat{u}, \hat{\alpha}); T)]m$$

$$\equiv \hat{\psi}(\sigma)m > \psi(\gamma(L, u, \alpha); T)m.$$ 

And (6) becomes

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

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

$$\frac{\partial R(L, u, \alpha)}{\partial \sigma} = \frac{(1 + \rho)}{T^2}\left[\frac{\hat{\psi}(\sigma)}{T}\right]^{-1[(T+1)/T]}\left[\psi(\gamma(L, \hat{u}, \hat{\alpha}); T) - \psi(\gamma(L, u, \alpha); T)\right] < 0.$$ 

For given $\sigma$, 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 $\alpha$ or a shift up in the function $\beta(u, L)$.\textsuperscript{13}

To the extent that conditions in the securities market are changing over time, the model predicts that there will be 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 subclasses of very low risk borrowers where $\gamma(L, \hat{u}, \hat{\alpha}) = \gamma(L, u, \alpha) = 1$. Thus, we would expect shifts in the supply curve to be most pronounced for riskier subclasses of borrowers, particularly those where purchasers of securities have more favorable views of recovery rates than mortgage lenders.
V. 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 us. 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), thus:

$$R_{irt} = H(L_{irt}, D_{rt}, X_{irt}, U_{irt}),$$  \hspace{1cm} (8)

where $R_{irt}$ is the interest rate relative to the funding rate, $D_{rt}$ are macro covariates that 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 ($D$, $X$, $U$). Variation in $L_{irt}$ conditional on ($D$, $X$, $U$) can be thought of as being due to “taste” variation, for example, preferences for housing and family composition.

A. 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. One of the implicit presumptions upon which this strategy relies is that 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 this presumption is unlikely to hold. First, different borrowers face (and are likely to be priced for) different risks in a way that depends on (a) characteristics observed by both the lender and the econometrician (such as demographics, income, property value and location, down payment, etc.); and (b) 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 following econometric analysis, reveal that our data, which cover
about 600,000 housing transactions, feature a large extent of heterogeneity and significant departures from normality.

The aforementioned considerations suggest that there is a wealth of information that could be lost by focusing 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 known, 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 that 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 percent of the observations on either side of the regression’s slope, the estimate of the $q$th percentile is defined as the solution to the minimization problem that leaves $q$ percent of the observations on one side of the $q$th regression’s 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.

B. The QR Approach

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, $Q_{\tau}$, of the potential outcome distributions conditional on covariates are denoted by:

$$Q_{\tau}(R_{it} \mid L_{it}, D_{it}, X_{it}) \quad \text{with } \tau \in (0, 1).$$

(9)

Our benchmark results will assume that $L_{it}$ is exogenous. This is relaxed in section IX and appendix C. The effect of a change in loan size, $L_{it}$ (the “treatment”), on different points of the marginal distribution of the potential outcome is given by:

$$Q_{TE, \tau} = \frac{\partial Q_{\tau}(R_{it} \mid L_{it}, D_{it}, X_{it})}{\partial L}.$$  

(10)

The quantile treatment model can then be written as:

$$R_{it} = q(L_{it}, D_{it}, X_{it}, U_{it}) \quad \text{where } U_{it} \mid L_{it} : U(0, 1).$$

(11)

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

Since we are treating loan size, $L_{it}$, as exogenous, the methods outlined in Koenker and Bassett (1978) can be used to estimate quantile effects on the basis of the conditional moment restrictions:

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

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 $\tau$th quantile distribution takes the following form:

$$Q_{\tau}(R_{it} \mid \cdot) = a_L(\tau) L_{it} + a_x(\tau) X_{it} + a_D(\tau) D_{it}.$$  

(12)

The variable $L_{it}$ is the log of the real loan size. The vector $X_{it}$ 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 $D_{it}$ 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 $\tau$. 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 $U_{ir}$.

VI. Results

The rest of the paper presents our main results. We kick off by contrasting, in this section, the estimated average effects for the whole sample with the estimated effects for each quantile. Section VII focuses on subsample instability while after the interpretations in section VIII, we present results from treating loan size as endogenous in section IX.

