Leverage Regulation and Market Structure:

A Structural Model of the UK Mortgage Market *

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Abstract

I develop a structural model of mortgage demand and lender competition to study how leverage regulation affects the equilibrium in the UK mortgage market. Using within-lender variation in risk-weighted capital requirements across mortgages with differential loan-to-values, I show that a one-percentage-point increase in risk-weighted capital requirements increases the average interest rate by 10 percent (28 basis points). I use the estimated model to study proposed leverage regulations. Counterfactual analyses show that large lenders exploit a regulatory cost advantage, which increases concentration of mortgage originations by 20-30 percent, and suggest that banning high loan-to-value mortgages may reduce large lenders' equity buffer.

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1 Introduction

Mortgages represent the most important liability for households in developed countries and they played a central role in the financial crisis and its aftermath (Campbell and Cocco, 2003; Mian and Sufi, 2011; Corbae and Quintin, 2015). To prevent excessive leverage in the mortgage market, several European countries and the U.S. have introduced new regulations, such as minimum capital requirements for lenders and limits to loan-to-income and loan-to-value for households (Acharya et al., 2014; Behn et al., 2016b; DeFusco et al., 2017; Jiménez et al., 2017). The goal of this paper is to study the costs of leverage regulations and their wider effects on the mortgage market.

While the majority of policy makers and academics favor increases in capital requirements for lenders to enhance the stability of the financial system, financial intermediaries oppose them as they raise compliance costs, potentially increasing lending rates and impairing credit access (Hanson et al., 2011; Admati and Hellwig, 2014; Kisin and Manela, 2016; Dagher et al., 2016). Following the financial crisis, policy makers allowed lenders to invest in internal rating-based models to tie capital requirements to asset classes with different risks. Large lenders adopted internal rating-based models, while the vast majority of small lenders opted for the standard regulatory approach. As a result, a two-tier system prevails to calculate risk-weighted capital requirements. This heterogeneity across different lenders and asset classes can have unintended consequences, such as potential regulatory arbitrage and reduced competition in the market (Acharya et al., 2013; Behn et al., 2016a; Greenwood et al., 2017).

In this paper I develop a structural empirical model to quantify the cost of risk-weighted capital requirements and to study the equilibrium impact of heterogeneous leverage regulations on interest rates, market structure and risk. To capture the richness in product differentiation, households' choices and lenders' capital requirements in the UK mortgage market, I take an approach inspired by the industrial organization literature on differentiated product demand. I estimate my model using loan-level data on the universe of mortgage originations in the UK and a new identification strategy that exploits exogenous variation from leverage regulation both across lenders and within lender across mortgages with differential loan-to-values.

On the demand side, I model households' mortgage choice as a discrete logit function of interest rates, characteristics (rate type, lender and maximum leverage) and latent demand, and I use Roy's identity to derive the continuous conditional loan demand from the indirect utility. The discrete-continuous choice allows me to decompose the elasticity of demand to the interest rate into a product elasticity and a loan demand elasticity. The former captures the effect of the interest rate on product market shares; the latter captures the effect of the interest rate on loan size, conditional on mortgage product. In this way I model the joint decision by consumers of the mortage contract and the house value and I can disentangle the separate effects of higher rates on substitution across mortgage products and aggregate deleveraging.

In the estimation of the discrete-continuous demand choice model I address two key endogeneity concerns. First, I estimate the product and loan demand jointly to account for the selection bias that otherwise arises because the continuous loan choice depends on the endogenous discrete product choice. To facilitate the separation of the discrete and continuous parts I assume that local branch presence affects the probability of choosing a mortgage but not the conditional loan demand. This exclusion restriction is supported by a reduced-form regression of market shares and loan amounts on lenders' branch networks, controlling for differences across lenders and markets with fixed effects. I find that a higher local branch presence affects lenders' market share, but has no differential effect on loan amounts. Second, lenders endogenously set mortgage rates which can be correlated with other mortgage product characteristics that affect mortgage demand and are unobservable to the econometrician, thus biasing demand estimates. To address this omitted variable problem I adopt an instrumental variable approach. I assume that the risk-weighted capital requirements are uncorrelated with the unobservable demand shocks and I use them as product-level cost shifters to identify the demand elasticity to the endogenous interest rate. The intuition behind the exclusion restriction is that capital requirements do not enter directly borrowers' utility, but generate variation in mortgages rates because they affect lenders' cost of issuing different mortgage products.

On the supply side, I model lenders as heterogeneous multi-product firms offering differentiated mortgages and competing on interest rates, subject to regulatory leverage constraints. I use the elasticity parameters from the demand estimation together with lenders' optimal interest rates and additional loan-level data on arrears to back out unobservable marginal costs at the product level. I estimate the supply side with a new identification strategy that exploits variation in risk-weighted capital requirements both across lenders and within lender across leverage levels. This strategy allows me to identify the shadow cost of capital regulation controlling for: 1) differences across lenders, that are common among products (lender shocks), and 2) differences across products, that are common across lenders (market shocks). I find that a one-percentage-point higher risk-weighted capital requirement increases the marginal cost by 11 percent and the interest rate by 10 percent (28 basis points) for the average mortgage product. Moreover, internal rating-based models give large lenders a competitive advantage allowing them to raise mortgage interest rates by about 50 percent less than small lenders with the standard regulatory approach following a common increase in capital requirements.

I exploit exogenous variation from the approval of an internal rating-based model and the introduction of a leverage limit to provide evidence on the effects of observed leverage regulations on mortgage rates and originations. I then use the estimated structural model to investigate the equilibrium effects of counterfactual leverage regulations in the mortgage market. The structural model allows me to account for changes in the best response of lenders affected by the proposed regulations as well as for changes in their competitors' behavior.

Motivated by proposals to reform capital requirements (Basel Committee on Banking Supervision, 2016a,b), I compare a regime in which all lenders are subject to the same regulatory risk-weighted capital requirements to an alternative case in which all lenders are entitled to an internal model to calculate the risk weights. Imposing the same regulatory risk weights increases costs for large lenders, who pass it on to borrowers with large decreases in demand along both the intensive and extensive margins. Providing an internal model to small lenders also addresses competitive distortions due to differential regulatory treatment but with limited impact on credit access and no effects on the riskiness of the largest systemic lenders. Overall, removing the policy-driven difference in risk weights reduces concentration in the market by between 20 and 30 percent.

Finally, I explore with the estimated model possible interactions between capital requirements and limits to household leverage that have recently been discussed and implemented in some countries (Consumer Financial Protection Bureau, 2013; Bank of England, 2014; DeFusco et al., 2017; Acharya et al., 2018). I introduce a maximum loan-to-value limit that rules out mortgages with a leverage larger than 90 percent, both in an economy with risk-weighted capital requirements and in a counterfactual economy with homogeneous capital requirements (which was the case before the financial crisis under Basel I). I find that a regulation removing high loan-to-value mortgages is effective in reducing borrower defaults, but has a negative impact on originations and consumer surplus, as first-time buyers value mortgages with high leverage. My counterfactual analysis also uncovers potential unintended consequences of policies regulating household leverage, as banning the highest loan-to-value mortgages reduces large lenders' risk-weighted equity buffers, potentially affecting systemic risk.

Literature review. This paper contributes to three main strands of literature. First, I provide a new framework to study households' mortgage demand and optimal leverage, which complements existing approaches in household finance (Campbell and Cocco, 2003; Campbell, 2013; Best et al., 2018; Fuster and Zafar, 2015; DeFusco and Paciorek, 2017). My structural model is inspired by the industrial organization literature on differentiated product demand systems and on multiple discrete-continuous choice models (Lancaster, 1979; Dubin and McFadden, 1984; Berry et al., 1995; Hendel, 1999; Thomassen et al., 2017). The characteristics approach captures rich heterogeneity in household preferences and product availability along several dimensions, which are otherwise hard to model together. The discrete-continuous approach allows me to decompose the impact of interest rates on households' choice of the lender, leverage and house size, which I could not achieve with a purely reduced form strategy. Within the household finance literature, my paper is one of the first to also account for lenders' response to demand preferences with a structural equilibrium model.

Second, my work parallels recent papers that employ structural techniques to understand competition and policy in financial markets, like retail deposits (Egan et al., 2017; Xiao, 2018), insurance (Koijen and Yogo, 2016), corporate lending (Crawford et al., 2018), pensions (Hastings et al., 2017) and mortgages (Buchak et al., 2018). This paper is one of the first to apply similar techniques to the mortgage market and to study the implications of leverage regulation for consumers and market structure. Most notably, while previous studies focused on a "representative" product for each provider and only model the choice across providers, I exploit more granular variation in risk weights *within* a lender across asset classes to identify the elasticity of demand and the impact of leverage regulation.

Finally, this paper contributes to the growing literature assessing the effectiveness of new macro-prudential regulation both theoretically (Freixas and Rochet, 2008; Vives, 2016; Admati and Hellwig, 2014) and empirically (Hanson et al., 2011; Acharya et al., 2014; Behn et al., 2016b; DeFusco et al., 2017) and the role of lenders' market power for the transmission of policy interventions (Scharfstein and Sunderam, 2016; Drechsler et al., 2017; Agarwal et al., 2017a). I develop a tractable empirical equilibrium model of the UK mortgage market, that allows me to quantify the trade-offs between risk, competition and access to credit, and evaluate counterfactual policies. My paper adopts a partial equilibrium approach and focuses on the cost side of leverage regulations, thus providing a building block for a more general equilibrium analysis of macro-prudential regulation (Justiniano et al., 2015; Greenwald, 2018; Begenau and Landvoigt, 2017; Corbae and D'Erasmo, 2017). I explicitly model the interaction between leverage regulation and the competitive environment, and its implication for the pass-through of capital requirements to lending rates. I show that market structure is an endogenous outcome of leverage regulations that have been adopted and cannot be taken as given in the analysis of policy transmission to the real economy. This equilibrium interaction between leverage regulation and market structure has important implications for the design of policies to promote both stability and competition in the banking industry.

Overview. The remainder of the paper is organized as follows. Section 2 describes the data sources and provides motivating evidence and empirical facts in the UK mortgage market. Section 3 develops the demand and supply model. Section 4 describes the estimation approach and the identification strategy. Section 5 discusses the results. Section 6 describes the estimates from the counterfactual exercises. Section 7 concludes.

2 Data and Setting

2.1 Data

My paper combines different sources of administrative data. The main dataset is the Product Sales Database (PSD) on residential mortgage originations collected by the Financial Conduct Authority (FCA). The dataset includes the universe of residential mortgage originations by regulated entities since 2005.[1] I observe the main contract characteristics of the loan (rate type, repayment type, initial period, interest rate, lender); the borrowers (income, age) and the property (value, location, size). For the structural estimation I focus on the years 2015 and 2016, in which all lenders report all contract characteristics that I exploit in the analysis.

I complement information about mortgage originations with four additional datasets. First, I use an additional source also collected by the FCA with information from lenders' balance sheets on the performances of outstanding mortgages as of June 2016. Second, I exploit data on lenders' capital requirement and resources from the historical regulatory databases held by the Bank of England together with additional information from a survey of all lenders adopting Internal Rating Based Models in the UK on risk weights applied to mortgages by loan-to-value.[2] Third, I collect for all lenders in my sample postcode level data on their branches in the UK in 2015 from SNL financial. Fourth, I match the borrower'

[1]The FCA Product Sales Data include regulated mortgage contracts only, and therefore exclude other regulated home finance products such as home purchase plans and home reversions, and unregulated products such as second charge lending and buy-to-let mortgages.

[2]The data on capital requirements are standard and have been used in previous studies (Harimohan et al., 2016; De Ramon et al., 2016). The information on risk-weights has been collected by the Bank of England and the Competition and Market Authority to study the effects of the change from Basel I to Basel II on mortgage prices and it is described in detail in Benetton et al. (2016).

house with house price index at the postcode level from the ONS statistics database.

Panel A of Table 1 shows summary statistics for the universe of mortgages originated in the UK in 2015 and 2016 with a loan-to-value above 50 percent.[3] In Panel A I show the main dataset about mortgage originations. I observe more than 1 million mortgage contracts, with an average rate of about 2.7 percentage points and an origination fee of £600. Mortgages fixed for 2 and 5 years account together for more than 85 percent of all originations.[4] The average loan value is about £170 thousands, with a loan-to-value of 77 percent and a loan-to-income of 3.3. The sample is balanced across first-time buyers, home movers and remortgagers. The average maturity is 25 years, and the average borrower is 35 years old with an income of around £57 thousands.

In Panel B of Table 1 I show summary statistics for lenders' capital requirements, risk weights and branches. The capital requirement includes both minimum requirements under Basel II (Pillar I, or 8 percent of RWAs) as well as lender-specific supervisory add-ons (Pillar II). Total capital resources include all classes of regulatory capital, including Common Equity Tier 1, Additional Tier 1, and Tier 2. The average capital divided by total risk-weighted assets is 17 percent, when I focus only on Tier 1, and 21 percent, when I include all classes of regulatory capital; the average capital requirement is 12 percent, ranging from the minimum requirement of 8 percent to a maximum of 22 percent, including all the add-ons. The average risk weight is 27 percent and there is a lot of variation across lenders, leverage and over time: the standard deviation is 23 percent and risk weights rate from a minimum of 3 percent to a maximum of almost 150 percent. The average number of lenders' branches in each postcode area is about 7, from a minimum of 1 to a maximum of 63.

Finally Panel C of Table 1 reports statistics on mortgage performances as of June 2016. On average 2 percent of outstanding mortgages are in arrears and approximately 78 percent of mortgages are not paying the standard variable rate, which on average is around 3.5 percent. The standard variable rate (SVR) is a variable rate that borrowers pay when the fixed rate period or discounted variable rate period expires, until they refinance the loan or until maturity. The SVR is in most cases higher than the initial rate when the mortgage is issued.

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[3]My analysis focuses on leverage regulation and risk, so I exclude all mortgage transactions in which borrowers have more than 50 percent of their equity in the house. These are mainly remortgagers with a probability to be in arrears below 0.1 percent.

[4]Badarinza et al. (2017) study mortgage rates both across countries and over time. They show that in the US the dominant mortgage is normally a 30-year fixed rate mortgage, but they also find that adjustable rate mortgages were popular in the late 1980s, mid 1990s, and mid 2000s. My evidence for the UK is consistent with their finding that in the UK most mortgages have a fixation period for the interest rate that is below five years.

Table 1: Summary statistics

	OBS	MEAN	SD	MIN	MAX
Panel A: loan-borrower					
Interest Rate (%)	1,155,079	2.65	0.81	1.24	5.19
Fee (£)	1,155,079	631.50	602.25	0.00	2381.00
Fix 2 years	1,155,079	0.64	0.48	0.00	1.00
Fix 5 years	1,155,079	0.22	0.42	0.00	1.00
Loan value (£.000)	1,155,079	177.89	93.94	47.99	631.29
LTV (%)	1,155,079	77.60	12.16	50.00	95.00
LTI (%)	1,155,079	3.32	0.89	1.09	5.00
First-time buyers (%)	1,155,079	0.34	0.47	0.00	1.00
Home movers (%)	1,155,079	0.32	0.47	0.00	1.00
Remortgagers (%)	1,155,079	0.32	0.47	0.00	1.00
Maturity (Years)	1,155,079	25.69	6.64	5.00	40.00
Gross income (£.000)	1,155,079	57.08	30.86	16.79	233.72
Age (Years)	1,155,079	35.73	8.15	17.00	73.00
Panel B: lender					
Capital ratio tier 1 (%)	192	17.24	7.19	6.93	43.50
Capital ratio total (%)	192	21.11	6.73	9.90	44.20
Capital requirement (%)	192	12.03	2.40	8.00	22.54
Risk weights (%)	224	27.01	23.34	2.81	140.40
Branches (Number)	1506	6.90	7.10	1.00	63.00
Panel C: performances					
Arrears (%)	3,868,792	0.02	0.13	0.00	1.00
Refinancing (%)	3,868,792	0.78	0.41	0.00	1.00
SVR (%)	3,868,792	3.47	0.85	2.25	4.74

Note: Summary statistics for the main variables used in the analysis. In panel A I show the main variable used in our analysis for the universe of mortgages originated in the UK in 2015 and 2016 with a LTV above 50 percent. Interest rate is the interest rate at origination expressed in percentage points; fee are origination fee in pounds; fix for two and five years are dummies for products with an initial period of two and five years; loan value is the loan amount borrowed in thousands pounds; LTV and LTI are the loan-to-value and loan-to-income in percentage points; first-time buyers, home movers and remortgagers are dummies for type of borrowers; maturity is the original maturity of the mortgage in years; gross income is the original gross income in thousands pounds; age is the age of the borrowers in years. In panel B I show variables for the lenders. The capital requirements include both minimum requirements under Basel II (Pillar I, or 8 percent of RWAs) as well as lender-specific supervisory add-ons (Pillar II). Total capital resources include all classes of regulatory capital, including Common Equity Tier 1, additional Tier 1, and Tier 2. I report them as a percentage of total risk-weighted assets. Risk weights are expressed in percentgage points. Branches is the number of branches for each lender in each postcode area. In panel C we report data on mortgage performances. Arrears is the fraction of outstanding mortgages in arrears as of June 2016. Refinancing is the fraction of mortgages not paying a standard variable rate as of June 2016. SVR is the standard variable rate expressed in percentage points.

2.2 Setting

In this section, I provide a brief overview of leverage regulation, pricing, originations and performances in the UK mortgage market. The empirical facts presented in this section guide some assumptions of the structural model of Section 3 and illustrate the variation used in the identification strategy described in Section 4.

I first define two key objects in my analysis: market and product. In my setting a market

Provider	Initial monthly cost	Initial rate	Type of mortgage	Max LTV	Product fees	Overall cost for comparison
HSBC	£ 635.05	1.99% then 3.94%	Fixed for 25 months	90%	Yes	3.8% APRC representative
The Loughborough Building Society	£ 639.44	2.05% then 4.99%	Discounted Variable for 24 months	90%	Yes	4.6% APRC representative
Yorkshire Building Society	£ 641.64	2.08% then 4.99%	Fixed for 25 months	90%	Yes	4.7% APRC representative
Leek United Building Society	£ 642.37	2.09% then 5.19%	Fixed for 27 months	90%	Yes	4.7% APRC representative
first direct	£ 646.05	2.14% then 3.69%	Fixed for 24 months	90%	Yes	3.6% APRC representative

Figure 1: CHOICE-SET

Note: Snapshot from https://www.moneysupermarket.com/mortgages/ of the cheapest five mortgages offered in a market after filling information about the value of the property and the loan amount.

is a borrower type-quarter combination. I define a borrower type based on the purpose of the transaction: refinancing an existing property (remortgager), buying a property (home mover), or buying a property for the first time (first-time buyer).[5] A product is a combination of brand, interest rate type and maximum loan-to-value (e.g., Barclays, two year fixed rate, 90 percent maximum loan-to-value). In Figure 1 I show a snapshot from a popular search platform for mortgages in the UK after filling information on the value of the property and the loan amount. The key mortgage characteristics are the provider of the loan, the type of interest and the maximum loan-to-value. The market and the chosen product determine jointly the borrower monthly cost.

The UK mortgage market has been historically very innovative, with a large number of products offered (Cocco, 2013). However, the market is concentrated in terms of both lenders and interest rate types. The largest six lenders account for about 70% of new mortgage originations and the most popular product is the fixed rate for two years, which accounts for more than 60% of originations to first-time buyers and more than 50% to home movers and remortgagers.[6] In terms of the maximum loan-to-value there is more heterogeneity depending on the borrower type. First-time buyers take higher leverage mortgages, with almost 60 percent borrowing more than 80 percent of the value of the house. Home movers

[5] I focus on these three categories of owner occupied mortgages, that account for more than 95% of originations in 2015-2016, and exclude buy to let. While some products are offered across all types, others are tailored to the type. In Section 4.1 I describe in details how I construct the borrower specific choice set.

[6] In the UK mortgage market the vast majority of products have an initial period rarely longer than five years with a fixed rate and a standard variable rate thereafter. In Appendix A I report the market shares of prime residential mortgages originated in 2015-2016. The products that I consider, account for more than 80% of originations for first-time buyers, and more than 70% for home movers and remortgagers.

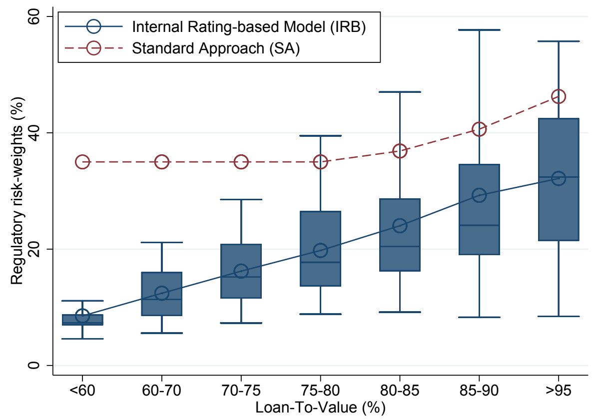


Figure 2: Risk-weights across lenders and loan-to-values

Note: Average risk weight for two groups of lenders at different loan-to-values. IRB includes all lenders in the sample adopting an internal rating base model for the calculation of their capital requirements. The internal model of the lender are subject to supervisory approval. The distributions of IRB risk weights within each loan-to-value band are represented by Tukey boxplots, where the box represents the interquartile range (IQR) and the whiskers represent the most extreme observations still within 1.5 $\times$ IQR of the upper/lower quartiles. SA includes all lenders in the sample that adopt the standardized approach. For the latter group the risk weights are set by the regulator in a homogeneous manner across bank and varies between 35 percent and 45 percent based on the loan-to-value of the loan.

are more evenly distributed across loan-to-values, while more than 50 percent of remortgagers refinance less than 75 percent of the value of their property.

2.2.1 Leverage Regulation

I focus on two types of leverage regulation: risk-weighted capital requirements for lenders and maximum loan-to-value limits for borrowers. Since 2008 two approaches to calculate risk-weighted capital requirements coexist: the standard approach (SA) and the internal rating-based approach (IRB). Figure 2 shows risk weights for UK lenders in 2015 as a function of the loan-to-value. For lenders adopting the standardized approach risk weights are fixed at 35 percent for loan-to-values up to 80 percent, and they increase to 75 percent on incremental balances above 80 percent. In contrast, lenders adopting an internal rating based model have risk weights that increase with the loan-to-values along the whole distribution. The average gap between the average IRB risk weight and the SA risk weight is about 30 percentage points for loan-to-values mortgages below 50 percent, compared to less than 15 percentage points for mortgages with leverage above 80 percent.

The largest six lenders in the UK (the so called "big six") all adopted internal rating based models since 2008 when the capital regulation changed from Basel I to Basel II. Medium and small lenders, with very few exceptions, opted for the standard approach, mostly because of the large fixed compliance cost associated with internal rating-based models (Competition and Markets Authority, 2015; Benetton et al., 2016).

An alternative way to regulate leverage in the mortgage market is by imposing explicit limits to how much households can borrow, such as maximum loan-to-value, loan-to-income or payment-to-income (DeFusco et al., 2017; Acharya et al., 2018). In Appendix B I discuss the introduction of a loan-to-income limit in the UK mortgage market and provide empirical evidence of its effects on mortgage originations. In reality capital requirements and limits to household leverage are potentially complementary tools and their interaction can have important equilibrium effects, which I study in the counterfactual analysis of Section 6.

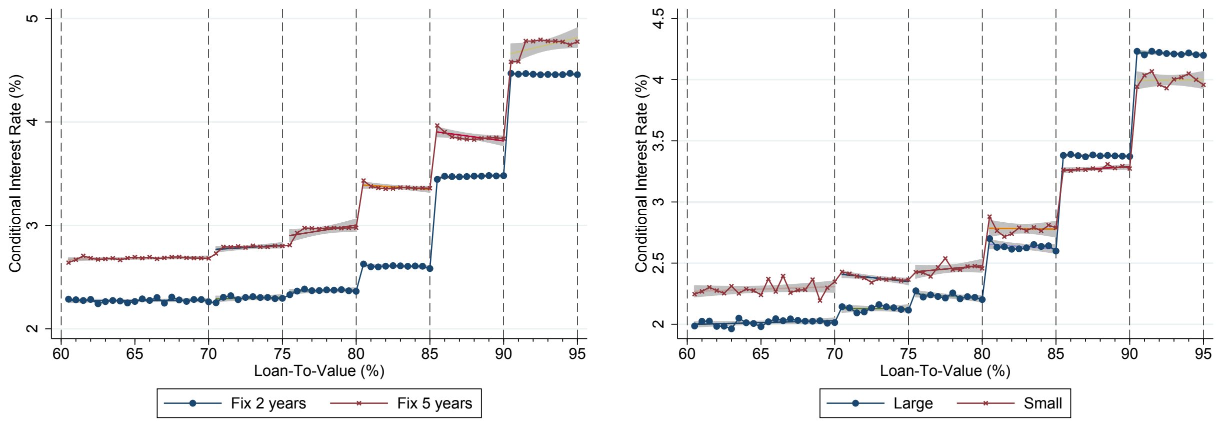
2.2.2 Mortgage Pricing

The price of a mortgage is given by the interest rate and the origination fee. In the UK, unlike other countries such as the US and Canada, there is no consumer based pricing or negotiation between the borrower and the lender (Allen et al., 2014). As a result, the advertised rate is the rate that the borrower pays.[7] I test this claim in Appendix A in which I show the results of a regression of the loan-level interest rate on product fixed effects and additional controls. My product definition based on the type of mortgage, the lender and the maximum loan-to-value captures more than 70 percent of the full variation in the loan-level rate. The R^2 reaches 85 percent when I interact the product dummies with time dummies, and more than 90 percent when I also include dummies for the origination fees. Adding dummies for the location of the house and borrower level controls (age, income, house value, joint application, employment status) does not explain the residual variation in the rate.[8]

Figure 3 explores the variation in rates across different product characteristics and lenders. I show the mean predicted interest rates from a regression including mortgage and borrowers controls as a function of the loan-to-value. Three main patterns emerge. First,

[7]Moneyfacts reports: "A personal Annual Percentage Rate is what you will pay. For a mortgage this will be the same as the advertised APR, as with a mortgage you can either have it or you can't. If you can have the mortgage, the rate doesn't change depending on your credit score, which it may do with a credit card or a loan" (source: `https://moneyfacts.co.uk/guides/credit-cards/what-is-an-apr240211/`).

[8]The remaining variation is due to two possible reasons. First, unobservable product characteristics. Even if I control for the main factors affecting price, there can be some other product characteristics that lenders use to segment the market. Second I observe the date when the borrower gets a mortgage, but I do not know when exactly the deal was agreed. The time dummies capture the variation in the price imperfectly. I also replicate the exercise for origination fees, also reported in Appendix A. The product market fixed effects explain only about 35 percent of the loan-level variation, adding dummies for interest rate increases the R^2 to about 65 percent, and adding location and demographics bring it to about 70 percent. The larger dispersion that we find in the loan-level fees can by attributable to the same unobservable attributes that could affect the rate. Moreover, while the interest rates are not negotiated, there can be more flexibility with respect to fees. For example, borrowers have the opportunity to roll-over the fees on their loans and this option is often used.



(a) Default and Refinancing Risk

(b) Capital Regulation

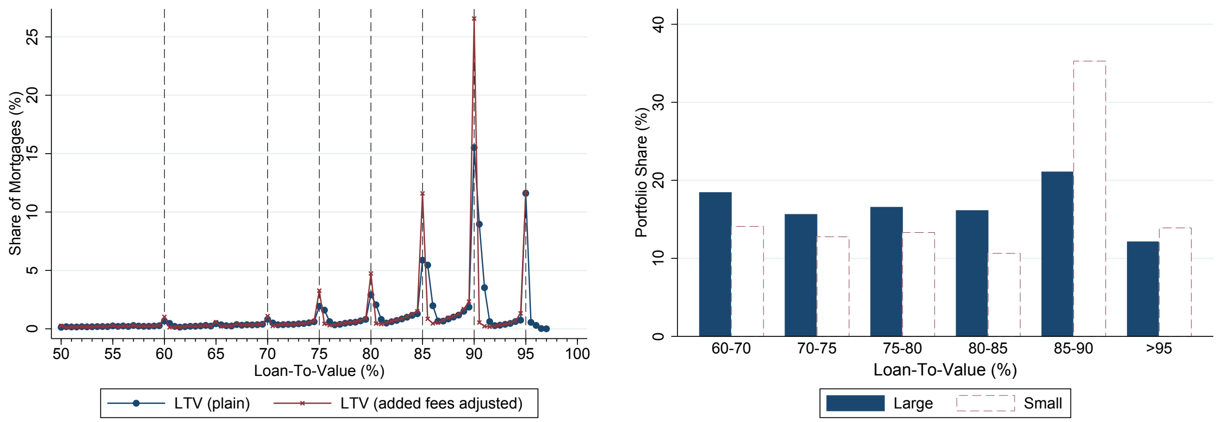
Figure 3: Pricing

Note: Conditional interest rate from the following regression: $r_{jt} = \gamma_j + \sum_{j=50}^{95} ltv_j$, where γ_j are fixed effects for market, type and lenders and ltv_j are loan-to-value bins. The dotted vertical lines denotes the maximum loan-to-value of 60, 70, 75, 80, 85, 90, and 95 percent. Panel (a) shows the average schedule in the first-time buyers market for products with the two most popular products: fixed rate mortgages for 2 and 5 years. Panel (b) reports the schedule for a representative large lender adopting the internal model and a representative small lender opting for the standardized approach.

lenders set the interest rate as a increasing schedule of the loan-to-value, which captures default risk (Schwartz and Torous, 1989; Campbell and Cocco, 2015), with discrete jumps at certain maximum loan-to-value thresholds as already documented by Best et al. (2018).

Second, for the same loan-to-value mortgage with a longer fixed rate are always more expensive that mortgages with a shorter fixed rate. This finding is consistent with higher refinancing risk embedded in a contract with a longer fixed duration (Deng et al., 2000; Rose, 2013; Beltratti et al., 2017).

Third, I study the effect of regulation on risk-weights for mortgage rates and in Figure 3 (b) I compare a representative large lender adopting an internal model with a small lender using the standardized approach. The rate schedule of the large lender shows clear discontinuous jumps at maximum loan-to-values, while the small lender increases the rate only for loan-to-values above 80 percent, when risk weights start increasing as shown in Figure 2. The large lender offers a more competitive interest for low loan-to-value mortgages. The gap in prices closes for intermediate loan-to-value mortgages and even reverses for products with a loan-to-value above 85 percent, consistent with the shrinking gap in the risk weights between internal model and standardized approach. In Appendix B I provide additional reduced-form evidence of the effect of risk weights on mortgage rates.



(a) Market share

(b) Portfolio share

Figure 4: Originations Across Loan-To-Values

Note: Panel (a) shows the share of mortgages originated at different loan-to-value bins for first-time buyers. Each bin is 0.5pp wide. The blue line shows the plain distribution where the loan-to-value is computed as the ratio between the loan value divided by the house value. The red line control for the fees, by subtracting the fees added to the loan from the loan value. The dotted vertical lines denotes the maximum loan-to-value of 60, 70, 75, 80, 85, 90, and 95 percent. Panel (b) shows the portfolio shares for a representative large lender adopting the internal model and a representative small lender opting for the standardized approach.

2.2.3 Mortgage Originations

I next show equilibrium mortgage originations across loan-to-values and lenders. Figure 4 (a) shows the loan-to-value choice of first-time-buyers. The vast majority of first-time buyers are concentrated at high maximum loan-to-values, with more than 25 percent borrowing (almost) exactly 90 percent of the value of their house.[9]. This behavior allows me to model the leverage choice as a discrete choice. Figure 4 (b) shows the portfolio share of a large lender adopting the internal rating based model and a small lender with the standardized approach. The large lender portfolio is evenly distributed across all leverage levels, while the small lender issues most mortgages at high loan-to-values, where the risk-weight gap with the large lender is lower and its pricing is more competitive (see Figures 2 and 3 (b), respectively).

Figure 5 explores the lender choice. Figure 5 (a) shows the price and market share for two mortgage products with the same maximum loan-to-value (60 percent), interest rate type (2 years fixed), and loan size (£140-160.000) but offered by two different lenders. The mortgage with the higher price has the higher market share for the whole period under analysis. In my empirical model I account for factors (e.g., brand value) that can explain this counter-

[9] Best et al. (2018) show a similar but less pronounced pattern for remortgagers. The more pronounced pattern I find for first-time-buyers can be due to the fact that they do not have the flexibility that equity extraction may offer to remortgagers.

intuitive effect and I explore with the available data the role of lenders' branch network in affecting borrowers' choices.[10] Figures 5 (b) and (c) show that areas in which a lender has a large share of branches, the same lender originates more mortgages.[11] Accounting for these features in the demand model is important to capture factors that can affect the demand elasticity (e.g. limited substitution due to local shopping), as the distance between the borrower and the lender continues to play an important role even in modern lending markets (Becker, 2007; Scharfstein and Sunderam, 2016; Nguyen, 2014).

2.2.4 Mortgage Performances

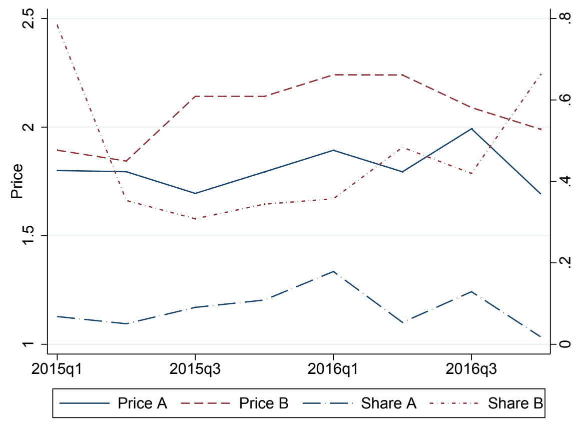
Finally, in Table 2 I study some patterns in default and refinancing for different lenders and maximum loan-to-values. I capture the default risk by looking at mortgages originated since 2005, that are in arrears in 2016. Column (1) of Table 2 reports the fraction of outstanding mortgages in 2016 which are in late payment (90 days delinquent) out of total number of mortgages in lenders' balance sheet for each specific product. The average fraction of arrears is around 1.3 percent. Building societies have less than 1 percent mortgages in arrears, followed by the challengers banks at 1 percent, while the six lenders have about 1.7 percent of outstanding mortgages in arrears. The fraction of arrears increases monotonically with the maximum loan-to-value, from 0.6 percent for mortgages with a loan-to-value below 60 percent, to more than 3 percent for mortgages with a loan-to-value above 90 percent. This pattern is reflected in the pricing schedules of Figure 3.[12]

To capture refinancing risk, I consider for each product the fraction of outstanding mortgages in 2016 that are on a standard variable rate (SVR) out of the total mortgages in the

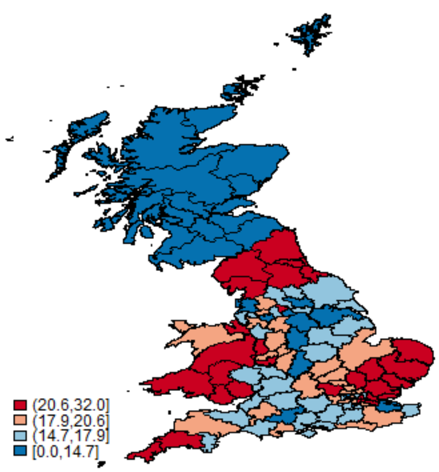
[10] A possible explanation also comes from the supply side, with the low price - low market share products only approved to some customers. Due to data limitations I cannot test this hypothesis, but given the low leverage (60 percent), rejections are less likely to be a concern. I do not have information on the lenders approval decision, so I need to assume that all borrowers of a certain type have access to the advertised rate and take the best alternative. To limit concerns about rejection, I restrict the choice set based on observable borrowers characteristics and affordability criteria as explained in Section 4.1. Furthermore, a prohibitive high interest rate for a mortgage product will make demand for that product close to zero, thus resembling an indirect form of rejection as discussed in Crawford et al. (2018).

[11] This relation is not driven by smaller lenders (e.g. building societies). In Appendix A I show the correlation for the largest lenders between the branch share and the mortgage share in each postcode area, and I find a strong positive relationship. To control for differences in the nationwide popularity and to local differences in market demand and branch networks, I run a difference-in-difference specification with lender and area fixed effects. I find that a lender has a 3 percent higher mortgage share in an area where it is in the top quintile of the branch share distribution compared to an area where it has no branches.

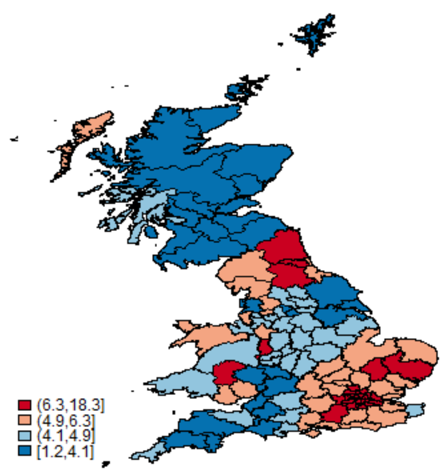
[12] The increase in arrears with the loan-to-value can be due to both adverse selection, with more risky borrowers choosing higher LTV mortgages, and moral hazard, because the higher rate increase the likelihood of default. Even if we cannot distinguish between these different sources, we consider in the pricing model how lenders account for asymmetric information and default risk when setting mortgage prices.



(a) "Dominated" products



(b) Branch Share



(c) Mortgage Share

Figure 5: Originations Across Lenders

Note: Panel (a) shows the price and market shares for two products for first-time buyers offered by two different lenders with the same initial period (2 years), the same maximum loan-to-value (70 percent) and similar quantities (£140-160.000). The price is the full APR which include the initial interest rate and the origination fees. The market share is computed as the fraction of people buying that product in a specific quarter over the total of mortgage borrowers in that quarter. Panel (b) shows the market share of all branches for a lender in the sample by postcode area in the UK. Panel (c) shows the market share of the same lender for mortgage originations.

lenders' balance sheet. The refinancing variable is defined as one minus the share paying the SVR, which is the reset rate that borrowers pay at the end of the initial fixed or discounted period. From Table 2 I see that in 2016 almost 80 percent of consumers refinance their mortgage before the switch to the SVR. The fraction of borrower refinancing is slightly higher for the largest banks and and it seems to decrease with loan-to-value, but with no large differences along any of these dimensions.

Finally, column (3) of Table 2 shows the SVR. The standard variable rate is always around

Table 2: Mortgage Performances

	Arrears (1)	Refinancing (2)	SVR (3)
Full sample	1.3	77.3	3.8
Lender			
Big six	1.7	80.2	3.7
Challenger	1.0	76.1	4.0
Building society	0.9	74.3	4.0
Max LTV			
50-60	0.6	82.6	3.8
60-70	0.8	78.3	3.9
70-75	1.0	77.1	4.0
75-80	0.9	75.6	4.0
80-85	1.2	74.8	4.0
85-90	1.3	76.5	3.8
90-95	3.1	76.5	3.7

Note: Fraction of mortgages in arrears, fraction of borrowers not paying the standard variable rate and median standard variable rate for different lenders and maximum loan-to-values.

4 percent. Challenger lenders and building societies have a higher SVR, while the SVR does not seem to vary across loan-to-values, in a way similar to the origination rate. The SVR is almost always larger than the origination rate, giving a strong incentive to refinance the mortgage at the end of the initial period (Cloyne et al., 2017).

3 A Structural Model of the UK Mortgage Market

In this section I develop a structural model of mortgage demand and pricing to study the equilibrium implications of changes in leverage regulation. First, I specify household utility as a function of product characteristics and derive both product and loan demand. Then, I develop a pricing equation that incorporates capital requirements and the empirical facts described in Section 2.2.

3.1 Household Demand

In each market m there are I_m heterogeneous households indexed by i, choosing a mortgage to buy a house. Households choose simultaneously their mortgage product, among all lenders, rate types and maximum loan-to-values available to them (discrete product choice), and their loan amount, given their preferences and budget constraint (continuous quantity choice). I follow the characteristics approach (Lancaster, 1979) and assume that each mortgage can be represented as a bundle of attributes and that borrowers have preferences over these attributes. The indirect utility for household i taking product j in market m is given by:

$$V_{ijm} = \bar{V}_{ijm}(Y_i, D_i, X_j, r_{jm}, A_{ij(l)}, \zeta_i, \xi_{jm}; \theta_i) + \varepsilon_{ijm}, \tag{1}$$

where Y_i is household income; D_i are other household demographics (e.g. age, location); r_{jm} is the interest rate for product j in market m; X_j are time invariant product characteristics (rate type, lender, maximum loan-to-value); $A_{ij(l)}$ is lender l branch network in the location of household i; ζ_i captures household unobserved characteristics (e.g. wealth, risk-aversion, housing preferences); ξ_{jm} captures unobservable product characteristics (e.g. advertising, screening) affecting the utility of all borrowers in market m; ε_{ijm} is an idiosyncratic taste shock; and θ_i collects the demand parameters that I allow to vary across households.

I assume households choose the mortgage product that gives them the highest utility, among the products available to them. This assumption is particularly suitable for the mortgage market, in which the vast majority of borrowers take only one mortgage product at a time. I construct the choice set comparing borrowers with similar observable characteristics and I impose two additional restrictions based on affordability and liquidity constraints. First, households may not be able to borrow up to the desired leverage, due to supply side restrictions (such as loan-to-value or loan-to-income limits). Second, liquidity constraints may limit the ability of the household to increase the down-payment and consider products with lower maximum leverage. Both types of constraints restrict the choice set of the households in terms of maximum loan-to-value accessible among the full set available in the market.[13]

The constrained problem becomes:

$$\begin{aligned} &\max_{j \in J_i} V_{ijm} = \bar{V}_{ijm} + \varepsilon_{ijm}, \\ &\qquad with\ J_i \subseteq J_m \quad Affordability\ constraint \\ &\qquad\qquad j \in J_i\ if\ j \in \{max\ LTV_i - 1, max\ LTV_i, max\ LTV_i + 1\}, \end{aligned}$$

where J_m is the total number of products available in a given market m. In the standard case the borrower has access to all products, so that $J_i \equiv J_m$. I implement affordability constraints by: 1) restricting the choice set of the borrower to products with the chosen maximum loan-to-value and only one step above and below; and 2) considering a representative product with the chosen maximum loan-to-value as the outside option. An individual chooses product j if $V_{ijm} > V_{ikm},\ \forall j \in J_i$.