A. The Interest Rate and Loan Size

In figure 12, we present the estimates (and the 95 percent confidence intervals) of the coefficient on loan in a QR equation of the form (12). To emphasize the importance of risk heterogeneity, we compare these results with the estimates (and the 95 percent confidence intervals) from using OLS (ordinary least squares), 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 semielasticity of spread with respect to loan size for borrowers below the seventieth 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 percent increase in the size of the real loan is associated with an interest rate spread that is 6 basis points higher irrespective of the borrower’s position in the conditional distri-
This understates the effect at higher quantiles and overstates it at lower quantiles.

B. 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 13, 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 represent QR estimates. The results from LS are reported as dotted lines.
For all individual characteristics but income, figure 13 finds significant extent of heterogeneity. The estimates based on least square miss the significant differences across borrowers in the highest part of the conditional distribution.

The pattern for the effect of down payment size on the interest rate spread is intuitive. There is little 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.

As for age, the QR method estimates that the age of an individual paying a higher conditional interest rate spread is significantly more important for her or 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 some evidence of heterogeneity. While there is a downward slope at the highest quantiles, the results tend to be imprecisely estimated. Even at the ninetieth percentile, however, the magnitude of the coefficient seems too small for the first-time buyer status to be of great economic significance.

C. Regional Features

Turning to the effects of regional characteristics on mortgage conditions, figure 14 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 more favorable treatment by lenders, consistent with the view that the latter factor in expectations of future price increases into their lending criteria. The QR estimates, however, do not seem to indicate a clear pattern of heterogeneity across households.

Regional unemployment in contrast appears to be of little economic and statistical significance, with the possible exception of the right tail of the interest rate spread conditional distribution. For both variables, the LS estimates suggest significantly smaller values than those implied by the QR estimates over most quantiles.

VII. 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 in assessing 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 QR analysis for three different subperiods spanning the decades 1975 to 1985, 1986 to 1995, and 1996 to 2005. While this specific division is somewhat arbitrary, it represents an even
split of the thirty years spanned by the data. Furthermore, the subsample selection lines up well with some of the main institutional regimes in the UK mortgage that we discussed in section II and in appendix A.

The estimated effects of loan size on borrowing rates are reported in figure 15 and they reveal significant time variation across subsamples. During the period 1975 to 1985, for instance, only 30 percent of borrow-

**Fig. 15.** Subsample estimates of the effect of loan size on individuals’ interest rate spread conditional on covariates (by quantile)

Notes: Coefficients on loan size from 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 QR (LS) estimates in solid lines (dashed lines) refer to quantile (least squares) regressions. Shaded areas (dotted lines) are 95 percent confidence intervals estimated using robust standard errors. Estimates are reported for $\tau \in [0.05, 0.95]$ at 0.05 unit intervals.
ers were offered contracts for which the interest rate is independent of the loan size. The remaining 70 percent of households face an upward sloping credit supply function, which becomes steeper at a higher level of the conditional distribution of interest rate that we interpret as risk. Furthermore, the riskiest borrowers are charged an additional 30 basis points for every 1 percent increase in their loan demand. This contrasts with only 7 basis points using QR over the full sample. Furthermore, the coefficient on loan size estimated by LS over the period 1975 to 1985 seems to place a disproportionate weight on the riskiest borrowers with a point value around 23 basis points.

The central panel of figure 15 reports estimates for the years between 1986 and 1995. In contrast to the previous decade, now 80 percent of borrowers are offered very similar interest rates despite different loan size. At the upper tail of the conditional interest rate distribution, a 1 percent rise in loan demand is associated with an 8 basis point increase in the borrowing rate, which is significantly higher than the LS estimated average effect, the latter being statistically indistinguishable from zero.

The most striking change, however, occurs in the final decade of the sample. The bottom panel of figure 15 reveals that the 1996 to 2005 period is characterized by a lack of both risk pricing and heterogeneity. In particular, the QR estimates are never statistically different from the LS estimates, and according to both the heterogeneous response and the homogeneous response specifications, the charged interest rate spread tends to be insensitive to the size of the loan, with confidence sets including zero across virtually all quantiles.

VIII. Interpretations

The finding that risk pricing in the UK 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, Dykan, 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 microbased approach does provide a window on this and invites speculation about the link to the macroeconomic 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 that have begun over this period. Moreover, the so far relatively modest increases in mortgage market defaults postcrisis are perhaps indicative of some justification for the belief that much lending was indeed to creditworthy clients who were correctly scored. This would certainly set the UK housing market apart from that in many other countries, especially the United States.