I assume that ε_{ijm} in equation (1) is identically and independently distributed across

[13] I discuss in detail the construction of the borrower specific choice set in Section 4.1.

households and mortgage products with a type I extreme value distribution. Then, the demand by borrower i in market m for product j is given by:

$$s_{ijm} = \frac{\exp(\bar{V}_{ijm}(Y_i, D_i, X_j, r_{jm}, A_{ij(l)}, \zeta_i, \xi_{jm}; \theta_i))}{\sum_{k=0}^{J_i} \exp(\bar{V}_{ikm}(Y_i, D_i, X_k, r_{km}, A_{ik(l)}, \zeta_i, \xi_{km}; \theta_i))}. \tag{2}$$

At the chosen product, the borrower decides the optimal quantity (q_{ijm}), which I obtained using Roy's identity, along the lines of Dubin and McFadden (1984):

$$q_{ijm} = -\frac{\frac{\partial V_{ijm}}{\partial r_{jm}}}{\frac{\partial V_{ijm}}{\partial Y_i}} = q_{ijm}(Y_i, D_i, X_j, r_{jm}, \zeta_i, \xi_{jm}; \theta_i). \tag{3}$$

The demand model jointly described by equations (2) and (3) captures in a flexible ways several factors that are likely to affect households' mortgage choice. First, the sensitivity to the interest rate r_{jm}, which I allow to vary across different products consistent with the non-linearities in the pricing schedules from Section 2.2.[14] In this way I capture a standard intertemporal trade off between consumption today and consumption tomorrow (Brueckner, 1994). A higher leverage (i.e., a larger maximum loan-to-value captured in the X_j) implies a higher repayment burden in the future, thus lowering consumption via a larger monthly payment.

Second, additional characteristics such as the interest type and brand in X_j allow for horizontal differentiation. Furthermore, the number of branches of the lender captures borrowers' costs associated with the application process and the formation of the choice set, along the lines of Hastings et al. (2017). Higher branch presence can increase the utility for households, because they generate spatial differentiation. For example, a large branch presence allows the household to walk in to a branch when needed, thus lowering transaction costs. However, more branches can make the lender more salient to the borrower, by increasing the probability that the borrower will consider it. Moreover, in the absence of data on borrowers' assets, the local share of branches can proxy for pre-existing relations between the borrower and the lender (e.g., current account).[15]

[14] The evidence supports my assumption that in the UK mortgage market lenders set for each product they offer national prices, which do not vary geographically or based on borrowers' demographics. In priciple individual specific pricing can be accommodated in the model by allowing the interest rate to vary across individuals given a product-market pair (r_{ijm} in place of r_{jm}).

[15] In the UK mortgage market borrowers search for mortgage products and apply via branches, intermediaries and on-line comparison website. The application process is long and can be very costly. Ideally I would like to observe the true household choice set when applying for mortgages, but this information is not available in most settings, especially for administrative datasets. See Basten and Koch (2015) and

Third, I allow for unobservable product heterogeneity (ξ_{jm}) to affect the household mortgage and quantity choice. In the case of mortgage products the unobservable term can capture "quality" as in standard IO models (Berry et al., 1995; Nevo, 2001). Even if I observe the most relevant mortgage characteristics, lenders can offer optional services and contracts can include additional features (e.g., cash back, payment holidays) that may increase the "quality" of the product, coeteris paribus. Advertising plays an important role in the mortgage industry and could also justify the inclusion of unobservable product heterogeneity (Goeree, 2008; Gurun et al., 2016).[16]

Two remarks are in order. First, I fix the interest rate set at origination, which implies that borrowers expect future interest rates to reflect current interest rates. This assumption holds for fixed rate mortgages until the end of the initial period and is reasonable for variable rate mortgages, given the short horizon before remortgaging. Second, I develop a static model, which does not allow me to study issues related to the timing of purchasing, refinancing or defaulting. This will complicate the analysis, given that the timing for these choices will be affected by many additional factors not limited to the mortgage market (e.g., housing and labor markets). At origination, the "participation decision" of buying versus renting can be added as an additional binary decision in the model, but will require additional data on renters and an assumption on their targeted unobserved loan-to-value to construct their counterfactual choice set. After origination, my static model assumption is supported by the fact that the vast majority of households refinance at the end of the initial period or shortly thereafter, to avoid paying the significantly higher reset rate (see Section 2.2.4 and Cloyne et al. (2017)). Furthermore, strategic default is unlikely to be the main trigger since in the UK mortgage market all loans are recourse, which implies that households are responsible for payment even beyond the value of the house. Defaults on mortgages are therefore very costly and empirical evidence from survey data confirms that arrears are the consequence of inability to meet the monthly payment, rather than a choice.[17]

Michelangeli and Sette (2016) for examples of settings in which the choice sets are observable.

[16] So far I have assumed that borrowers have full knowledge of prices and characteristics of all mortgages in their choice set when they make their decision. The UK mortgage market has a large number of products and both the turnover rate and the frequency of price change are high. However, detailed information about products is readily available from price comparison websites and many borrowers use a broker to arrange the transaction. Given the relevance of the choice for the household budget it is likely that borrowers will collect all the relevant information before making a decision. With additional information on advertising analyzing its effect for mortgage choice with a limited information model will be an interesting area for future research.

[17] This is consistent with recent evidence from the US. Ganong and Noel (2017) study underwater borrowers in the US and find that default is driven by cash-flow shocks such as unemployment rather than by future debt burdens.

3.2 Lender Pricing

In each market m there are L_m lenders that maximize (expected) profits by setting a price for each product they offer.[18] I assume the main source of revenue for lenders is the net interest income from the monthly payments. The present value of net interest income from a risk-free mortgage to borrower i with fixed rate r_{jm} and maturity T_i is given by:

$$PV(q_{ijm}, r_{jm}, c_{jm}, T_i) = q_{ijm} \sum_{k=1}^{T_i} \left[\frac{r_{jm}(1+r_{jm})^{T_i}}{(1+r_{jm})^{T_i}-1} - \frac{c_{jm}(1+c_{jm})^{T_i}}{(1+c_{jm})^{T_i}-1} \right], \tag{4}$$

where q_{ijm} is the outstanding mortgage quantity and c_{jm} is the marginal cost of providing mortgage j in market m.

Equation (4) does not account for the two key risks in the mortgage market: default and refinancing. First, default risk raises the expected cost for the lender to issue a mortgage. I assume that lenders setting interest rate do not forecast the probability of default in each period, but consider an average expected probability of default as in Crawford et al. (2018). Second, given the high level of refinancing at the end of the initial period it is unreasonable to assume that lenders compute the present value as if all mortgages are held until maturity. I assume that lenders expect borrowers to refinance at the end of the initial period.[19]

For long maturity, equation (4) with refinancing and default risks is given by the following approximation:

$$\begin{aligned} PV(q_{ijm}, r_{jm}, c_{jm}, t_j, d_{ijm}) &\approx q_{ijm} t_j (r_{jm} - c_{jm}) - d_{ijm} q_{ijm} t_j r_{jm} = \\ &= q_{ijm} t_j r_{jm} (1 - d_{ijm}) - q_{ijm} t_j c_{jm}, \end{aligned} \tag{5}$$

where t_j is the initial period and d_{ijm} is the expected default probability for borrower i taking product j in market m, which I allow to also be a function of the interest rate.[20]

[18] Unlike other retail products, such as cars, I cannot simply take the difference between the price and the unit cost to study the incremental profitability from an additional sale. The key difference in the case of loans is that the profitability from a sale is not realized when the sale takes place, but over time.

[19] In Appendix C I derive a more flexible specification in which some borrowers fail to refinance at the end of the initial period and pay the standard variable rate until maturity. Even if borrowers can refinance the mortgage in any month, I capture this risk in a simpler way by allowing one remortgaging opportunity at the end of the initial period. As already mentioned in Section 2.2.4 the vast majority of borrowers refinance their mortgage at the time their initial rate expires. Furthermore, in the period I analyze there is almost no variation over time in the standard variable rate, so that it is captured by the lender dummies.

[20] Equation (5) assumes that the remaining interest payment is lost upon default. In the case of collateralized lending, such as mortgage lending, the lender may be able to recover some fraction of the balance from the house sale and further actions against the defaulted borrower. Adding a positive recovery rate in case of default would increase the complexity of the model requiring lenders to form expectation on future house

Lenders decide in each market m the initial rate for each product j they offer, taking as given the rates set by their competitors. Given the demand system and the approximation of the present value of the net revenue from interest payment (5), I can write the problem of the lender as:

$$\begin{aligned}
\max_{r} \Pi_{lm}(r_{jm}) &= \sum_{j \in J_{lm}} \Pi_{jm}(r_{jm}) = \\
&= \sum_{j \in J_{lm}} \sum_{i \in I_m} s_{ijm}(r_{jm}, r_{-jm}) \times PV(r_{jm}) = \\
&= \sum_{j \in J_{lm}} \sum_{i \in I_m} s_{ijm}(r_{jm}, r_{-jm}) \times q_{ijm}(r_{jm}) \times \left[t_j r_{jm}(1 - d_{ijm}(r_{jm})) - t_j c_{jm}\right]. \quad (6)
\end{aligned}$$

I sum over all products offered by lender l in market m ($\sum_{j \in J_{lm}}$) and over all borrowers in market m ($\sum_{i \in I_m}$) to compute expected demand at the lender level. Note that the price of other products enter the product demand (s_{ijm}), but not the present-value, which only depends on the conditional loan demand (q_{ijm}). The derivative of the profits with respect to the price of product j is given by:

$$\begin{aligned}
\frac{\partial \Pi_j}{\partial r_j} &= S_j Q_j (1 - D_j) t_j + S_j \frac{\partial Q_j}{\partial r_j} \left[t_j r_j (1 - D_j) - t_j c_j\right] \\
&\quad + \sum_{k \in J_l} \frac{\partial S_k}{\partial r_j} PV_k - S_j Q_j \frac{\partial D_j}{\partial r_j}(t_j r_j) = 0, \quad (7)
\end{aligned}$$

where I remove the market subscript m for simplicity and the capital letters denote aggregate values at the product level after summing across all households in a market. The first term gives the extra profits from the higher rate on the quantity sold; the second term captures the changes in loan demand from a higher rate; the third term collects the impact of a higher rate on the choice probability for all products offered by the lender; and the last term captures the impact of the higher rate on the default probability. Solving for the optimal interest rate gives:

price values and the cost of collecting debt which I do not observe, but would not affected the cross-sectional nature of regulation and competition which is the focus of this paper.

$$r_j^* = \overbrace{\frac{c_j}{(1-D_j) - \frac{\frac{\partial D_j}{\partial r_j}}{\frac{\partial S_j}{\partial r_j}\frac{1}{S_j} + \frac{\partial Q_j}{\partial r_j}\frac{1}{Q_j}}}}^{\text{Effective marginal cost}} - \overbrace{\frac{1}{\frac{\partial S_j}{\partial r_j}\frac{1}{S_j} + \frac{\partial Q_j}{\partial r_j}\frac{1}{Q_j} - \frac{\partial D_j}{\partial r_j}\frac{1}{1-D_j}}}^{\text{Full mark-up}}$$
$$\underbrace{- \sum_{k \neq j \in J_l} \frac{\frac{\partial S_k}{\partial r_j} PV_k}{t_j\left(\frac{\partial S_j}{\partial r_j} Q_j(1-D_j) + S_j \frac{\partial Q_j}{\partial r_j}(1-D_j) - S_j Q_j \frac{\partial D_j}{\partial r_j}\right)}}_{\text{Other products}}. \tag{8}$$

Note that if there is no default risk ($\frac{\partial D_j}{\partial r_j} = 0$ and $D_j = 0$), all lenders offer only one product and all households make only the discrete product choice ($Q_j = 1$), then equation (8) collapses to the standard mark-up pricing formula: $r_j^* = c_j - \frac{S_j}{\frac{\partial S_j}{\partial r_j}}$.

Equation (8) characterizes the unconstrained optimal interest rate for lenders, but in reality lenders set rates accounting for regulatory constraints in place. In the model I focus on two leverage regulations that have been at the center of the recent policy and academic debate. First, I add a risk-weighted capital constraint to the bank optimization problem. Even if lenders' balance sheets have other assets than mortgages, I assume that when they set rates for mortgages they behave so that they account for the capital requirement constraint. Second, I embed in the model regulation on household leverage, along the lines of recently implemented policies in the US and the UK (Consumer Financial Protection Bureau, 2013; Bank of England, 2014). I achieve that by imposing a 15 percent quota on the share of mortgages with a loan-to-income above 4.5, along the lines of Goldberg (1995) for cars' import.[21] The problem for constrained lenders becomes:

$$\begin{aligned} \max_r \Pi_{lm}(r_{jm}) &= \sum_{j \in J_{lm}} \Pi_{jm}(r_{jm}) \\ s.t.\ \ \underline{\mathrm{K}}_{lm} &\sum_{j \in J_{lm}} S_{jm} Q_{jm} \rho_{jm} \leq K_{lm} && \textit{Capital constraint} \\ &\frac{\sum_{j \in J_{lm}} S_{jm} \mathbb{I}[LTI > 4.5]}{\sum_{j \in J_{lm}} S_{jm}} \leq 0.15 && \textit{LTI constraint,} \end{aligned}$$

where K_{lm} is actual capital resources; $\underline{\mathrm{K}}_{lm}$ is the lender-specific minimum capital requirement; ρ_{jm} is the risk weight for mortgage product j; and $\mathbb{I}[LTI > 4.5]$ is an indicator for

[21]The 15 percent limit comes from a recommendation by the Financial Policy Committee of the Bank of England in June 2014. For more details see Bank of England (2014) and Appendix B.

mortgages with a loan-to-income greater than 4.5. The Lagrangian multipliers associated with the constraints represent the shadow cost of leverage regulations.

The equilibrium in the mortgage market is characterized by lenders optimal pricing subject to leverage regulations and borrowers optimal mortgage choice taking as given prices and other product characteristics.

4 Estimation and Identification

In this section I take the model to the data. First, I describe how I build households' choice sets, in the presence of unobservable choice sets and affordability criteria. Then, I discuss the variation that I use for identification, endogeneity concerns and supply-side instruments.

4.1 Counterfactual Choice Set

I proceed in three steps to determine the products available in borrowers' choice set. First, following the literature I focus on the most popular mortgage types offered by the largest lenders, and I group mortgages offered by other lenders and mortgages with a market share below 0.3% in a representative "outside" product.[22]

Second, within each market given by a borrower type-quarter pair I classify borrowers into groups based on income, age and region. I construct the counterfactual choice set for borrower i including all products sold in each market-group combination to which borrower i belongs.[23] The rationale for this restriction come from the fact that borrowers with similar observable characteristics will have access to similar alternatives. Restricting the choice set using borrowers demographics could partially compensate for the absence of data on mortgage application and on banks' loan approval decisions. For example, a credit card company reports that in the UK rejection rates are low in the mortgage market, but vary with demographics such as age (observable) which can be correlated with credit history (unobservable).

[22] Among others, Goeree (2008) studies households' choice of their personal computer and consider as the outside good non-purchase, purchased of a used computer and purchase of a new computer from a firm not in the data. In applications to financial markets, Egan et al. (2017) study households' choice of their deposits and consider as the outside good all the banks outside the top sixteen.

[23] I break the population into four demographics groups based on age and income below and above the median and interact them with the borrower region where the house is located. In a recent paper Crawford et al. (2016) describe the use of the choice set of similar consumers as the interpersonal logit model.

A major drawback of the approach to define the choice set so far is that I can include products that are not in households i choice set (Goeree, 2008; Gaynor et al., 2016). Maximum loan-to-income and loan-to-value limits can impose an upper bound on households leverage, while unobservable differences in wealth can act as a lower bound. As a result, two households in the same market-group may shop at different maximum loan-to-values. I address these additional constraints in a third step, in which I further restrict the number of products available to household i by limiting the choice set to all products in household i group with a maximum loan-to-value equal to the one chosen by i or just above and below.[24] In this way I allow borrowers to shop locally in terms of the down-payment decision, consistent with the bunching behavior from Figure 4.

Given the national nature of the market I do not impose additional restrictions to the choice set based on geographical location, beyond the grouping by region. My analysis focuses on the largest lenders, which have their portfolios widespread across the UK, and even products from smaller lenders, with a more local business model, can be sold nationally via Internet, phone and brokers. Ruling out products from households' choice sets based on their within region location seems to be somewhat extreme and unrealistic in a market such as the UK. However, I allow for geography to play a role by affecting the application cost through the branch network of the lender.

4.2 Estimation

Demand. My demand model in Section 3.1 predicts for every household mortgage demand and loan size as a function of observable household characteristics, random preferences, products attributes and a vector of parameters to be estimated. I estimate the demand model described with two assumptions on the structural unobservables error terms. I assume that ε_{ijm} in equation (1) is identically and independently distributed across households and mortgage products with a type I extreme value distribution. Then, the conditional probability that borrower i in market m chooses product j is given by:

$$Pr(i \ chooses \ j) = p_{ijm}(\zeta_i) = \frac{\exp(\bar{V}_{ijm})}{\sum_{k=0}^{J_i} \exp(\bar{V}_{ikm})}, \tag{9}$$

and the unconditional probability can be found by integrating out borrowers unobservable heterogeneity, which I assume follows a normal distribution with variance σ ($\zeta_i \sim N(0, \sigma)$):

[24] As a example a household buying in equilibrium a product with a maximum loan-to-value of 90 percent will have in the choice set mortgage with a maximum loan-to-value of 90, 85 and 95 percent.

$$s_{ijm} = \int_{\zeta} p_{ijm}(\zeta_i) dF(\zeta_i). \tag{10}$$

I also make a parametric assumption on the indirect utility $\bar{V}_{ijm}$ following Train (1986):

$$\bar{V}_{ijm} = \frac{\gamma}{1-\phi} Y_i^{1-\phi} + \mu \exp(-\alpha r_{jm} + \beta X_j + \xi_{jm} + \eta D_i + \zeta_i) + \lambda A_{ij(l)}. \tag{11}$$

Using Roy's identity I obtain the loan demand function q_{ijm} for borrower i in market m, conditional on choosing mortgage j:

$$\ln(q_{ijm}) = \ln\left(-\frac{\frac{\partial \bar{V}}{\partial r}}{\frac{\partial \bar{V}}{\partial y}}\right) = \phi \ln(Y_i) + \ln(\frac{\mu\alpha}{\gamma}) - \alpha r_{jm} + \beta X_j + \xi_{jm} + \eta D_i + \zeta_i. \tag{12}$$

From equation (12) and the normal distribution assumption for ζ_i, the probability of the conditional loan demand is:

$$\begin{aligned} f(\ln(q_{ijm})|j, j \neq 0) = \frac{1}{\sqrt{2\pi\sigma^2}} \times \exp\Bigg[-\frac{1}{2\sigma^2}\Bigg(\ln(q_{ijm}) \\ -(\phi \ln(Y_i) + \ln(\frac{\mu\alpha}{\gamma}) - \alpha r_{jm} + \beta X_j + \xi_{jm} + \eta D_i)\Bigg)^2\Bigg]. \end{aligned} \tag{13}$$

Then the joint log likelihood for individual i to buy product j and borrow an amount q_{ijm} is given by:

$$\ln(L_i) = \sum_{j=0}^{J_i} \mathbb{I}_{ijm} \left[\ln(s_{ijm}) + \ln(f(\ln(q_{ijm})|j, j \neq 0))\right], \tag{14}$$

where $\mathbb{I}_{ijm}$ is an dummy equal to one if borrower i chooses product j and zero otherwise. I address the simultaneity bias that arises if I do not account for the discrete product choice (equation 10), when I estimate the continuous quantity choice (equation 12), by estimating both choices simultaneously in one step. I also take explicitly into account a possible correlation between the interest rate (r_{jm}) and unobservable product characteristics (ξ_{jm}). Let $\delta_{jm} = -\alpha r_{jm} + \beta X_j + \xi_{jm}$ be the product-market fixed effects. In the first step, I estimate the joint likelihood (14) with product-market fixed effects and obtain the utility parameters (ϕ, η, λ), the scaling factors (σ, μ), and the product-market fixed effects (δ_{jm}). In the second step, I recover the impact of the interest rate and other product characteristics using the estimated fixed effects as dependent variable, as follows:

$$\hat{\delta}_{jm} = -\alpha r_{jm} + \beta X_j + \xi_{jm}. \tag{15}$$

To account for endogeneity in the interest rate I estimate the second step with instruments that I discuss in Section 4.3:

Supply. The estimation of the supply side parameters is based on the optimal pricing formula derived in Section 3.2. To compute the full mark-up and isolate the marginal costs I need information on the average expected default rate and on the increase in defaults as a result of changes in interest rates. I back out the latter using a cross-section of data about mortgage performances as of June 2016 and the linear probability model given by:

$$d_{ijt} = \beta r_{jt} + \eta X_i + \gamma_t + \gamma_j + \epsilon_{ijt}, \tag{16}$$

where d_{ijt} is a dummy equal to one if borrower i who took product j in period t is in arrear in June 2016; X_i are borrower characteristics at origination; γ_t and γ_j are cohorts and product fixed effects. The key parameter is β, which captures the direct effect of the interest rate on arrears. To identify it I control for product and cohort fixed effects and borrower level demographics. Equation (16) estimates the effect of variables at originations on ex-post outcomes. As some variables will change over time (e.g. income, house value) a fully specified model should control for the actual value of these variables. Unfortunately I do not have a panel that will allow me to do that. However, variables at origination play an important role for pricing of the *expected* probability of arrears, which is the object of interest in the pricing function.[25]

I compute the unobservable marginal costs at the product level inverting equation (8) and solving for the marginal costs as a function of observed interest rates, the estimated mark-ups, the estimated default parameters and the observed regulatory constraints. I then obtain a two-step estimator of the cost parameters with the following fixed effects model:

$$c_{jm} = \psi \underline{\mathrm{K}}_{lm} \rho_{jm} + \tau X_j + \gamma_m + \gamma_{j(l)} + \kappa_{jm}, \tag{17}$$

where the dependent variable is the estimated marginal cost; $\underline{\mathrm{K}}_{lm} \rho_{jm}$ is the risk-weighted

[25] I use the estimated parameters from equation (16) in my counterfactual exercises, as changes in cost will have an impact on arrears via two channels. Lenders will pass changes in costs on to interest rates, which have a direct impact on arrears, captured by β in equation (16), and an indirect impact via both the discrete mortgage choice and the continuous quantity choice. To use the parameters from the default model in the counterfactual analysis I need to assume that the change in the regulation does not change the relation between interest rate and default.

regulatory capital requirement; X_j are the same product characteristics that affect borrower demand (rate type, maximum loan-to-value); γ_m and $\gamma_{j(l)}$ are market and lender fixed effects; and κ_{jm} is a structural error term capturing unobservable cost determinants.

4.3 Identification

In this section I discuss the sources of variation that identify the different structural parameters and how I address the endogeneity concerns arising from the simultaneity problem and from unobservable attributes affecting demand. I address the simultaneity problem by estimating the discrete and continuous choice jointly, as shown in equation (14). In this way I solve the bias that can arise if I do not account for the discrete product, when I estimate the continuous quantity choice. To achieve the separate identification of the discrete and continuous choices, I assume that lenders' local branch presence affects the borrowers' choice among lenders, but does not affect the conditional choice of the quantity. Since I estimate the model in each region separately and I control for lender fixed effects, my assumption requires that within a region, a larger branch presence of a lender in a postcode area does not differentially affect the loan demand of borrowers choosing that lender.[26] I exploit variation in the branch network together with variation on the location of the borrowers' houses at the postcode level to identify application costs ($A_{ij(l)}$).

I consider exogenous time-invariant characteristics (X_j), such as lender, interest rate type and maximum LTV, but I allow for time-varying unobservable attributes that can affect demand (e.g. advertising, screening, cash-back) to be correlated with the interest rate. The price setting decision of the lender can be taken as exogenous from the point of view of the borrower, and I can also rule out reverse causality from the "atomistic" individual borrower to the lender. However, the use of individual data does not solve the endogeneity problem, as unobservable attributes at the product level can be correlated with interest rates, thus biasing my results. As an example consider a lender that relaxes screening or offer a cash-back for a specific product and at the same time increases the interest rate on that product. Screening effort and the cash-back option are not observable to the econometrician, thus entering the error term (ξ_{jm}) and may be correlated with the interest rate, such that $E[\xi_{jm}|X_j, r_{jm}] \neq 0$. As a result, I may see borrowers still choosing the product and mistakenly conclude that

[26]This exclusion restriction is supported by the empirical evidence. In Appendix A I regress market shares and loan amounts on quartiles of branches, controlling for differences across lenders and postcodes with fixed effects. I find that a higher branch presence affect the lenders' market share, but has no differential effect on loan amounts. Furthermore, my assumption resembles previous studies estimating discrete-continuous supermarket choice models (Smith, 2004; Dubois and Jódar-Rosell, 2010).

they are not responding to the higher interest rate, while the effect of the higher rate has been countervailed by the differential screening effort or the cash-back option.

To account for endogeneity in the interest rate I include dummies for markets and lenders. In this way I control non-parametrically for time-invariant average unobservable differences across lenders and I identify the interest rate elasticity from the within lender variation across products and over time. Even in this difference-in-difference setting, unobservable (to the econometrician) attributes can affect borrower utility and be correlated with interest rates. I instrument interest rates using variation in risk-weighted capital requirements that affects the cost for lenders of issuing a particular product. Differently from previous papers that develop cost-shifters at the *firm* level (Egan et al., 2017; Koijen and Yogo, 2016), I exploit the institutional features of the leverage regulation in place in the UK, that I described in Section 2.2.1, to construct cost-shifters at the *product* level. The identification assumption for the demand parameters is:

$$E\left[\xi_{jm} | X_j, Z_{jm} = \underline{\mathrm{K}}_{lm} \rho_{jm}\right] = 0. \tag{18}$$

Equation (18) says that regulation is uncorrelated with demand shocks, conditional on observable characteristics. The reason behind this assumption is the following exclusion restriction: the only way through which risk-weighted capital requirements affect borrowers utility for a particular mortgage is via their effect on interest rates.

Endogeneity in the regulatory instrument that is correlated with unobservable household preferences can pose a threat to my identification strategy. However, my identification assumption is conditional on product characteristics, which include lender fixed effects, thus requiring a *differential* change in risk weights across loan-to-values *within* lender, as an average change will be captured by the fixed effects. Furthermore, changes in the internal models need to be approved by the regulators, thus limiting lenders' discretion in setting them.[27] Finally, I extend the intuition in Berry et al. (1995) to instrument prices with exogenous characteristics of competitor products and I exploit the regulation of other lenders as an instrument for interest rates.

The identification of the supply side parameters comes from variation in refinancing risk, captured by the length of the initial period, and in default risk, captured by the maximum loan-to-values. Variation in risk-weighted capital requirements identifies the shadow cost

[27] In a recent paper Behn et al. (2016a) show that lenders with internal models under-report risk weights. In my context lender fixed effects control non-parametrically for lender-wide differences in reported risk weights. Only differential reporting within lender across loan-to-values could be a concern for the validity of the instrument to the extent that this behavior is also correlated with unobservable factors affecting households utility.

of leverage regulation. Given that capital requirements vary across products offered by the same lender, due to the risk weights adjustment, I control for lender average differences in cost by adding lender fixed effects. In this way, I identify the effect of relaxing the constraint only with variation within lender across products. My identification strategy for the shadow cost of regulation improves with respect to previous studies based on variation across lenders, as other unobservable confounding factors can be correlated with average differences across lenders. I also explore the heterogeneity in the shadow cost of leverage regulation across lenders, by interacting the constraints with the lender type and the equity buffer. Finally, to address potential concern about endogeneity in the regulation and omitted variable bias also on the supply side, I follow the same intuition for the demand estimation and I use the regulation of other lenders as an instrument for a lender's own regulation.

5 Estimation results

5.1 Demand Parameters

In this section I present the results from the estimation of the structural model, using data for first-time buyers.[28] Table 3 shows the estimated demand parameters averaged across all groups.[29] The main parameter of interest is α, which captures the effect of interest rate on the indirect utility. As expected the coefficient is negative and significant. Given the functional form of the indirect utility, I cannot directly interpret the magnitude of the interest rate coefficient, so I compute the discrete and continuous elasticities using the formulas reported in Appendix C. I find an average loan demand elasticity of about 0.07 and a product demand elasticity of 5.9.[30] These elasticities imply that a 10 basis points increase in the interest rate (a 3.5 percent increase) for a mortgage product decreases loan demand by 0.25 percent and the product market share by 22 percent, and it increases other products market share by 0.2 percent, on average.

Given that my product definition combines several elements of horizontal differentiation,

[28] Consistent with the reduced-form evidence in Appendix B, leverage regulation has a larger impact on interest rates and credit access for borrowers with higher leverage, while home movers and remortgagers may already have accumulated equity in their houses.

[29] Appendix D presents averages by income, age and selected regions. I also plot the distribution of the main parameters in each group. The parameter on mortgage attributes comes from the second stage estimation.

[30] The loan demand elasticity is consistent with previous studies using bunching techniques (Best et al., 2018; DeFusco and Paciorek, 2017) and survey data (Fuster and Zafar, 2015). The product demand elasticity is higher than what Crawford et al. (2018) find for corporate loans. The difference can be due to the standardized nature of mortgage products, which facilitates comparison and shopping, relative to the corporate lending market, where relationships and soft information play a more important role.

Table 3: Structural demand estimates

	Structural Demand Parameters					
	Interest (α)	Leverage (β_1)	Fix Period (β_2)	Branches (λ)	Income (ϕ)	Heterogeneity ($log(\sigma)$)
Average	-0.0251***	0.0103***	0.0247***	0.0192*	0.7003***	-1.6080***
	0.0023	0.0019	0.0033	0.0112	0.0007	0.0091

Note: Structural demand estimates of the econometric demand model of Section 4.2. The model is estimated separately in each group (income-age-region) and the table reports the average point estimate and standard error in each group. The total number of borrowers is 370,575 and the average number of product-market observations is 773. The standard error for the parameters in the first stage are computed by the inverse of the information matrix; the standard errors for the mortgage attributes estimated in the second stage are computed by bootstrapping. All estimates include lender and market fixed effects.

I can compute elasticities at various levels. In Table 4 (a) I show the average loan demand and own product demand elasticity across different mortgage characteristics. The largest six lenders and building societies have similar loan demand elasticity, while challenger banks face a higher demand elasticity. In terms of product demand, building societies have the lowest elasticity, followed by the largest six lenders. Challenger banks face the highest elasticities of mortgage demand. As a result, for the same percentage increase in interest rate, challenger banks both lose more customers and face a larger decrease in loan demand from customers who still buy their products. I also explore heterogeneity across leverage levels. Both loan and product demand elasticities increase with leverage. Mortgages with a maximum loan-to-value above 85 percent have on average a loan demand elasticity of 0.9 and a product demand elasticities of 7.5 relative to mortgages with a leverage below 70 percent whose elasticities are 0.6 and 4.8, respectively.[31]

In Table 3 I also study preferences for additional product characteristics, maximum leverage and the length of the fix period, which play a central role in mortgage choice (Campbell and Cocco, 2003; Badarinza et al., 2017). I find that first-time buyers value mortgages with a high leverage, which allow lower down-payments for credit constrained borrowers. I also find that borrowers prefer longer fixed rate period, which is consistent with the recent increase in products with longer duration. Finally, the fraction of branches in the postcode where households have their houses has a positive but only marginally significant impact on average.

So far I focused on average effects, but the estimated model allows for rich heterogene-

[31]Best et al. (2018) also find elasticities of demand that are larger at higher loan-to-value notches. In In Appendix D I report the estimated own- and cross-product demand interest rate elasticities for the ten most popular products in the first-time buyer market. A one-percent increase in the interest rate decreases the market share of the mortgage by 3-7 percent, while the shares of other mortgages increase by 0.01-0.07 percent.

Table 4: Elasticities: loan demand and own product demand

	Loan demand		Product demand	
	Mean	Sd	Mean	Sd
All	-0.073	0.022	-5.935	1.704
Lender type				
Big 6	-0.073	0.022	-5.963	1.737
Challengers	-0.076	0.022	-6.147	1.724
Building societies	-0.073	0.022	-5.709	1.572
Maximum LTV				
LTV $\leq$ 70	-0.058	0.012	-4.801	0.989
70 $<$ LTV $\leq$ 80	-0.065	0.015	-5.295	1.163
LTV $>$ 85	-0.096	0.018	-7.676	1.433
Fixed period				
2 years	-0.065	0.021	-5.284	1.638
5 years	-0.083	0.019	-6.694	1.446

Note: Interest rate elasticities for a random subsample of first-time buyers. I show the loan demand and own product demand elasticities. The elasticities are computed using the structural parameters from Table 3 and the formulas in Appendix C. I report the average elasticities for all products and by different product characteristics: lender type, maximum LTV and fix period.

ity, both observable and unobservable. Table 3 shows the effect of individual income and unobservable heterogeneity. The coefficient on income has a straightforward interpretation as it only enters in the quantity choice (ϕ in equation (12)) and measures the elasticity of loan demand to income. I find a positive and significant elasticity around 0.7. I also find significant unobservable heterogeneity across households even within my narrowly defined groups and controlling for observable demographics within group.[32]

5.1.1 Fit and Robustness

In Appendix D I look at the ability of the model to predict some key variables of interest on the demand side, namely loan demand, loan-to-income, loan-to-value and product market shares. Overall the model fits the data well, both in terms of mean and variance. The main limitation is that the model under-predicts the variance in loan-to-value shares, not being able to capture well the extreme leverage levels that are sometimes observed in the data. I also reports the out-of-sample fit of the model, using demand parameters in 2015-2016 and additional data for 2017 to predict loan demand, loan-to-income, market shares and loan-to-value in 2017. Also out of sample the model captures the data well.

[32]In Appendix D I explore further heterogeneity across groups that may be potentially important for evaluating the distributional effect of alternative leverage regulations.

Finally, in Appendix E I discuss several robustness checks. First, I instrument the endogenous interest rate for first-time buyers with the risk weights for the same maximum loan-to-value by other lenders. Second, I construct an initial annual percentage rate (APR) as a function of both the interest rate and the lender fee for a representative mortgage and use it as the price of the mortgage instead of the initial rate only. Third, I estimate the second step of the demand model (equation (15)) simultaneously with the supply side (equation (17)) using generalized method of moments. The demand estimates are robust to these different instruments, variable definitions and estimation methods.

5.2 Supply Parameters and The Cost of Capital Regulation

First, I discuss the results for the default model given by equation 16, whose parameters enter the calculation of the mark-ups and marginal costs. Table 5 shows the estimates. I find a statistically significant and robust positive relation between the interest rate and default: a 1 percentage point higher interest rate increases the probability of default by 0.15 percentage points.[33] I also study how loan-to-income and loan-to-value at origination affect the probability of default. Mortgages with loan-to-income above 3.5 and loan-to-value above 85 are always more likely to default.

Given that the estimates pool together mortgages from different years in columns (2) and (3) of Table 5 I split my sample into mortgages originated before and after the crisis. The relation between interest rate and default is positive and significant in both periods and stronger in magnitude before the crisis. For mortgages originated before the crisis a one-percentage-point higher interest rate increases the probability of default by 0.5 percentage points, while the effect is approximately five times smaller for mortgages issued after the crisis. Mortgages with higher loan-to-income are more likely to default when originated both before and after the crisis. Some differences emerge for high leverage mortgages originated after relative to those originated before the crisis. Controlling for the interest rate, high loan-to-value mortgages issued before the crisis are significantly more likely to default, while high loan-to-value mortgages issued after are less likely to default. A possible explanation for the latter result can be the increase in supply side restrictions and affordability checks after the crisis, which led to an overall low volume of originations at high leverage to a selected pool of low risk borrowers.

To address endogeneity concerns coming from omitted variables correlated to both the in-

[33]Given a baseline default rate of 1.5 percent, a 1 percentage point (100 basis points) rise in interest rate lead to an approximately 10 percent increase in the probability of arrears, which is slightly lower but in line with existing work on the US mortgage market (Fuster and Willen, 2017; Gupta, 2018).

Table 5: DEFAULT ESTIMATES

	FULL SAMPLE	PRE-CRISIS	POST-CRISIS	
	OLS	OLS	OLS	IV
	(1)	(2)	(3)	(4)
INTEREST (%)	0.0015***	0.0050***	0.0012***	0.0012***
	(0.0000)	(0.0005)	(0.0000)	(0.0003)
HIGH LTI	0.0007***	0.0025***	0.0003*	0.0003*
	(0.0002)	(0.0006)	(0.0001)	(0.0001)
HIGH LTV	0.0013***	0.0128***	-0.0009***	-0.0009*
	(0.0002)	(0.0007)	(0.0001)	(0.0004)
TIME F.E.	Yes	Yes	Yes	Yes
LENDER F.E.	Yes	Yes	Yes	Yes
RATE TYPE F.E.	Yes	Yes	Yes	Yes
POSTCODE DISTRICT F.E.	Yes	Yes	Yes	Yes
INDIVIDUAL CONTROLS	Yes	Yes	Yes	Yes
OBSERVATIONS	2708046	551840	2156171	2082421

Note: Default estimates from equation (16). The dependent variable is a dummy equal to one if a mortgage originated between 2005 and 2015 is in arrears in June 2016. I define arrears as being at least 3 months late in servicing the monthly payment. Column (1), column (2) focuses on mortgages originated before 2008, while columns (3) and (4) look at mortgages originated after 2008. Interest is the interest rate at origination expressed in percentage terms. High LTI is a dummy for mortgages with loan to income at originations above 3.5; High LTV is a dummy for mortgages with loan to value at origination above 85. Borrower controls include type of borrower, employment status, income, age, maturity and property value. In column (4) the excluded instrument for the interest rate is the mortgage risk weight.

terest rate and the default probability, I show the result of an instrumental variable approach in column (4) of Table 5. I instrument the interest rate with the risk weight, following the same identification assumption from section 4.3 for demand parameters. The IV estimates are almost identical to the OLS estimates.

With the estimated demand and default parameters I compute the mark-ups and marginal costs. The average markup is about 0.53 percentage points in the full sample, which correspond to about 18 percent of the average interest rate in the data, and the average marginal cost is 2.42 percentage points.[34]

I use the estimated marginal cost as a dependent variable in equation (17), to decompose the effect of product characteristics and identify the cost of capital regulation in the mortgage market. Table 6 shows the structural supply parameters. The main parameter of interest captures the impact of risk-weighted capital requirements on the marginal costs. I identify

[34]In Appendix D I break down markups and marginal costs by lender, loan-to-value and interest rate type. Estimate of markups at the product level for the mortgage market are not available, but Button et al. (2010) perform a decomposition of new lending rates for UK mortgages, into funding costs, capital costs and a residual. They find that after the financial crisis in 2008 the residual, which includes operating costs and markup, has risen. As operating costs are unlikely to have changed and if anything they may have decreased as results of consolidation, their finding is consistent with increasing markups.

Table 6: Structural supply estimates

	Main			Heterogeneity		IV
	(1)	(2)	(3)	(4)	(5)	(6)
RW Capital Req (%)	0.640***	0.268***	0.309***	0.426***	0.412***	0.282***
	(0.030)	(0.019)	(0.022)	(0.030)	(0.034)	(0.020)
High LTV		1.056***	1.005***	0.899***	0.980***	1.038***
		(0.039)	(0.040)	(0.044)	(0.040)	(0.039)
Fix 5		0.699***	0.699***	0.716***	0.707***	0.699***
		(0.023)	(0.023)	(0.022)	(0.022)	(0.023)
RW Capital Req (%)						
x Challenger				-0.219***		
				(0.030)		
x Building Society				0.173**		
				(0.088)		
x High buffer					-0.173***	
					(0.033)	
Market F.E.	Yes	Yes	No	No	No	Yes
Lender F.E.	Yes	Yes	No	No	No	Yes
Market-Lender F.E.	No	No	Yes	Yes	Yes	No
Marginal Cost (mean)	2.42	2.42	2.42	2.42	2.42	2.42
R^2	0.50	0.82	0.84	0.85	0.84	0.82
Observations	1046	1046	1046	1046	1046	1046

Note: Structural parameters of the supply model from equation (17). The dependent variable is the effective marginal cost at the product level. Risk weights are the regulatory risk weights expressed in percentage terms. High LTV is a dummy equal to one for products with a maximum loan-to-value above 85. Fix 5 is a dummy for mortgages with a fix period of 5 years. In column (6) the excluded instrument for the mortgage risk-weighted capital requirements is the closest risk weight for the same loan-to-value and rate type offered by another lender. Robust standard errors in parenthesis.

it by exploiting variation in risk-weighted capital requirements across lenders and leverage levels and over time. Column (1) of Table 6 shows the effect of capital regulation on effective marginal cost controlling for market and lender fixed effects. I find that a one-percentage-point higher risk-weighted capital requirement increases the marginal cost of lending to first-time buyers by about 65 basis points.

In column (2) of Table 6 I further control for other product characteristics that have an impact on the cost of issuing mortgages. As expected, we find that high leverage and longer fix rate mortgages have higher marginal costs. Once I control for these product attributes the coefficient on the risk-weighted capital requirements is reduced in magnitude, but the effect is still significant. A one-percentage-point higher risk-weighted capital requirement increases the marginal cost of lending to first-time buyers by approximately 27 basis points. The inclusion of the control for leverage, which captures the decrease in risk for mortgages with a lower leverage that is common across lenders, drives the decline in the effect.

In column (3) of Table 6 I add interacted market-lender fixed effects. In this way I only exploit the variation in risk-weighted capital requirement within a lender-time pair, ruling out concerns about other time-varying lender-specific factors affecting the cost of issuing mortgages. The coefficient that captures the impact of regulation on the cost of lending is still significant and the magnitude is larger than in column (2).

In columns (4) and (5) of Table 6 I explore the heterogeneity in the cost of risk-weighted capital requirements across lenders. Column (4) allows the effect of capital requirements to vary with the type of lender. The baseline is the largest six lenders. I find that the effect of capital regulation is stronger for building societies, whose business model is centered around mortgages, and weaker for challenger lenders, which have a more diversified portfolio. In column (5) I interact capital requirements with the lenders' capital buffer, defined as the difference between capital resources and capital requirements. I find that lenders with more capital relative to the requirement are less affected by the regulation.