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 that 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 overexuberant approach to risk pricing. It is difficult to find any evidence for this view in our estimates. 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 postmillennium world, as figure 17 shows. After all, this is one of the familiar tales 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 been deemed creditworthy. The latter was probably the story of the US subprime market and is consistent with the animal spirits view to the extent that the mortgage-backed securities were 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.

IX. Robustness to Endogeneity Concerns

The core results that we have presently treat $L_{it}$ as exogenous. 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 the discussion leading up to (7) suggests that this may be unsatisfactory. 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.

As a robustness exercise on our core results, appendix C proposes using stamp duty rates and bands induced by legislated tax changes on housing transactions to isolate exogenous variation in housing demand. This allows us to instrument loan size in equation (12) with stamp duty tax rates using the Instrumental Variable Quantile Regression (IVQR) estimator proposed by Chernozhukov and Hansen (2005). Details of the way in which we approach this and the first-stage equation on which the exercise is based are all detailed in the appendix. Successful identification requires that there is sufficient variation in loan size induced by the instrument across all quantiles of the conditional interest rate spread distribution. While there have been only few legislated tax changes over the sample period covered by our data, the results in this section provide a useful check on the broad patterns found in the previous sections. To this end, figure 16 reports the IVQR estimates of the coefficient on loan size based on the full sample as well as the three subsamples.

The qualitative picture from the QR results remains the same using an instrumental variable estimator. First, the evidence of heterogeneity with riskier borrowers charged increasingly higher mortgage rates is robust to instrumenting loan size with stamp duty rates. Corresponding to the comparison between OLS and QR approaches, the two-stage least square (TSLS) estimator, depicted as dashed lines, misses significantly the large extent of heterogeneity in the data. Third, the finding that the supply curve flattened out over time is also robust to using IVQR. That said, the estimated coefficient on loan size is significantly larger than its QR counterparts. Considering the full sample results, for instance, a 1 percent increase in loan size would be associated with a 60 basis point increase in the interest rate spread charged to the riskiest bor-
rowers in the sample. We regard this effect as implausibly large. And that seems most likely to be due to tax rate and bracket changes giving us insufficient variation across the quantiles to globally identify the model. So while there is some encouragement for this approach, it is clear that more work is needed to provide a convincing identification strategy.

In summary, the IVQR analysis of this section confirms by and large the features highlighted by the noninstrumental QR analysis in section VI. The IVQR estimates, however, imply a credit supply elasticity at the top end of the interest rate conditional distribution that seems implau-

**Fig. 16.** Full-sample and subsamples estimates of the effect of loan size (instrumented) on individuals’ interest rate spread conditional on covariates (by quantile)

Notes: 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. The IVQR (TSLS) estimates in solid lines (dashed lines) refer to quantile (two-stage least squares) regressions. Shaded areas (dotted lines) are 95 percent confidence intervals estimated using robust standard errors. The QR estimates from figure 1 are reported as solid line. Estimates are reported for \( \tau \in [0.05, 0.95] \) at 0.05 unit intervals.
This makes us lean toward placing relatively more weight on the magnitudes uncovered by the QR evidence.

X. Conclusions

This paper explores empirically how credit standards were relaxed in the UK 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. Individuals 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 a specific window on the relaxation of credit conditions in the period prior to the financial crisis that began in 2007.

All this said, the UK 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 the 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 that is making lenders extremely cautious. Volumes of lending in the United Kingdom 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 postcrisis period become available.

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 liberalization measures affecting the UK mortgage market.
For example, in 1979 exchange controls were removed, exposing the UK 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 thus 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.

A provision of the Building Societies Act (1986) was to allow building societies to convert to public limited company (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 demutualizations, from Abbey National in 1989 to Northern Rock, Alliance and Leicester, Woolwich, and Bradford and Bingley during the 1990s (table A2).