Finally in column (6) of Table 6 I address possible concerns about endogeneity of the regulation and omitted variable bias by exploiting the regulation of other lenders as an instrument for own regulation. Specifically, for each mortgage product I calculate the closest risk weight for the same loan-to-value and rate type offered by another lender and I use it as an instrument for the lender risk weight. The IV estimates are slightly larger, but not significantly different from the OLS estimates.

5.2.1 Discussion on Magnitude

The baseline estimate in column (2) of Table 6 shows an increase in the marginal cost of about 27 basis points for a one-percentage-point increase in the risk-weighted capital requirement. Given an average marginal cost of 2.4 percent, marginal cost increases by approximately 11 percent for the average mortgage product. This increase in marginal costs translates into a 28 basis points increase in the interest rate for the average mortgage product. To put my estimates of the cost of capital regulation into context, I simulate an increase in capital requirement by 10-percentage-points, along the lines of previous studies (Hanson et al., 2011; Baker and Wurgler, 2015; Firestone et al., 2017).[35] Previous papers find a wide range of values going from 3 basis points (Kisin and Manela, 2016), to 25-45 basis points

[35] In Appendix F I show the effects of a common increase in capital requirement by 10-percentage-points on marginal costs, rates and several additional variables of interest. Note that given an average risk weight of 0.27 a 10-percentage-points increase in capital requirement corresponds to approximately a 3-percentage-points increase in risk-weighted capital requirements.

(Hanson et al., 2011), up until 60-90 basis points (Baker and Wurgler, 2015). I find that increasing capital requirement by 10-percentage-points increase marginal costs by about 60 basis points in the mortgage market. This effect lies on the upper end of previous estimates and can be interpreted as an upper bound to the cost of a common increase in capital requirements, as I allow lenders to adjust to the new regulation *only* through one margin: repricing mortgages. In reality lenders can lower deposit rates, issue new equity and retain earnings, especially if the change in regulation is spread over time. These additional margins of adjustment will likely decrease the cost of increasing capital requirements (Elliott, 2009).

6 Counterfactual Leverage Regulations

In this section I use the estimated model to study alternative leverage regulations and their equilibrium impact on interest rates, market structure and risk. Section 6.1 compares two alternative counterfactuals that remove the risk-weight gap between large and small lenders that I document in Figure 2. Section 6.2 analyzes the interactions between risk-weighted capital requirements and regulations limiting household leverage.

6.1 Equilibrium Effects of Risk Weights

The reduced-form evidence from Section 2.2 suggests that risk weights affect pricing and specialization.[36] Figure 6 explores this relation further with an event study approach. I exploit variation over time *within* lender and an exogenous change in risk weights, following the approval of an internal rating-based model for a medium size lender. I compare the average risk weight and the average interest rate for the same lender for mortgages with a maximum loan-to-value of 95 percent relative to those with a maximum 70 percent. The relative risk weight of the lender jumps from slightly above one to more than four, as the lender adopts the internal model. At the same time the relative interest rate of the high leverage product increase from around one to approximately 1.5.

The adoption of an internal model by one lender is not enough to learn what would have happened in the mortgage market if all or some lenders are affected by changes in the leverage regulation. Furthermore, contemporaneous changes in market power and business models (e.g., securitization) can confound the effects coming from regulatory changes. To address these issues, I explore with the estimated model the equilibrium impact of changing

[36] In Appendix B I provide additional reduced-form evidence about the relation between risk weights and interest rates.

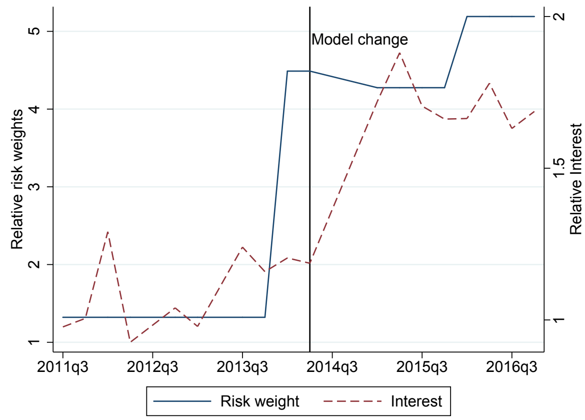


Figure 6: MODEL CHANGE

Note: Relative risk weight and interest rate of a maximum 95 LTV relative to a maximum 70 LTV for a lender before and after the adoption of the IRB model.

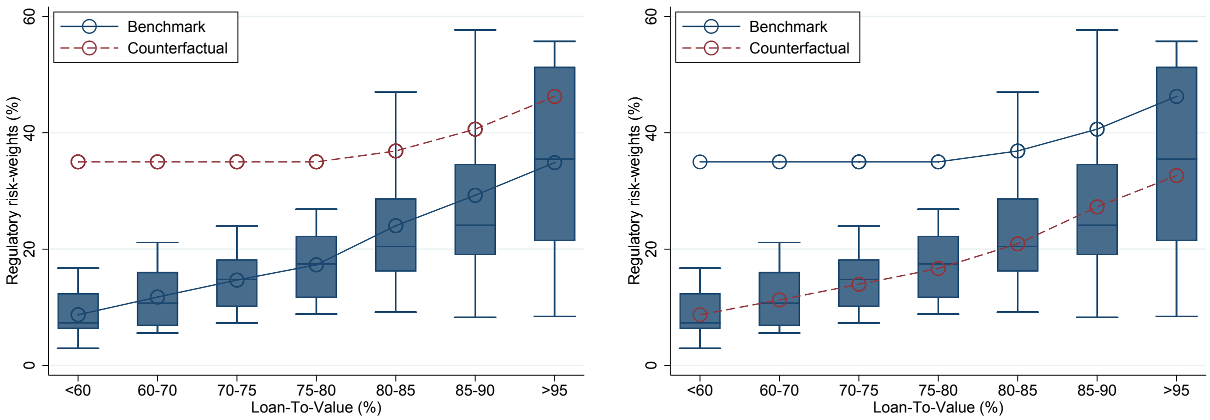
risk-based capital requirements keeping all else equal.

To illustrate the mechanism, consider two mortgages indexed by j with the same fix period and maximum loan-to-value, and the same expected default and refinancing risk (both equal to zero for simplicity). One mortgage is offered by a large lender adopting an internal model for the calculation of risk weights, while the other is offered by a small lender under the standardized regulatory approach. Under these simplifying assumptions using equation (8) and the risk-weighted capital constraint, the difference in prices between the two lenders for product j is be given by:[37]

$$r_{j,small} - r_{j,large} = \underbrace{\psi(\underline{K}_{small}\rho_{j,small} - \underline{K}_{large}\rho_{j,large})}_{\text{Regulation}} - \underbrace{\left[\frac{1}{\frac{\partial Q_{j,small}}{\partial r_{j,small}}\frac{1}{Q_{j,small}}} - \frac{1}{\frac{\partial Q_{j,large}}{\partial r_{j,large}}\frac{1}{Q_{j,large}}}\right]}_{\text{Market-power}} \tag{19}$$

The higher risk weights for the small lender translate into higher rates, ceteris paribus. If the elasticity of the product offered by the large lenders is lower, due to brand power, there is also an incumbent advantage, which further amplifies the price gap. In Appendix F I show that after a common increase in capital requirements large lenders with internal rating based models raise mortgage interest rates by on average about 50 percent less than

[37]The large and small lenders marginal costs of issuing a mortgage may differ for reasons other than regulation ($c_{j,small} \neq c_{j,large}$). In the estimation and I control for differences across lenders and products in the marginal costs and in the counterfactual analysis I keep this other factors unaffected.



(a) I: All standard approach

(b) II: All internal approach

Figure 7: Counterfactual risk-weighted capital requirements

Note: Risk weights distribution in the two counterfactual scenarios for the capital requirements. In Figure (a) I show the first counterfactual, in which all lenders adopt the standard approach for setting the risk weights. In Figure (b) I show the second counterfactual, in which I compute the mean risk weight across lenders with the internal model and assign it to the small lenders with the standard approach.

small banks with a standard regulatory approach.

I explore the consequences of changing the regulation on risk-weighted capital requirements with two counterfactual policies illustrated in Figure 7. First, I simulate an equilibrium without internal models for the calculation of capital requirements (Counterfactual I: All Standard). Second, I allow lenders adopting a standardized approach to develop an internal model, with the average risk weights of large lenders (Counterfactual II: All Internal).[38]

Table 7 shows the results for several variables of interest in a random subset of the first-time buyer market.[39] Panel A shows the effects of removing the heterogeneity in risk-weighted capital requirements on market structure. I measure concentration in the market looking at both the Herfindahl Index and the share of the largest six lenders for mortgage originations. As a result of the abolition of internal models the market becomes more competitive. Large lenders lose the regulatory advantage (first element in equation (19)) and increase their prices following an increase in the regulatory capital they have to hold. As a result of the higher rates, large lenders loose market shares in favor of smaller lenders already adopting the standard regulatory approach. The share of the largest six lenders drops from almost 85 to about 60 percent. The adoption of internal models for small lenders also has a pro-competitive effect on the market. I find that the Herfindahl index declines from 16 to

[38]The practical implementation of this policy may involve the development of an internal model by the central bank using data provided by private lenders.

[39]In Appendix F I present the results for the same variables computed separately for high and low loan-to-value mortgages.

about 13 percent, as smaller lenders reduce prices and gain more than 10 percent of market shares, following the decrease in regulatory costs. The redistribution from large to small lenders is overall less pronounced than in the first counterfactual.

Panels B and C of Table 7 look at the aggregate pass-through and the implication for access to credit. I find that eliminating internal models increase the cost in the market by about 49 basis points, which are passed on to borrowers via higher initial rates. The latter increase by approximately 50 basis points from 2.70 to approximately 3.20 percentage points. As a result of higher mortgage prices, demand decreases by 13 percent along the extensive margin, as more than 750 borrowers switch to the outside option. The average loan size decrease by approximately £1.5K, which is slightly higher than one percent of the average baseline balance. In the second counterfactual, marginal costs in the mortgage market go down by about 13 basis points, as a result of lower capital requirements for small lenders. This fall translates into a reduction in prices by about 14 basis points and an increase in mortgage demand by slightly more than one percent. I use the model to compute a measure of consumer surplus based on the sum of indirect utilities (see Appendix C for derivation and references). When all banks adopt the standard approach, as a result of overall higher prices, average consumer surplus decreases by more than 30 percent, while when all banks adopt an internal model the lower prices increase consumer surplus by about 6 percent.

Even if a full evaluation of the policy from a systemic point of view would require a general equilibrium approach, I can learn from the model the effects of changing capital regulation on risk in the mortgage market and its differential impact on large systemic lenders. In Panel D of Table 7, I first look at borrowers' default. The expected default predicted by the model in the baseline case is about 1.5 percent, which is in line with the empirical evidence in Section 2.2.4. With the abolition of internal models I observe an increase in the average default in the mortgage market by approximately 0.06 percentage points, as higher prices make it harder for borrowers to service their monthly payments. In the second counterfactual lower prices and relative small changes in credit access translate into lower defaults, which decrease by approximately 0.02 percentage points.

In Panel D of Table 7 I also report a measure of resilience for the overall mortgage market. I compute the equity buffer as the difference in pounds between lenders' equity and expected losses for each mortgage. Lenders' equity is given by the endogenous loan size multiplied by the lender-specific capital requirement and the counterfactual risk weights; expected losses come from expected default given by (16) after lenders re-optimize rates in reaction to the new risk-weighted capital requirements and borrowers adjust demand with the new prices. Abolishing internal models almost doubles the equity buffer in the mortgage

Table 7: Counterfactual risk-weighted capital requirements

	Baseline	Counterfactuals	
		I: All standard	II: All internal
	Value	Δ	Δ
	(1)	(2)	(3)
Panel A: Market structure			
Herfindahl index	15.97	-5.25	-2.87
Share top six	84.98	-25.69	-11.14
Panel B: Pass-through			
Cost	2.23	0.49	-0.13
Price	2.72	0.50	-0.14
Panel C: Credit access			
Demand (extensive)	5,529	-766	77
Demand (intensive)	134.96	-1.48	0.45
Consumer Surplus	1.12	-0.39	0.07
Panel D: Risk			
Default	1.48	0.06	-0.02
Buffer:			
All	2.21	2.57	-0.06
Top six	1.86	2.29	-0.01
Others	4.32	1.36	-1.34

Note: Baseline estimate of the model and two counterfacuals in a market for first-time buyers. In the first counterfactual scenario, all lenders adopt the standard approach for setting the risk weights. In the second counterfactual I compute the mean risk weight across IRB lenders and simulate a scenario in which SA lenders develop and internal model that gives them the average risk weight of their IRB competitors. Cost is the marginal cost in percentage points; price is the interest rate in percentage points; demand (extensive) is the total number of borrowers; demand (intensive) is the loan amount; consumer surplus is the log sum of the indirect utility of a representative consumer (see Appendix C); default is the average number of defaults in percentage points; buffer is the difference between the equity and the predicted loss. Small lenders include challengers and building societies. Value is the actual value in the benchmark and counterfactuals; Δ is the absolute change of the value in the counterfactual relative to the benchmark.

market, as large lenders are now forced to hold extra capital even for low risk mortgages. In the second counterfactual I find a small reduction in the extra buffer in the economy, which is exclusively driven by small lenders, experiencing a significant drop in risk weights, especially for low-risk mortgages. However, the buffer of small lenders remains positive and still higher than the one of large lenders, which experience almost no change as a result of the policy. Given the central role played by large lenders in a crisis (Acharya et al., 2012; Akerlof et al., 2014; Bianchi, 2016), my second counterfactual suggests that the reduction of risk weights for small lenders will not threaten the stability of the system. On the contrary, the pro-competitive effect will decrease the intermediation done by large lenders, thus reducing their systemic importance.

To summarize, I find that heterogeneous capital regulation accounts for between 20 and 30 percent of the concentration in the market. The abolition of internal models addresses the imbalance between large and small lenders in terms of capital requirements, but the higher capital reduces demand and consumer surplus. The provision of a representative internal model to small lenders could also address the competitive distortion due to the differential regulatory treatment, but with limited impact on credit access, ex-post mortgage defaults and the resilience of large lenders.[40]

6.2 Limits of Leverage Limits

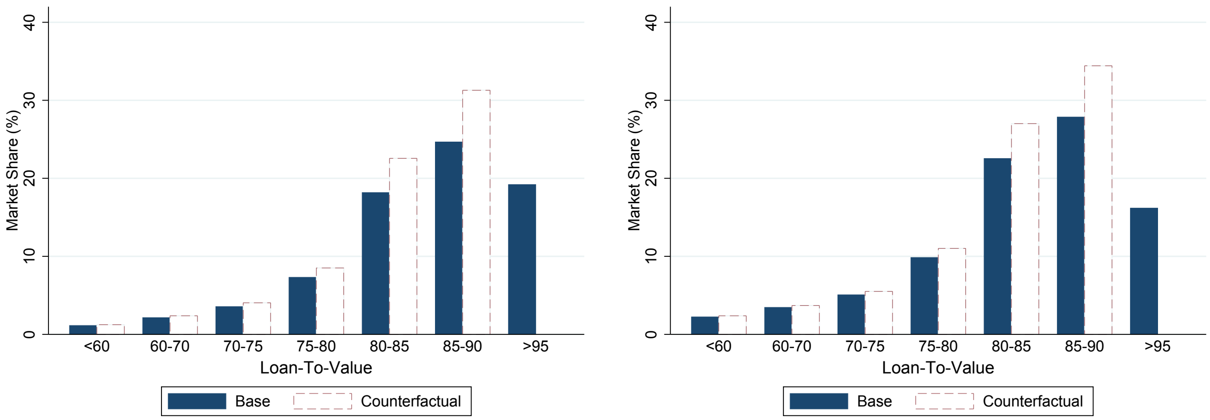
An alternative set of policies already implemented or currently under discussion to prevent the build up of risk in the mortgage market concerns explicit leverage limits (Consumer Financial Protection Bureau, 2013; DeFusco et al., 2017; Acharya et al., 2018). As an example, in the UK the Financial Policy Committee issued a recommendation in 2014 to limit new mortgage originations with a loan-to-income above 4.5 to no more than 15 percent of all new mortgage originations.[41] In this section I use the model to evaluate the equilibrium effects of an alternative policy that limits household leverage via loan-to-value limits. Most notably, I study the interaction of this policy with the capital requirement regime in place, which varies by loan-to-value as shown in Section 2.2. In this way I shed light on the equilibrium effects from jointly regulating both lenders' and borrowers' leverage.

Figure 8 shows the distribution of market shares by loan-to-value in the baseline and after the elimination of mortgages with a leverage above 90 percent. Panel (a) shows the equilibrium with a common capital requirement of 8 percent and a risk-weight of 50 percent for all lenders, as was the cases before the global financial crisis during the Basel I regime, while Panel (b) shows the equilibrium with the actual risk-weighted capital requirements. As expected mortgages with loan-to-values close to 90 percent experience the largest increase, but as prices adjust other products are affected in equilibrium.

Table 8 shows the quantification of costs and benefits, and explores potential unintended consequences due to the interaction of multiple leverage regulations. The marginal cost of lending in the market goes down, as a result of eliminating high leverage-high cost mortgages,

[40]The results in the second counterfactual are based on the assumption that the cost of developing the internal model is paid by the regulator, while if the burden falls on lenders the potential benefits may be limited. A back of the envelope calculation shows that the small lender that gains the most from the model will see an increase in profits in the mortgage market equivalent to 22 percent of its annual total profits.

[41]In Appendix B I provide evidence on the effect of the 2014 recommendation by the Financial Policy Committee on mortgage originations.



(a) Homogenous Capital Requirements (b) Risk-weighted Capital Requirements

Figure 8: Counterfactual leverage limits

Note: Mortgages in the two counterfactual scenarios for leverage regulation. In both counterfactuals I impose a maximum leverage limit at 90%, by excluding products with a maximum leverage above 90% from the choice set of all borrowers. In (a) I show the counterfactual with homogeneous capital requirements; in (b) I show the equilibrium with risk-weighted capital requirements.

and interest rates follow. The reduction in cost and rates is larger in the current regime with risk-weighted capital requirements, as high leverage mortgages require more equity funding because of the higher risk-weights.

Panel B of Table 8 shows the effect on mortgage demand and profits. Despite the overall lower rates, there is a reduction in mortgage originations for first-time buyers, dropping between 4 to 7 percent.[42] The reduction in consumer surplus as a result of the policy is even larger, despite the decrease in prices which should increase it. The large negative effect is driven not only by the extensive margin, but also by the positive valuation that households attach to high leverage mortgages, as I show in Table 3. Lenders' profits drop by around 10 percent, as the regulation removes a profitable segment of the market.

Panel C of Table 8 shows that regulating household leverage with loan-to-value limits affects risk in the mortgage market. Specifically, the limit to high leverage mortgages decreases defaults, which drop by about 9-10 percent in both cases as a result of both lower prices and lower leverage. To capture the overall riskiness in the mortgage market I also look at lenders' equity buffers. In the counterfactual with homogeneous capital requirement there is almost no change in the buffer or even a slightly positive change, as lower prices reduce defaults. In the scenario with risk-weighted capital requirements there is a 10 percent decrease in the

[42] This decrease can be seen as a lower bound to the true decrease in originations, as in the model only a small fraction of borrowers, less than 5% will be affected by this regulation. As we show in Table A8 our model slightly under-predicts mortgages with a maximum loan-to-value above 90 percent with respect to the data.

Table 8: Counterfactual leverage limits

	Capital Regulation			
	Homogenous (Pre-crisis)		Heterogeneous (Post-crisis)	
	Value (1)	Δ (2)	Value (3)	Δ (4)
Panel A: Pass-through				
Cost	2.60	-0.11	2.23	-0.17
Price	3.09	-0.11	2.72	-0.18
Panel B: Credit Access				
Demand	4,678	-356	5,354	-195
Consumer Surplus	0,7	-0,15	1,09	-0,09
Lender Profits	670,62	-77,58	810,48	-57,03
Panel C: Risk				
Default	1.38	-0.15	1.45	-0.13
Buffer				
All	3.95	0.01	3.03	-0.31
Large	3.95	0.01	2.59	-0.34
Others	3.96	0.01	4.38	-0.21

Note: Baseline estimate of the model and two counterfactuals in a market for first-time buyers. In both counterfactuals I impose a maximum loan-to-value limits of 90%. Cost is the marginal cost in percentage points; price is the interest rate in percentage points; demand (extensive) is the total number of borrowers; demand (intensive) is the average loan size; consumer surplus is the log sum of the indirect utility of a representative consumer (see Appendix C); profits is the average profit across lenders in thousand £; default is the average number of defaults in percentage points; buffer is the difference between the equity and the predicted loss. Value is the actual value in the benchmark; Δ is the change of the value in the counterfactual relative to the benchmark.

equity buffer in the market as a result of the ban on mortgages with the highest risk, but also the highest capital. According to my estimates, the decline in the buffer is even larger for the largest lenders, which experience a drop of about 13 percent, thus increasing their exposure to risk in the mortgage market.

To summarize, I find that a regulation targeting loan-to-value can be effective in reducing defaults, but with significant impact on mortgage originations. This finding resembles the results from DeFusco et al. (2017), who find a strong impact of demand and limited impact on default after the introduction of a down-payment to income limit in the US. Furthermore, I show how the interaction in equilibrium of two leverage regulations can have unintended consequences. Most notably, leverage limits applied in a market with risk-weighed capital regulation can reduce the equity buffer of large lenders, thereby increasing systemic risk.