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 securitization emerged in the United Kingdom during the late 1980s with the first centralized

<table>
<thead>
<tr>
<th>Date</th>
<th>Liberalization Measure</th>
</tr>
</thead>
<tbody>
<tr>
<td>1979</td>
<td>Removal of exchange controls</td>
</tr>
<tr>
<td>1980</td>
<td>Removal of supplementary deposit scheme</td>
</tr>
<tr>
<td>1981</td>
<td>BSA recommended rate becomes advisory</td>
</tr>
<tr>
<td>1983</td>
<td>Changes to building society tax position</td>
</tr>
<tr>
<td>1984</td>
<td>BSA recommended rate removed</td>
</tr>
<tr>
<td>1986</td>
<td>The Building Societies Act (1986)</td>
</tr>
<tr>
<td>1988</td>
<td>Raising of building societies wholesale funding limit to 40 percent</td>
</tr>
<tr>
<td>1991</td>
<td>Building Society Commission increased Prudential advice</td>
</tr>
<tr>
<td>1994</td>
<td>Raising of building societies wholesale funding limit to 50 percent.</td>
</tr>
<tr>
<td>1997</td>
<td>Amendment of the Building Societies Act (1986) takes permissive approach</td>
</tr>
<tr>
<td>2007</td>
<td>Building Societies (Funding) and Mutual Societies (Transfers) Act 2007</td>
</tr>
<tr>
<td></td>
<td>Increases wholesale funding limit to 75 percent</td>
</tr>
</tbody>
</table>

Note: This table indicates some of the major market legislative changes that have impacted the workings of the UK mortgage market.
mortgage lenders. However, it was not until the late 1990s that the UK residential mortgage-backed securities (MBS) market experienced rapid growth with the participation of many major banks and building societies.

Appendix B

Data Set 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 (SML) and its predecessor, the 5 percent Sample Survey of Mortgages (SBSM). These surveys are available in electronic format for the years 1975 to 2001 from the Data Archive at the University of Essex. Unfortunately, the year 1978 is missing. Data covering the period 2002 to 2005

<table>
<thead>
<tr>
<th>Institution</th>
<th>Date</th>
<th>Current Status</th>
<th>Latest Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>Abbey National</td>
<td>1989</td>
<td>Subsidiary of Santander</td>
<td>2004</td>
</tr>
<tr>
<td>Converted to p.l.c.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cheltenham and Gloucester</td>
<td>1994</td>
<td>Subsidiary of Lloyds Banking Group</td>
<td>1994</td>
</tr>
<tr>
<td>Takeover by Lloyds TSB</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>National and Provincial</td>
<td>1995</td>
<td>Name not in use</td>
<td></td>
</tr>
<tr>
<td>Takeover by Abbey National</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Alliance and Leicester</td>
<td>1997</td>
<td>Subsidiary of Santander</td>
<td>2008</td>
</tr>
<tr>
<td>Converted to p.l.c.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bristol and West</td>
<td>1997</td>
<td>Subsidiary of Bank of Ireland</td>
<td>1997</td>
</tr>
<tr>
<td>Takeover by Bank of Ireland</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Halifax</td>
<td>1997</td>
<td>Subsidiary of Lloyds Banking Group</td>
<td>2009</td>
</tr>
<tr>
<td>Converted to p.l.c.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Northern Rock</td>
<td>1997</td>
<td>Nationalized</td>
<td>2008</td>
</tr>
<tr>
<td>Converted to p.l.c.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>The Woolwich</td>
<td>1997</td>
<td>Subsidiary of Barclays</td>
<td>2000</td>
</tr>
<tr>
<td>Converted to p.l.c.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Birmingham Midshires</td>
<td>1999</td>
<td>Subsidiary of Lloyds Banking Group</td>
<td>1999</td>
</tr>
<tr>
<td>Takeover by Halifax</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bradford and Bingley</td>
<td>2000</td>
<td>Nationalized</td>
<td>2008</td>
</tr>
<tr>
<td>Converted to p.l.c.</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: One of the impacts of the Building Societies Act (1986) was to permit building societies to demutualize. Information in this table indicates major demutualizations and the current status of these institutions.
was obtained by the Bank of England from the Council of Mortgage Lenders (CML). To obtain our data set 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 Association’s 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 data set:

1. Discard individuals over the age of seventy-five and under twenty-one.
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 $\geq 10$, 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

Exploiting Variation in Stamp Duty Rates and Bands

This appendix describes how variation in stamp duty rates and bands, both over time and across individuals, can be used to try isolating exogenous movements in housing demand. For this purpose, 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 before, let $W(L, R, \theta)$ be the expected lifetime payoff from borrowing an amount $L$ at interest spread $R$. Then the optimal choice of loan is:

$$L_{\text{opt}} = \hat{L}(D_{\text{opt}}, X_{\text{opt}}, U_{\text{opt}}, Z_{\text{opt}}, V_{\text{opt}})$$
\[ \text{argmax} \{ W(L, R(L, D_{rt}, X_{irt}, U_{irt}), D_{rt}, X_{irt}, Z_{irt}, V_{irt}) \}. \]

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 that we interpret as the taste for housing.\(^{16}\)

In the following, we will discuss 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:

\[ R_{irt} = q(L_{irt}, X_{irt}, D_{rt}, U_{irt}) \text{ where } U_{irt} | Z_{irt} : U(0, 1) \] (13)

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

In particular, we require that, given \( (D_{rt}, X_{irt}) \), then \( \{U_{irt}\} \) is distributed independently of \( Z_{irt} \). For some random vector, \( \Sigma \), 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 nonstandard requirement relative to standard instrumental variables is the rank similarity condition that 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 denote by \( P \). We denote the rules governing stamp duty as \( S(P; \xi) \)—a piecewise linear function that depends on a set of time-varying policy rules denoted by \( \xi \). The price paid for a house is the sum of the down payment and the size of the loan:

\[ P_{irt} = W_{irt} + L_{irt}. \]

Our proposed instrument is therefore implicitly defined from:

\[ Z_{irt} = S(W_{irt} + \hat{L}(D_{rt}, X_{irt}, U_{irt}, Z_{irt}, V_{irt}); \xi). \]

As we have already noted, the validity of \( Z_{irt} \) as instrument hinges on variation in \( Z_{irt} \) being driven by underlying variation in \( (\xi, V_{irt}) \) 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 $U_{it}$. In fact, we adopt a conservative approach by dropping households who are within ±5 percent (by value) of the stamp duty thresholds. It is only among individuals who are close to the threshold where we would expect variations in $U_{it}$ to be correlated with $Z_{it}$. Thus we are confident that variations in $(\xi_{it}, \nu_{it})$ are inducing variation in $Z_{it}$.

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 he or she has a relatively stronger housing preference for given observed characteristics, the lender is charging him or 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 data set. 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 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 us a “first-stage” equation explaining the amount borrowed:

$$L_{it} = b_S Z_{it} + b_X X_{it} + b_D D_{it} + \eta_{it},$$

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

Results from estimating (14) are presented in table A3. The first
Table A3
First-Stage Regression

<table>
<thead>
<tr>
<th>Variables</th>
<th>Baseline</th>
<th>Collapsed</th>
<th>Full sample</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stamp Duty Rate</td>
<td>0.229***</td>
<td>0.065***</td>
<td>0.207***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.023)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Age</td>
<td>−0.009***</td>
<td>−0.016***</td>
<td>−0.009***</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.003)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Real income</td>
<td>0.600***</td>
<td>0.804***</td>
<td>0.602***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.063)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Real down payment</td>
<td>−0.009***</td>
<td>0.019***</td>
<td>−0.009***</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.008)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>FTB dummy</td>
<td>0.015***</td>
<td>0.135***</td>
<td>0.013***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.048)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Real regional house price</td>
<td>0.276***</td>
<td>0.205***</td>
<td>0.289***</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.037)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>Regional claimant count</td>
<td>0.002***</td>
<td>−0.007***</td>
<td>0.002***</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.002)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Observations</td>
<td>564,551</td>
<td>360</td>
<td>646,070</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.749</td>
<td>0.996</td>
<td>0.737</td>
</tr>
</tbody>
</table>

$F$-test for the insignificance of stamp duty rate

<table>
<thead>
<tr>
<th></th>
<th>$F(1,564,403) = 62,823$</th>
<th>$F(1,312) = 8.05$</th>
<th>$F(1,646,022) = 65,444$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\text{Prob}&gt;F$</td>
<td>0.00</td>
<td>0.005</td>
<td>0.00</td>
</tr>
</tbody>
</table>