7 Conclusion

Leverage regulation has been at the center of the academic and policy debate since the global financial crisis and there is an ongoing effort to understand better the channels through which it operates and evaluate its effectiveness. In this paper I focus on leverage regulation in the UK mortgage market, in which lenders with different capital regulations coexist and limits to household leverage have been recently introduced. I develop a tractable equilibrium model of the mortgage market that accounts for several features characterizing borrowers' demand and lenders' competition, and estimate it with a new identification strategy that exploits *within* lender variation in risk-weighted capital requirements.

I quantify the cost of capital regulation for lenders and find that a one-percentage-point increase in risk-weighted capital requirements raises the interest rate by 10 percent for the average mortgage product, when lenders can only react by adjusting their price. With the estimated model I show that heterogeneous leverage regulation shapes market structure, in particular removing the policy-driven difference in risk weights can promote competition without worsening risk. Finally, I find that loan-to-value limits reduce borrowers defaults, but have a large impact on originations and consumers' surplus, and can potentially reduce large lenders' risk-weighted equity buffers, thus affecting systemic risk.

My paper can be extended in several directions. The lender problem can be enlarged to account for the acceptance/rejection margin. This would allow leverage regulation to affect the loan supply not only through changes in loan rates, but also through changes in underwriting standards. So far, I have captured this channel in a reduced form way through affordability constraints and capital regulation affecting interest rates, as well as unobservable product characteristics. A more comprehensive model and empirical strategy that feature both the pricing and the rejection choices would be an interesting avenue for future research. Moreover, in this paper I focus mostly on the costs of risk-weighted capital requirements, their transmission on interest rates and their implications for market structure. It would be interesting to enrich my framework to account explicitly for strategic default choices on both the demand and the supply side. Adding the default option for borrowers will allow a comprehensive measure of consumers' surplus; while lenders' bankruptcy choice will provide an explicit micro-foundation for leverage regulation and a fully fledged quantification of the trade-offs. Finally, a general equilibrium approach requires house prices to adjust as well. Accounting for house price changes would create dynamic consideration on the demand side, affecting for example the extensive margin choice of buying vs renting, and feedback effects on the supply side via foreclosure externalities.

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Appendix For Online Publication

Appendix

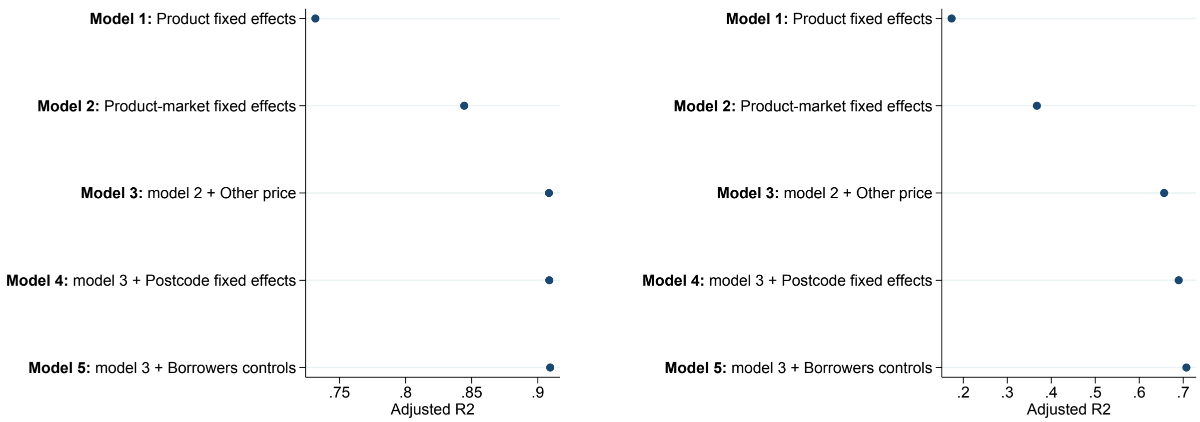
The appendix is structured as follows. Section A provides supplementary tables and figures about facts in the UK mortgage market. Section B presents additional reduced-form evidence on the effects of risk weights on mortgage rates and of loan-to-income limits on mortgage originations. Section C extends the lenders' problem when a fraction of borrowers does not refinance at the end of the initial period and completes the derivation of demand elasticities and consumer surplus. Section D provides supplementary tables and figures about the fit of the model. Section E discusses several robustness to the estimation strategy. Finally Section F provides supplementary tables and figures for the conterfactual analysis.

A Facts: Additional Material

Table A1: Market shares

	FTB	HM	RMGT
Full sample	81.5	72.5	72.5
Type			
Fix 2 years	61.7	52.8	50.7
Fix 5 years	19.9	19.7	21.8
Max LTV			
50-60	4.2	9.4	17.8
60-70	5.0	9.9	17.2
70-75	5.8	9.3	13.3
75-80	7.7	9.8	10.8
80-85	15.8	14.2	8.9
85-90	29.8	16.6	4.4
90-95	13.3	3.2	
Lender			
Big six	69.9	58.5	55.6
Challenger	4.9	5.7	7.4
Building society	6.7	8.2	9.4

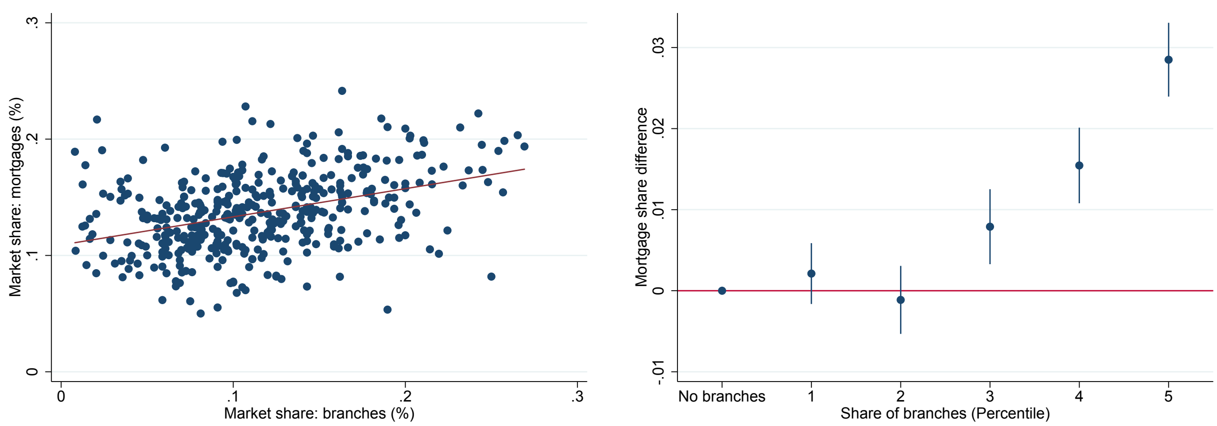
Note: Market share for different categories of product and borrower type. Shares are expressed as a ratio of the full sample of borrowers and mortgage products. The table excludes mortgages from the smaller lenders and product with a market share below 0.03%.



(a) Interest (b) Fee

Figure A1: Pricing in the mortgage supermarket

Note: Adjusted R^2 of regressions of borrower level interest rates and fees (r_{ijm} and f_{ijm}) on a set of dummy variables. Model (1) includes only dummy for the product, defined by the interaction of mortgage type, lender and loan-to-value band. Model (2) adds dummies for the market, defined by borrower type and month. Model (3) adds dummies for the other price, fee when rate is the dependent variable and viceversa. Model (4) adds dummies for the location of the house of the borrower and Model (5) includes borrower level controls (e.g. income, age).



(a) Correlation (b) Difference-in-difference

Figure A2: Branches and mortgage choice

Note: Panel (a) shows the correlation between the share of branches and the share of mortgages across postcode area in the UK for the largest six lenders. Panel (b) shows the coefficients β from the following difference in difference specification: $share_{la} = \gamma_l + \gamma_a + \sum_{k=1}^{5} \beta^k branch_{la}^k$, where γ_l and γ_a are lender and area (postcode) fixed effects and $branch_k$ are quintile of the branch share distribution. I normalize the constant to be the case of no branches in the postcode area.

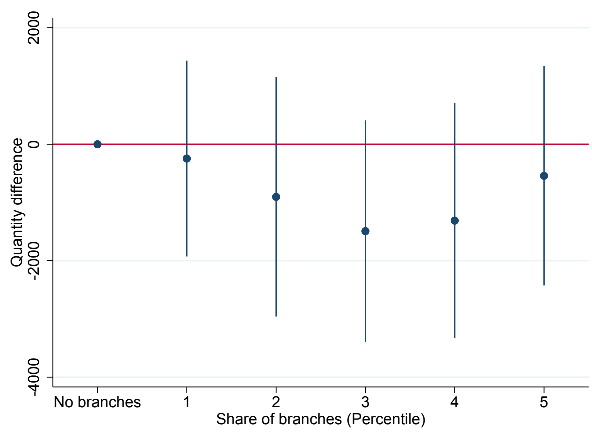


Figure A3: BRANCHES AND QUANTITY CHOICE

Note: Coefficients β from the following difference in difference specification: $q_{ila} = \gamma_l + \gamma_a + \sum_{k=1}^{5} \beta^k branch_{la}^k$, where q_{ila} is the loan amount taken by borrower i borrowing from lender l in area a, γ_l and γ_a are lender and area (postcode) fixed effects and $branch_k$ are quintile of the branch share distribution. I normalize the constant to be the case of no branches in the postcode area.

B Reduced-Form Evidence

This section add to the evidence provided in Section 2.2 and complements the counterfactual simulations of Section 6 by looking at the link between leverage regulation, mortgage pricing and mortgage originations.

Risk-weighted capital requirements. I test more formally the effect of risk weights on interest rates using the full variation across lenders, loan-to-values and over time with the following fixed effect model:

$$r_{jm} = \beta RW_{jm} + X_j + \gamma_m + \epsilon_{jm} \tag{20}$$

where r_{jm} is the interest rate in market m for product j; RW_{jm} is the risk weight; X_j are time-invariant product characteristics (fix rate period, lender dummies); γ_m are market fixed effects. The coefficient of interest is β, which captures the reduce form effect of risk weights on mortgage rates.

Table A2 shows the results. I find that a one-percentage-point higher risk weight leads to an approximately 1.5 basis point higher interest rate. In column (2) I show the specification with the full set of fixed effects, to control for time invariant differences across lenders and for time varying common factors that affect pricing, and in column (3) I add a full set of interacted market-lender fixed effects. The results are similar across these specifications. In the remaining columns I run model (20) separately for the different borrower types. I find a strong and significant effect of risk-adjusted capital requirements for first-time buyers. A one-percentage-point higher risk weight translates into a 3.4 basis points higher mortgage rate. The effect is lower, but significant for home movers, and not different from zero for remortgagers.

Leverage limits. I provide reduced-form evidence about the effects of regulating household leverage, exploiting variation from a recommendation by the Financial Policy Committee (FPC) in June 2014 that limited mortgage originations with a loan-to-income (LTI) above 4.5 to 15 percent of the total number of new mortgage loans (Bank of England, 2014).[43] I divide lenders into two groups based on their fraction of mortgages with a loan-to-income above 4.5 before the date of the recommendation, and I define as treated the lenders with a fraction above the median. Figure A4 shows the quarterly change in the share of mortgages above the limit for the two groups. Until the recommendation date, the two groups' trend are very similar, while a gap opens between them

[43] For more details about the recommendation see `http://www.bankofengland.co.uk/financialstability/Pages/fpc/loanincome.aspx`. The main statement says: "The Prudential Regulation Authority (PRA) and the Financial Conduct Authority (FCA) should ensure that mortgage lenders do not extend more than 15 percent of their total number of new residential mortgages at loan to income ratios at or greater than 4.5. This recommendation applies to all lenders which extend residential mortgage lending in excess of £100 million per annum. The recommendation should be implemented as soon as is practicable."

Table A2: Risk weights and pricing

	Whole sample			Borrower type		
	(1)	(2)	(3)	(FTB)	(HM)	(RMGT)
Risk weights (%)	0.014***	0.014***	0.016***	0.034***	0.011*	0.005
	(0.003)	(0.004)	(0.004)	(0.006)	(0.005)	(0.005)
Fix 5		0.731***	0.733***	0.692***	0.731***	0.739***
		(0.047)	(0.047)	(0.061)	(0.063)	(0.049)
Min down (%)		-0.043***	-0.042***	-0.044***	-0.046***	-0.032***
		(0.004)	(0.004)	(0.005)	(0.006)	(0.004)
Market F.e.	Yes	Yes	No	Yes	Yes	Yes
Lender F.e.	No	Yes	No	Yes	Yes	Yes
Market-Lender F.e.	No	No	Yes	No	No	No
R^2	0.17	0.72	0.75	0.77	0.72	0.75
Observations	3423	3423	3423	1070	1248	1105

Note: Coefficients of regression (20). The depedent variable is the interest rate at the product level. Risk weights are the regulatory risk weights expressed in percentage terms. Fix 5 is a dummy for mortgages with a fix period of 5 years. Max LTV is the maximum LTV the mortgage product. The columns FTB, HM and RMGT shows the result of the models with lender and time fixed effects in the subsample of first-time buyers, home movers and remortgagers, respectively. All standard errors are double clustered at the product-time level.

after the event. Lenders in the treatment group reduce more new high loan-to-income mortgages relative to the control group.

To study the effect of loan-to-income limits on mortgage originations, I exploit variation coming from the FPC recommendation in a difference-in-difference setting:

$$Share_{lm} = \beta_1 Treatment_l + \beta_2 Post_m + \beta_{12} Treatment_l \times Post_m + \epsilon_{lm} \tag{21}$$

where $Share_{lm}$ is the portfolio share of mortgages offered by lender l with an LTI above 4.5 in market m; $Treatment_l$ is a dummy equal to one if the lender is above the median market share of high LTI before the introduction of the limit; $Post_m$ is a dummy equal to one from June 2014 onwards. The coefficient of interest is β_{12}, which captures the reduce form effect of the policy change on high loan-to-income originations.

Table A3 shows the results. In column (1) I show the baseline difference-in-difference model and I find that treated lenders reduce their fraction of high LTI mortgages by almost four percent more relative to control lenders. In column (2) I add a full set of time and lender fixed effects. The result is still significant and the magnitude is unaffected. Finally, in the remaining columns of table A3 I explore heterogeneity across borrower types. I find that the impact of the FPC recommendation on loan-to-income limits is strongest for first-time buyers and lower for home movers and remortgagers. In the next section I focus on the effects of regulating household leverage on the first-time buyer market that is the most likely to be affected, as the reduced form evidence suggests.

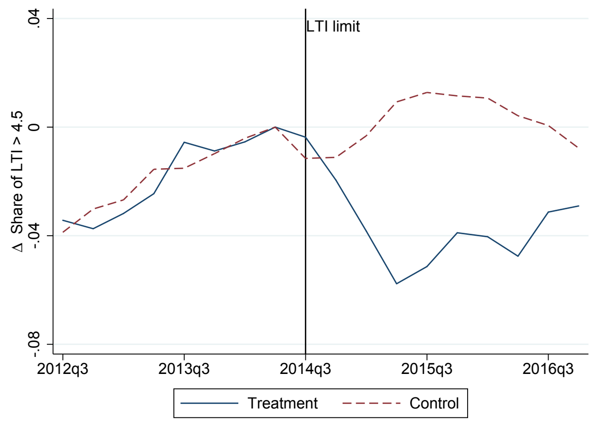


Figure A4: Loan-to-income limit and originations

Note: change in the percentage of mortgages with a loan-to-income (LTI) above 4.5 for two groups of lenders in each quarter. Treatment includes all lenders in the sample with an average share of LTI above 4.5 higher than the median in the period before the treatment.

Table A3: LTI limits and originations

	Whole sample		Borrower type		
	(1)	(2)	(FTB)	(HM)	(RMGT)
Treatment	0.066***				
	(0.011)				
Post	0.018**				
	(0.007)				
Treatment × Post	-0.039***	-0.039***	-0.076***	-0.025*	-0.015*
	(0.011)	(0.013)	(0.025)	(0.012)	(0.008)
Time F.E.	No	Yes	Yes	Yes	Yes
Lender F.E.	No	Yes	Yes	Yes	Yes
R^2	0.18	0.37	0.47	0.73	0.78
Observations	756	756	252	252	252

Note: Coefficients of regression (21). The dependent variable is the share of LTI above 4.5 in lenders' portfolio share. Treatment is a dummy equal to one is the lender is above the median in the fraction of mortgages with an LTI above 4.5 before the date of the recommendation. Post is a dummy equal to one in all periods after the FPC reccommendation in June 2014. The columns FTB, HM and RMGT shows the result of the models with lender and time fixed effects in the subsample of first-time buyers, home movers and remortgagers, respectively. All standard errors are double clustered at the lender-time level.

C Model: Additional Material

This section extends the lender problem in the model of Section 3.2 to the case when a fraction of borrowers does not refinance at the end of the initial period and derives the demand elasticities reported in Section 5 and the consumer surplus reported in the counterfactual analysis of Section 6.

Profit maximization. Here I derive the more general model for the pricing of mortgages, that accounts for a fraction of households not refinancing at the end of the initial period. The present value adjusted for refinancing risk is given by:

$$PV(q, r, R, t, T) = q \sum_{k=1}^{t} \left[\frac{r(1+r)^T}{(1+r)^T - 1} - \frac{c(1+c)^T}{(1+c)^T - 1} \right] + \gamma b \sum_{k=t+1}^{T} \left[\frac{R(1+R)^{T-t}}{(1+R)^{T-t} - 1} - \frac{c(1+c)^{T-t}}{(1+c)^{T-t} - 1} \right], \tag{22}$$

where $R > r$ is the reset rate, t is the length of the initial period and b the remaining balance at the end of the initial period. I also allow for the possibility that borrowers default like in the model from Section 3.2, assuming that lenders setting interest rate do not forecast the probability of default in each period, but consider an average proability of default, as in Crawford et al. (2018). The net return becomes:

$$PV(q, r, R, t, T) \approx q\left[t(r-c) + \gamma(T-t)(R-c)\right] - dq\left[tr + \gamma(T-t)R\right] = q\left[tr + \gamma(T-t)R\right](1-d) - q\left[tc + \gamma(T-t)c\right]. \tag{23}$$

Given the demand system and the present value of the net revenue from interest payment 23, the problem of the lender becomes:

$$\max_r \Pi_{lm}(r_{jm}) = \sum_{j \in J_{lm}} \Pi_{jm}(r_{jm}) = \sum_{j \in J_{lm}} \sum_{i \in I_t} s_{ijm}(r_{jm}, r_{-jm}) \times PV(r_{jm}) = \sum_{j \in J_{lm}} \sum_{i \in I_m} s_{ijm}(r_{jm}, r_{-jm}) \times q_{ijm}(r_{jm}) \times \underbrace{\left[(t_j r_{jm} + \gamma_j(T_j - t_j)R_j)(1 - d_{ijm}) - (t_j + \gamma_j(T_j - t_j))c_{jm}\right]}_{\chi_{jm} = \text{Effective mark-up}}. \tag{24}$$

If we assume that the initial interest rate does not affect the probability of remortgaging $\frac{\partial \gamma}{\partial r} = 0$, the derivative of the profits with respect to the price of product j is given by (we remove the market subscript m for simplicity):

$$\frac{\partial \Pi_j}{\partial r_j} = S_j Q_j (1 - D_j) t_j + S_j \frac{\partial Q_j}{\partial r_j}\left[(t_j r_j + \gamma_j(T_j - t_j)R_j)(1 - D_j) - (t_j c_j + \gamma_j(T_j - t_j)c_j)\right] + \sum_{k \in J_l} \frac{\partial S_k}{\partial r_j} PV_k - S_j Q_j \frac{\partial D_j}{\partial r_j}(t_j r_j + \gamma_j(T_j - t_j)R_j) = 0, \tag{25}$$

where the capital letters denote aggregate values at the product level. Solving for the initial interest rate gives:

$$r_j^* = \overbrace{\frac{c_j(t_j+\gamma_j(T_j-t_j))}{t_j\left((1-D_j)-\frac{\frac{\partial D_j}{\partial r_j}}{\frac{\partial S_j}{\partial r_j}\frac{1}{S_j}+\frac{\partial Q_j}{\partial r_j}\frac{1}{Q_j}}\right)}}^{\text{Effective marginal cost}} + - \overbrace{\frac{1}{\frac{\partial S_j}{\partial r_j}\frac{1}{S_j}+\frac{\partial Q_j}{\partial r_j}\frac{1}{Q_j}-\frac{\partial D_j}{\partial r_j}\frac{1}{1-D_j}}}^{\text{Full mark-up}}$$
$$-\underbrace{\gamma_j\frac{R_j(T_j-t_j)}{t_j}}_{\text{“Add-on” effect}} - \underbrace{\sum_{k\neq j\in J_l}\frac{\frac{\partial S_k}{\partial r_j}PV_k}{t_j\left(\frac{\partial S_j}{\partial r_j}Q_j(1-D_j)+S_j\frac{\partial Q_j}{\partial r}(1-D_j)-S_jQ_j\frac{\partial D_j}{\partial r_j}\right)}}_{\text{Other products}}. \tag{26}$$

Note that if there is no default risk ($\frac{\partial D_j}{\partial r_j}=0$ and $D_j=0$), all borrowers remortgage at the end of initial period ($\gamma_j=0$) and demand one unit of loan ($Q_j=1$), and all lenders offer only one product then equation (26) collapses to the standard mark-up pricing formula: $r_j^*=c_j-\frac{S_j}{\frac{\partial S_j}{\partial r_j}}$. Compare to the optimal price from Section 3.2 the marginal cost is higher to account for the fraction that does not refinance the loan, but the add-on effects lower the optimal rate, as the lenders are getting the revenues from the reset rate.

Demand elasticities. The discrete-continuous choice model loan demand elasticity and product share demand elasticity are respectively given by:

$$\epsilon^q_{ijm}=\frac{\partial q_{ijm}}{\partial r_{jm}}\frac{r_{jm}}{q_{ijm}}=\frac{\partial\ln(q_{ijm})}{\partial r_{jm}}r_{jm}=-\alpha r_{jm} \tag{27}$$

$$\begin{aligned}\epsilon^d_{ijm} &= \frac{\partial s_{ijm}}{\partial r_{jm}}\frac{r_{jm}}{s_{ijm}}=-\mu\exp(-\alpha r_{jm}+\beta X_j+\xi_{jm}+\eta D_i+\zeta_i)s_{ijm}(1-s_{ijm})\times\frac{r_{jm}}{s_{ijm}}\\ &= -\alpha\mu\exp(-\alpha r_{jm}+\beta X_j+\xi_{jm}+\eta D_i+\zeta_i)(1-s_{ijm})r_{jm}\end{aligned} \tag{28}$$

The elasticity at the product-market level are computed by averaging across consumers:

$$\epsilon^q_{jm}=\frac{1}{N_{jm}}\sum_{i=1}^{N_{jm}}\frac{\partial q_{ijm}}{\partial r_{jm}}\frac{r_{jm}}{q_{ijm}} \tag{29}$$

$$\epsilon^d_{jm}=\frac{1}{N_{jm}}\sum_{i=1}^{N_{jm}}\frac{\partial s_{ijm}}{\partial r_{jm}}\frac{r_{jm}}{s_{ijm}} \tag{30}$$

Consumer surplus. I calculate expected consumer surplus following Small and Rosen (1981). To convert the utility measure into money terms I face a complication due to the fact that income enters non-linearly. Herriges and Kling (1999) discuss alternative options to allow for non-linear income effects. I adopt the representative consumer approach and compute welfare within each group type, thus allowing for observable heterogeneous effects for different income and age groups and regions. The expected compensating variation $E[cv]$ for a change in interest rate, all else equal, is given implicitly by:

$$E\left[\max_{j\in J^0} U(y, r_j^0, X_j, \epsilon_j)\right] = E\left[\max_{j\in J^0} U(y, r_j^1 - cv, X_j, \epsilon_j)\right] \tag{31}$$

Where r_j^0 is the price of product j before the change and r_j^1 is the price after the change. The expected compensating variation when I remove products from the choice set as a result of the leverage limit, is given by:

$$E\left[\max_{j\in J^0} U(y, r_j^0, X_j, \epsilon_j)\right] = E\left[\max_{j\in J^1} U(y, r_j^1 - cv, X_j, \epsilon_j)\right] \tag{32}$$

Where J^1 is the new choice set. The change in expected consumer surplus is then given by:

$$\Delta E[CS] = \frac{1}{\lambda}\left[\ln(\sum_{j=1}^{J^1} \exp(V_j^1)) - \ln(\sum_{j=1}^{J^0} \exp(V_j^0))\right] \tag{33}$$

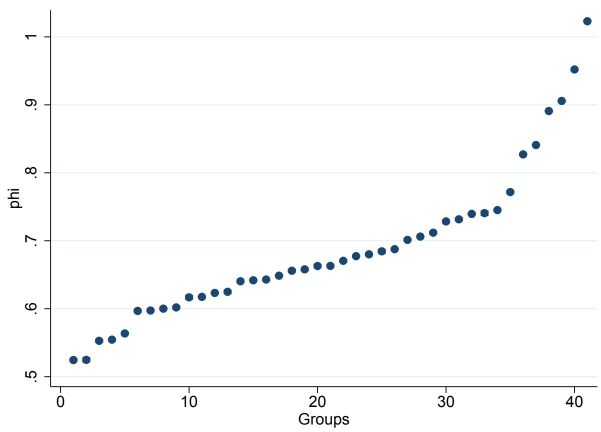
With $\lambda = \gamma Y^{-\phi}$.

D Fit: Additional Material

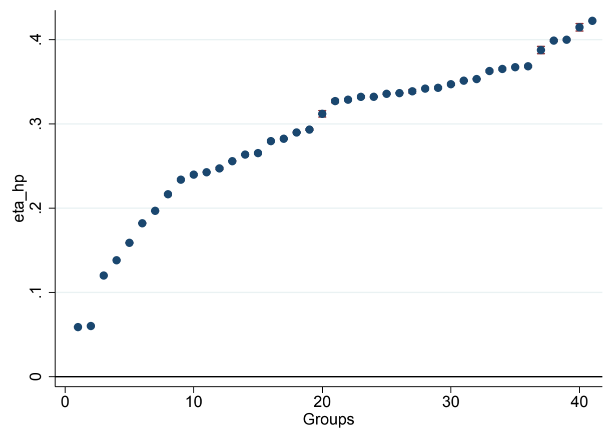
Table A4: Structural demand estimates: heterogeneity

	All	Income		Age		Region		
		poor	rich	young	old	London	West Mid	Scotland
Demographics								
Income (ϕ)	0.7003	0.7342	0.6664	0.7005	0.7000	0.8298	0.6509	0.6849
	0.0007	0.0006	0.0008	0.0006	0.0008	0.0005	0.0007	0.0008
Age (η)	0.0003	-0.0011	0.0017	0.0040	-0.0052	0.0012	-0.0011	0.0012
	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
house price (η)	0.2658	0.2202	0.3115	0.2495	0.2904	0.1083	0.3077	0.3027
	0.0005	0.0004	0.0005	0.0004	0.0005	0.0003	0.0005	0.0005
Mortgage attributes								
Interest ($-\alpha$)	-0.0251	-0.0261	-0.0241	-0.0246	-0.0257	-0.0334	-0.0258	-0.0227
	0.0023	0.0022	0.0024	0.0023	0.0023	0.0028	0.0023	0.0023
High LTV (β)	0.0103	0.011	0.0095	0.0101	0.0105	0.0156	0.0106	0.0057
	0.0019	0.0018	0.0019	0.0019	0.0018	0.0023	0.0018	0.0019
Fix 5 (β)	0.0247	0.0255	0.0237	0.0244	0.025	0.0318	0.027	0.021
	0.0033	0.0032	0.0034	0.0033	0.0033	0.0043	0.003	0.0033
Application costs								
Branches (λ)	0.0192	0.0479	-0.0095	0.0020	0.0451	-0.0149	0.0731	0.0176
	0.0112	0.0121	0.0103	0.0120	0.0100	0.0167	0.0112	0.0084
Heterogeneity-scaling								
σ (log)	-1.6080	-1.7213	-1.4948	-1.7097	-1.4556	-2.0137	-1.5974	-1.4159
	0.0091	0.0090	0.0091	0.0092	0.0088	0.0109	0.0088	0.0084
μ	24.6685	31.9220	17.4150	25.2748	23.7590	46.3085	18.5678	19.9492
	0.0575	0.0731	0.0419	0.0562	0.0594	0.1013	0.0452	0.0479
$\ln(\frac{\alpha}{\gamma})$	-2.0815	-2.2392	-1.9239	-2.0300	-2.1588	-2.3085	-1.8684	-2.1812
	0.0026	0.0022	0.0031	0.0024	0.0030	0.0020	0.0026	0.0030
Elasticities								
Loan demand	-0.08	-0.08	-0.07	-0.07	-0.08	-0.08	-0.08	-0.07
Product demand	-6.40	-6.46	-6.29	-6.32	-6.51	-7.12	-6.34	-5.94
Fixed effects								
Lender	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F stat	178	190	164	180	176	167	197	177
N likelihood	609,878	652,732	567,024	661,456	532,510	719,920	577,760	586,975
N second stage	773	819	720	772	774	682	853	776
N borrowers	370,575	185,291	185,286	191,209	179,368	48,018	32,781	35,919

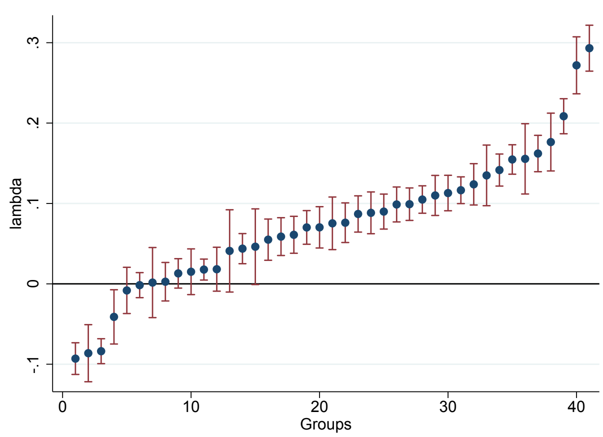
Note: Structural demand estimates of the econometric demand model of Section 4.2. The model is estimated separately in each group and the table report the average point estimate and standard error in each group. The standard error for the paramters in the first stage are computed by the inverse of the information matrix; the standard errors for the mortgage attributes estimated in the second stage are computed by boostrapping. The loan demand and product demand elasticities follows from assumption on the indirect utility and are described in Appendix C. The F stat is the average F statistics for the exluded instrument in the second stage instrumental variable regressions in each group. N likelihood is the average number of observation in the first stage (borrower-product pairs); N second stage is the average number of observation in the second stage (product-market); N borrowers in the total number of borrowers in each column.



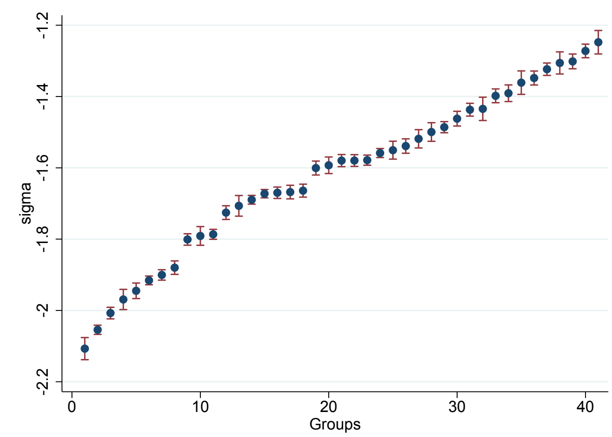
(a) Income (log)



(b) House prices (log)



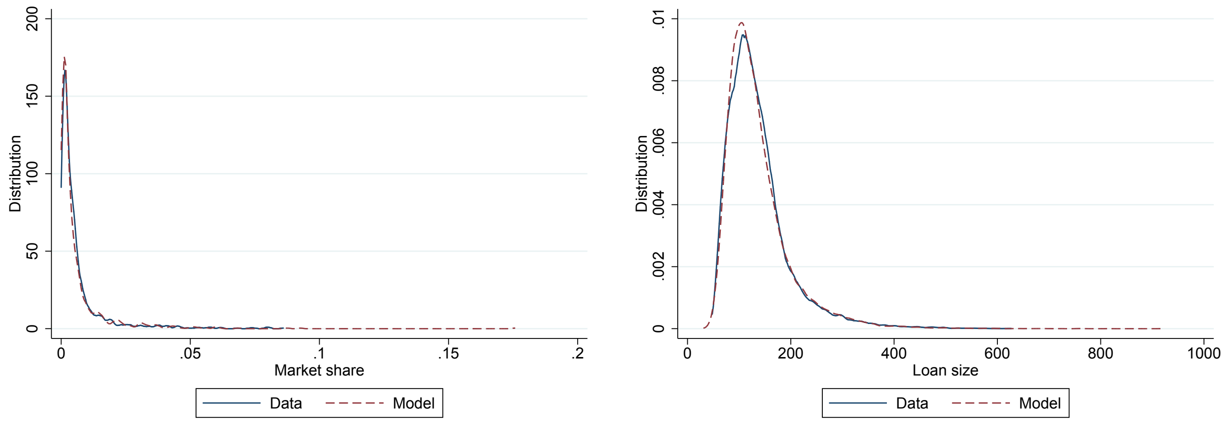
(c) Branches (log)



(d) Heterogeneity

Figure A5: Demand parameters: first stage

Note: Structural demand parameters estimated in the first step by maximum likelihood for each group. The standard error are computed by the inverse of the information matrix. In each panel the coefficients are ordered in ascending way. The blue dots represent point estimates; the red bars 95% confidence intervals.

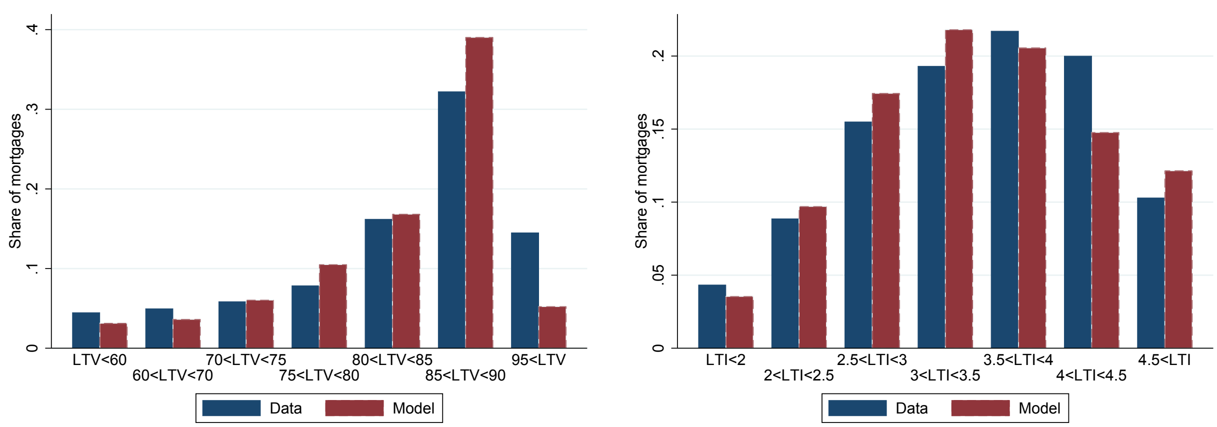


(a) Product share

(b) Loan demand

Figure A6: Model fit: product and loan demand

Note: Panel (a) shows the kernel density for the market share of all product. Panel (b) shows the kernel density for the loan value. The blue bars are the data, while the red bars the model. The market share in the data are computed as the sum of mortgage originations for each product in each market divided by the total number of households. The market share for the model comes from the sum of the individual predicted probabilities. Loan demand is the actual loan value for the chosen product, while for the model we use the predicted loan demand for the chosen product in the true data. I use a random subsample of 10% of the whole population.



(a) Loan-To-Value

(b) Loan-To-Income

Figure A7: Model fit: LTV and LTI

Note: Panel (a) shows the percentage of borrowers in each LTV band. Panel (b) shows the percentage of borrowers in each LTI band. The blue bars are the data, while the red bars the model. The LTV distrution from the data is computed as the share of LTV within each maximum LTV. The LTV distrubution for the model is computed by summing the predicted probabilities at each maximum LTV. The LTI distribution use the loan demand from chart A6 and sum across maximum LTI. I use a random subsample of 10% of the whole population.

Table A5: Elasticities: own and cross product demand

-5.66	0.01	0.00	0.07	0.07	0.07	0.07	0.06	0.06	0.02
0.05	-6.92	0.00	0.07	0.07	0.07	0.07	0.06	0.06	0.02
0.05	0.01	-4.95	0.07	0.07	0.07	0.07	0.06	0.06	0.02
0.05	0.02	0.00	-2.90	0.07	0.07	0.07	0.07	0.06	0.02
0.05	0.01	0.00	0.08	-3.25	0.07	0.07	0.06	0.06	0.02
0.05	0.01	0.00	0.08	0.07	-3.17	0.07	0.06	0.06	0.02
0.05	0.01	0.00	0.08	0.07	0.07	-3.20	0.06	0.06	0.02
0.05	0.01	0.00	0.07	0.07	0.07	0.07	-3.43	0.06	0.02
0.05	0.01	0.00	0.07	0.07	0.07	0.07	0.06	-5.73	0.02
0.05	0.01	0.00	0.07	0.07	0.07	0.07	0.06	0.06	-7.15

Note: Interest rate elasticities for a random subsample of first-time buyers. The elasticities are computed using the structural parameters from Table 3 and the formulas in Appendix C. I show the own- and cross-product demand elasticities for the ten most popular products in a market.

Table A6: Mark-ups

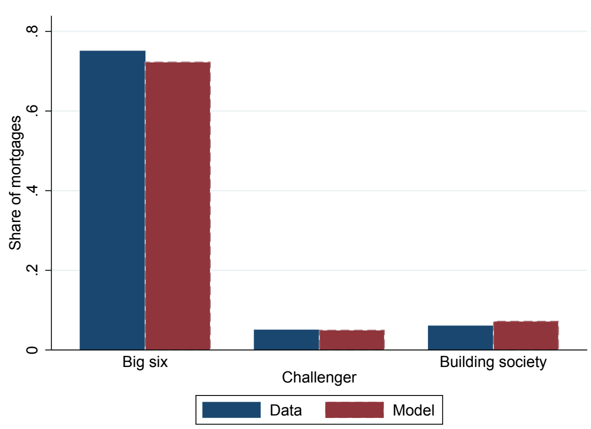
	Obs	Only disc		Disc-Cont		Full	
		(pp)	(%)	(pp)	(%)	(pp)	(%)
All	1,070	0.525	19.3	0.496	18.3	0.493	18.1
Lender type							
Big 6	662	0.510	18.9	0.482	17.9	0.480	17.8
Challengers	168	0.550	19.2	0.519	18.1	0.517	18.0
Building societies	240	0.549	20.5	0.517	19.4	0.515	19.3
LTV band							
LTV $\leq$ 70	224	0.477	22.0	0.451	21.0	0.449	20.7
70 $<$ LTV $\leq$ 80	512	0.525	21.1	0.495	19.9	0.492	19.8
LTV $>$ 85	334	0.558	14.8	0.527	14.0	0.525	13.9
Deal type							
2 years	576	0.522	21.6	0.492	20.3	0.489	20.2
5 years	494	0.529	16.7	0.501	15.8	0.498	15.7

Note: Markups for first-time buyers. The number of observations is given by the product-market pairs. Only disc indicates the case with only the discrete choice. Disc-cont reports the markup of the discrete-continuous choice model, without additional information about performances. Full includes both the discrete-continuous choice and default risk, captured by average arrears at the product level and the average response of arrears to the interest rate. PP stays for percentage points, while % is then we divide the markup in percentage points by the interest rate, also in percentage points. I report the average elasticities for all products and by different product characteristics: lender type, maximum LTV and fix period.

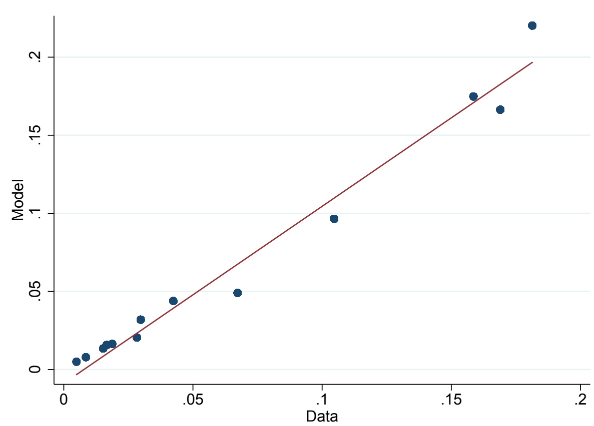
Table A7: Marginal costs

	Obs	Marginal Cost (No default)		Effective marginal cost (With Default)	
		No add-on	With add-on	No add-on	With add-on
All	1,070	2.411	4.780	2.431	4.828
Lender type					
Big 6	662	2.420	4.995	2.434	5.036
Challengers	168	2.525	4.576	2.543	4.615
Building societies	240	2.306	4.330	2.341	4.402
LTV band					
LTV $\leq$ 70	224	1.783	4.362	1.793	4.396
70 $<$ LTV $\leq$ 80	512	2.095	4.070	2.104	4.092
LTV $>$ 85	334	3.316	6.148	3.358	6.245
Deal type					
2 years	576	2.117	5.605	2.098	5.543
5 years	494	2.775	3.890	2.796	3.921

Note: Marginal costs for first-time buyers. The number of observations is given by the product-market pairs. Marginal cost indicate the case of equation (8) without default risk ($D_j = 0$ and $\frac{\partial D_j}{\partial r_j}$). Effective marginal cost includes both the discrete-continuous choice and default risk, captured by average arrears at the product level and the average response of arrears to the interest rate. Without add-on is the case of equation (8) with every borrowers refinancing at the end of the initial period t ($\gamma_j = 0$), while with add-on is the case with a fraction $\gamma_j > 0$ paying the higher standard variable rate. The marginal costs are expressed in percentage points. I report the average elasticities for all products and by different product characteristics: lender type, maximum LTV and fix period.