$F$-test for the null of joint insignificance of the regional dummies

<table>
<thead>
<tr>
<th></th>
<th>$F(11,564,403) = 384$</th>
<th>$F(12,312) = 13.3$</th>
<th>$F(11,646,022) = 437$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\text{Prob}&gt;F$</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
</tbody>
</table>

$F$-test for the null of joint insignificance of the year dummies

<table>
<thead>
<tr>
<th></th>
<th>$F(29,564,403) = 2,241$</th>
<th>$F(28,312) = 37.6$</th>
<th>$F(29,646,022) = 2,546$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\text{Prob}&gt;F$</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
</tbody>
</table>

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 thousands of January 1987 pounds. The “Baseline” column refers to the sample that excludes house buyers within $\pm 5$ percent (by value) around the stamp duty thresholds. The “Collapsed” column refers to the sample that collapses the data by regions and years. The “Full Sample” column refers to the sample that places no restrictions on the distance from the stamp duty threshold values. Standard errors are reported in parentheses.

*** $p$-value <0.01.
** $p$-value <0.05.
* $p$-value <0.1.

This column uses the baseline sample, which drops observations that are within $\pm 5$ percent of any of the stamp duty thresholds. This is the sample that we have used to present results for the credit supply relation in section IX 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 percent 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.\textsuperscript{18}

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 $\xi_t$, 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; that is, without trimming the data around stamp duty thresholds. As can be seen, the results are broadly similar to those in the first column.

**Endnotes**

This paper uses data on about 600,000 mortgage contracts to estimate a credit supply function that allows for heterogeneity in risk pricing. The results for the period 1975 to 2005 are suggestive of significant price heterogeneity with riskier borrowers increasingly penalized for borrowing more. A subsample 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. We are grateful to Daron Acemoglu, Orazio Attanasio, Giovanni Dell’Ariccia, Domenico Giannone, Jonathan Parker, David Romer, Michael Woodford, and seminar participants at ECARES, ECB, IMF, Birkbeck College, and London Business School for comments. Surico gratefully acknowledges financial support from the European Research Council Starting Independent Grant (Agreement 263429). Special thanks to our discussants Bernard Salanie and Jose-Luis Peydro for valuable suggestions. The views expressed in this paper are those of the authors, and do not necessarily reflect those of the Bank of England or the members of the Monetary Policy Committee. Correspondence: London School of Economics, Department of Economics, Houghton Street, London WC2A 2AE, United Kingdom. E-mail: t.besley@lse.ac.uk, neil.meads@bankofengland.co.uk, psurico@london.edu. For acknowledgments, sources of research support, and disclosure of the authors’ material financial relationships, if any, please see http://www.nber.org/chapters/c12744.ack.

1. The dispersion of income and down payment are also far smaller than the dispersion of the interest rate.
2. The switch between the SBSM and the SML reflects the changing institutional nature of the UK mortgage market.
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 percent of their funding, a limit that has been steadily increased. De-mutualizations 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 liberalization and demutualizations.
4. Mortgage indemnity insurance has been offered on UK 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 United Kingdom, with no equivalent to US public insurance funds, and the effect may be lessened by legislation ensuring that...
borrowers remain liable for mortgage shortfalls for up to twelve years. Over our sample period, both mortgage indemnity insurance and pursuit of mortgage shortfalls has had limited take-up.


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.

7. Appendix B provides additional information on the construction of the data set.

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

9. Obviously, we could allow $\alpha$ to depend on $T$. But in a more general model, we could allow $\alpha$ to depend on $T - t$; that is, the remaining mortgage term.

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

$$n(L, u, \alpha) = \Lambda \frac{L(1 + \rho)^T}{\phi(y(L, u, \alpha); T)}.$$  

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 later.

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.

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

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


15. Another change over time that we do not have any evidence on is the increased use of mortgage brokers and the proliferation of mortgage products. Woodward and Hall (2012) argue that borrower confusion can lead borrowers to overpay for brokerage services.

16. Thus $\theta_{int} = (D_{int}, X_{int}, Z_{int}, V_{int})$.

17. Nearly 13 percent of our sample lies within ±5 percent of the stamp duty thresholds. As a robustness check we also tested a sample where only observations within the 5 percent 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 the appendix.

18. 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 following, 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.

References