(a) Lender type



(b) Lender

Figure A8: Model fit: Lender

Note: Panel (a) shows the percentage of borrowers for each lender type. I divide lenders into three groups: largest six lender, challengers lenders and building societies. The blue bars are the data, while the red bars the model. Panel (b) shows the correlation between the market share in the data and the market share predicted by the model. I use a random subsample of 10% of the whole population.

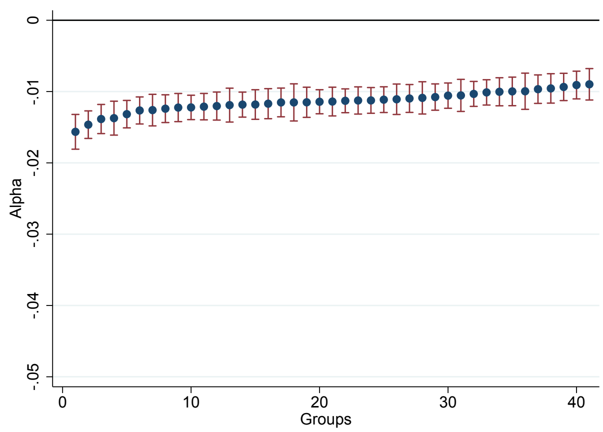
Table A8: Model fit

	In sample					Out of sample				
	mean	sd	p10	p50	p90	mean	sd	p10	p50	p90
Loan value										
Data	136.4	64.6	75.0	121.7	212.2	140.9	66.2	76.5	126.0	220.0
Model	135.3	64.5	76.3	119.7	213.8	141.4	66.4	79.2	125.5	221.8
LTI										
Data	3.5	0.8	2.3	3.6	4.6	3.6	0.8	2.4	3.6	4.6
Model	3.5	0.9	2.4	3.5	4.6	3.6	0.9	2.4	3.5	4.8
Shares										
Data	1.2	2.1	0.1	0.4	3.0	1.2	2.4	0.1	0.5	2.8
Model	1.2	2.4	0.1	0.4	2.9	1.2	3.0	0.0	0.3	2.6
LTV										
Data	80.7	11.2	62.5	84.8	90.0	81.4	11.2	63.1	85.0	90.7
Model	83.4	5.4	74.8	85.1	88.8	84.9	4.6	76.9	86.5	90.0

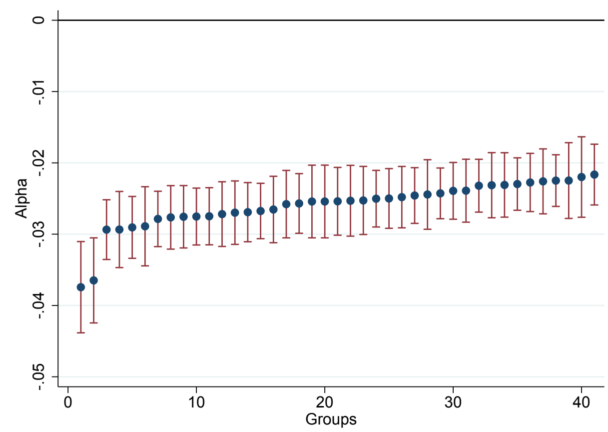
Note: Fit of the estimated demand model for several variables both in sample and out of sample. The out of sample use the parameters estimated with 2015-2016 data on a random subsampe of 2017 data. Loan value for the data is the actual loan value for the chosen product, while for the model I use the predicted loan demand for the chosen product in the true data. The LTI distribution use the true and predicted loan value for the chosen product and the income from the data. The product shares in the data are computed as the sum of mortgage originations for each product in each market divided by the total number of households. The market share for the model comes from the sum of the individual predicted probabilities. The LTV from the data use the true LTV for the chosen product. The LTV distribution for the model is computed by summing the predicted probabilities at each maximum LTV.

E Robustness

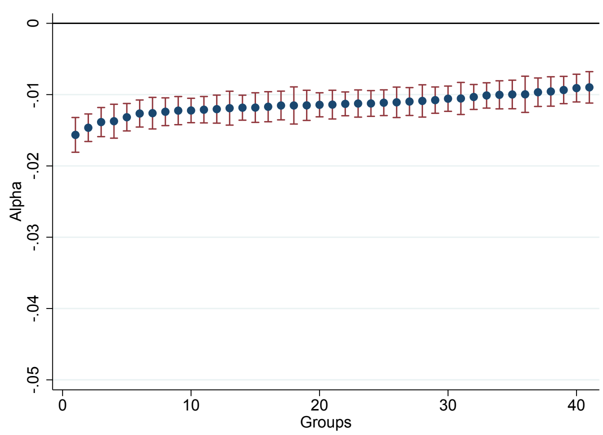
In this section I show several robustness checks for the main demand parameter estimates that I presented in Section 5.1. Figure A9 shows the structural parameters capturing the demand elasticity to the interest rate for the OLS model and two IV models. Panel b shows the case in which we use the risk-weights of the lender originating the mortgage as an instrument for the interest rate; Panel d shows the case in which we use the average risk-weights of other lenders as an instrument for the interest rate. Figure A10 reports the same parameter for two additional exercises. In Panel a I estimate the model using the Annual Percentage Rate (APR) as the price variable, thus also including information on the fees. In Panel b I estimate jointly the second step demand parameters and the supply parameters with simulated method of moments. I construct the moments using the structural demand error term in each group of borrowers from equation (15) and the structural supply error term from equation (17).



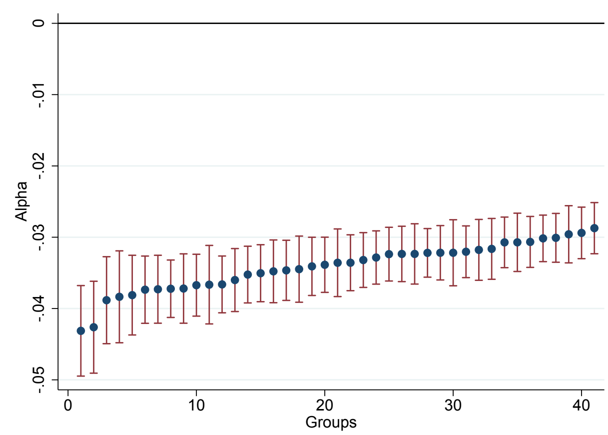
(a) OLS



(b) IV: Risk weights



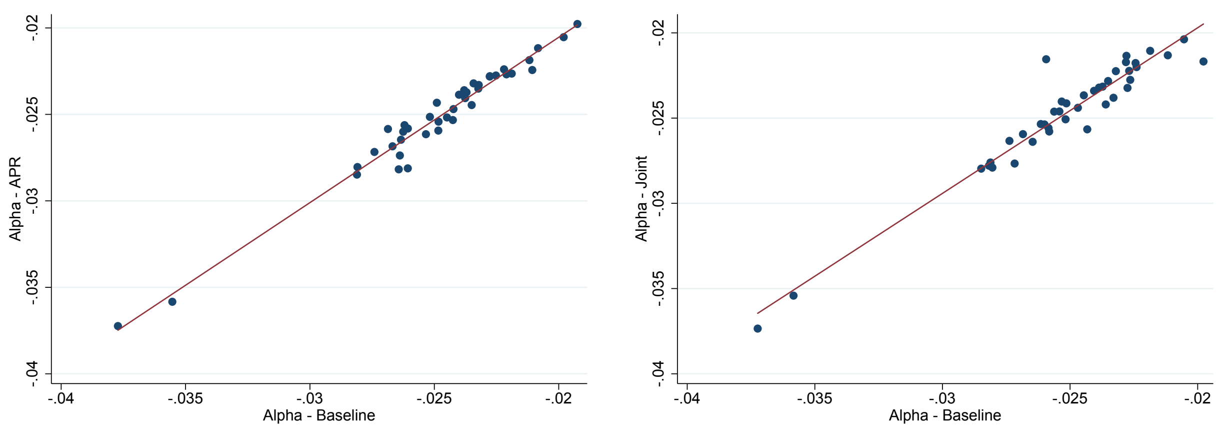
(c) OLS



(d) IV: Risk weights (others)

Figure A9: Demand parameters: second stage - OLS and IVs

Note: Coefficient on the interest interest rate (α) of the structural demand model. Figure (a) and (c) report the ordinary least square estimates; Figure (b) reports the instrumental variable estimates using regulatory risk weights; Figure (d) reports the instrumental variable estimates using regulatory risk weight of other lenders. Groups are defined as in Section 4.1 based on region, income and age. Robust standard errors in parenthesis. In each panel the coefficients are ordered in ascending way. The blue dot represent the point estimates; the red bar the 95% confidence intervals.



(a) Annual Percentage Rate (APR)

(b) Joint estimation

Figure A10: Demand parameters: second stage - APR and joint estimation

Note: Panel (a) shows the correlation between the alpha coefficient for my baseline model and the same model in which we substitute the initial interest rate with the annual percentage rate (APR). The APR is computed using the initial interest rate and origination fee and a representative loan size, as advertised in https://www.moneysupermarket.com/mortgages/. Panel (b) shows the correlation between the alpha coefficient for my baseline model and the same model when I estimate jointly the second step demand parameters and the supply parameters with simulated method of moments.

F Counterfactuals: Additional Material

This section describes additional results related to the discussion on the magnitude of the effects of changes in capital requirement of Section 5.2.1 and the counterfactual simulations of Section 6.

Table A9 shows the results from a common increase in capital requirements by 10 percentage points for all lenders. As a result of the increase in capital requirements the marginal cost of lending increase by about 60 basis points and mortgage rates increase by 63 basis point. The higher prices lead to a decrease in product demand by approximately 15 percent, while loan amount decrease by about 2 percent. For the household that continue to borrow from the lenders after the policy change the monthly payment increase by about £60 and the monthly payment to gross income ratio raise from about 20 to 22 percent. As a result consumers surplus decrease by approximately 50 percent and lenders' profits decrease by almost 40 percent. The higher debt burden leads to an increase in borrowers' default by about 10 percent, but the average capital buffer across lenders increases by almost 90 percent, thus increasing their loss absorbing capacity.

Table A9: Common increase in capital requirements

	Value	Δ	Δ (%)
Cost	2.23	0.60	28.51
Price	2.71	0.63	23.89
Demand	5,364.60	-812.04	-15.14
Quantity	134.91	-2.43	-1.80
Monthly payment	662.59	60.79	9.21
PTI	20.28	1.86	9.21
Consumer surplus	1.10	-0.47	-53.73
Lender profits	798.64	-121.95	-39.40
Default	1.08	0.11	10.27
Buffer	3.03	2.68	88.44
HI	16.71	7.19	43.03
Big Six	86.27	6.73	7.80

Note: Results from the counterfactual simulation in which I increase the capital requirements by 10 percentage points for all lenders in a random subsample of first-time buyers. Cost is the marginal cost in percentage points; price is the interest rate in percentage points; demand is the total number of borrowers; quantity is the average loan amount; monthly payment is the monthly payment from the mortgage; PTI is the monthly payment divided by the gross income of the borrower; consumer surplus is the log sum of the indirect utility of a representative consumer (see Appendix C); lender profits is the average profit across lenders in thousand £; default is the average number of defaults in percentage points; buffer is the difference between the equity and the predicted loss. Value is the actual value in the benchmark and counterfactuals; Δ is the absolute change of the value in the counterfactual relative to the benchmark; Δ% is the percentage change of the value in the counterfactual relative to the benchmark.

Finally, the common increase in capital requirements lead to a higher concentration in the mortgage market, as measured by both the HI and the share of the big six. Figure A11 shows the average change in mortgage rates after a common increase in capital requirements by 10 percentage points for all lenders. Large banks increase rates by about 45 basis points on average, while small banks raise them by more than 80 basis points. Largest lenders suffer less from the common increase

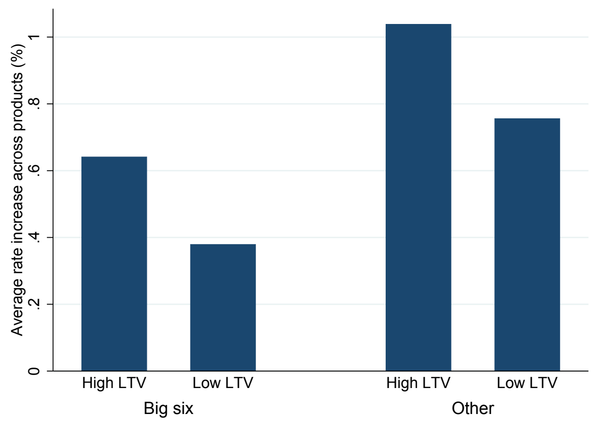


Figure A11: Mortgage rate changes after common capital increase

Note: Average change in interest rate across products from the counterfactual simulation in which I increase the capital requirements by 10 percentage points for all lenders in a random subsample of first-time buyers. Average changes are for large and small banks and for mortgages with high and low loan-to-value. High loan-to-value is defined as mortgages with a maximum loan-to-value greater than 85 percent.

in capital requirements, because of their lower risk-weighted adjusted increase, thus gaining market shares from their smaller competitors.

Table A10 shows the results of the counterfactuals analysis of Section 6.1 for different loan-to-values. Panel A shows the effects of removing the heterogeneity in risk-weighted capital requirements on market structure. The market at low loan-to-values is more concentrated to start with. The average HI is 22 percent and the largest six lenders originate almost 90 percent of new low loan-to-value mortgages, relative to an HI of about 13 and a market share of approximately 80 percent for high loan-to-value mortgages. As a result of the abolition of internal models the market becomes more competitive. Large lenders lose the regulatory advantage, increase rates and loose market shares in favor of smaller lenders already adopting the standard regulatory approach. Both the HI and the share of the largest six lenders drop as a result, but according to the HI the effects are stronger for low loan-to-value mortgages, while the share of the largest six lenders has a larger decline for high loan-to-value mortgages. The adoption of internal models for small lenders also has a pro-competitive effect on the market. In this case the redistribution from large to small lenders is stronger for low loan-to-value mortgages according to both measures.

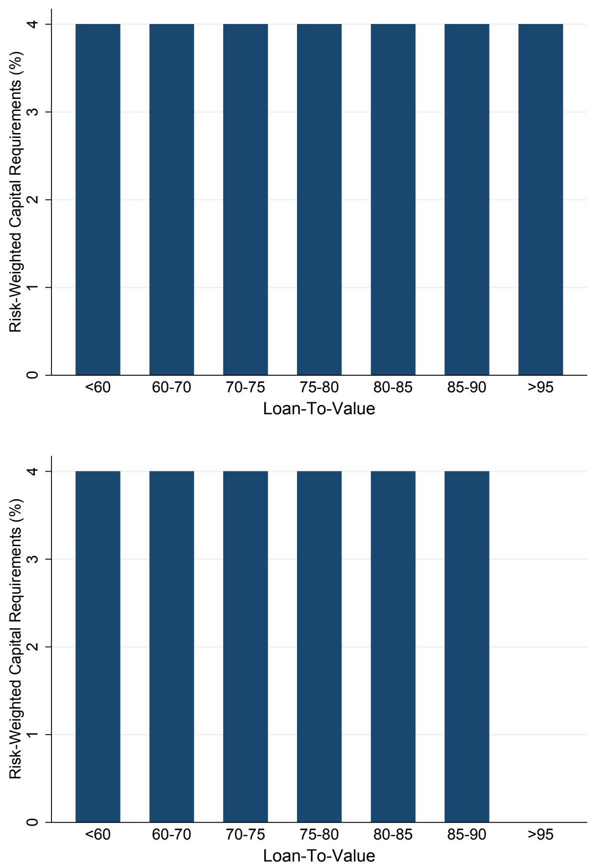
Panels B and C of Table A10 look at the aggregate pass-through and the implication for access to credit. As expected marginal costs and prices are higher for high loan-to-value mortgages in the baseline scenario. I find that eliminating internal models increase the cost in the market by about 35 basis points for high loan-to-value mortgages and almost twice as much for low loan-to-value mortgages. The latter are the mortgage products more directly affected by the elimination of the internal rating based models. As a result of higher mortgage prices, demand decreases by about 2 percent along the extensive margin, as about 70 high loan-to-value borrowers switch to the outside option. For low loan-to-values the drop in demand is about 30 percent. The average loan size (intensive margin) decrease by approximately £1.2K for high loan-to-value mortgages and by about £600 more for low loan-to-value mortgages, as a result of the larger increase in prices. In the second counterfactual, marginal costs in the mortgage market go down by about 13 basis points, as a result of lower capital requirements for small lenders. This fall translates into a reduction in prices by about 14 basis points and an increase in mortgage demand by one percent for high loan-to-value mortgages and 2 percent for low loan-to-value mortgages. When all banks adopt the standard approach, as a result of overall higher prices, average consumer surplus decreases by more than 30 percent, while when all banks adopt an internal model the lower prices increase consumer surplus by about 6 percent for both high and low loan-to-value mortgages.

In Panel D of Table A10, I first look at borrowers' default. The expected default predicted by the model in the baseline case is about 1.6 percent for high loan-to-value and 1.4 for low loan-to-value mortgages. With the abolition of internal models I observe an increase in default which is larger for low loan-to-value mortgages that experience a larger increase in the price. In the second counterfactual lower prices and relative small changes in credit access translate into lower defaults, which decrease by approximately 0.02 percentage points. I also report the equity buffer as the difference in pounds between lenders' equity and expected losses for each mortgage. Abolishing internal models almost doubles the equity buffer in the mortgage market, as large lenders are now forced to hold extra capital even for low risk mortgages. In the second counterfactual I find a small reduction in the extra buffer in the economy, which is exclusively driven by small lenders, experiencing a significant drop in risk weights, especially for low-risk mortgages. However, the buffer of small lenders remains positive and still higher than the one of large lenders, which experience almost no change as a result of the policy.

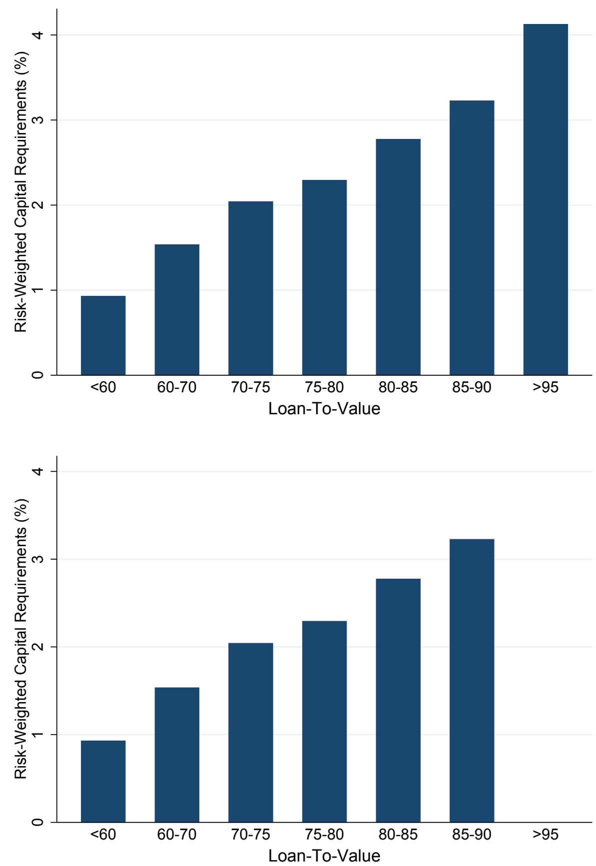
Table A10: Counterfactual risk-weighted capital requirements: by LTV

	High LTV			Low LTV		
	Baseline	I: All standard	II: All internal	Baseline	I: All standard	II: All internal
	Value	Δ	Δ	Value	Δ	Δ
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Market structure						
Herfindahl index	13.82	-0.82	-2.30	22.43	-10.31	-4.19
Share top six	81.83	-29.26	-10.65	89.39	-16.84	-11.86
Panel B: Pass-through						
Cost	3.05	0.32	-0.12	1.86	0.57	-0.14
Price	3.56	0.32	-0.13	2.34	0.58	-0.14
Panel C: Credit access						
Demand (extensive)	3,226.81	-65.25	33.22	2,303.47	-700.94	44.25
Demand (intensive)	134.18	-1.22	0.43	135.93	-1.80	0.47
Consumer Surplus	1.11	-0.41	0.08	1.14	-0.37	0.07
Panel D: Risk						
Default	1.55	0.05	-0.02	1.38	0.08	-0.02
Buffer:						
All	2.60	2.52	-0.06	1.67	2.41	-0.06
Large	2.16	2.05	-0.01	1.47	2.56	-0.01
Other	4.67	1.42	-1.19	3.45	0.77	-1.33

Note: Baseline estimate of the model and two counterfacuals in a market for first-time buyers. High loan-to-value is defined as mortgages with a maximum loan-to-value greater than 85 percent. In the first counterfactual scenario, all lenders adopt the standard approach for setting the risk weights. In the second counterfactual I compute the mean risk weight across IRB lenders and simulate a scenario in which SA lenders develop and internal model that gives them the average risk weight of their IRB competitors. Cost is the marginal cost in percentage points; price is the interest rate in percentage points; demand (extensive) is the total number of borrowers; demand (intensive) is the loan amount; consumer surplus is the log sum of the indirect utility of a representative consumer (see Appendix C); default is the average number of defaults in percentage points; buffer is the difference between the equity and the predicted loss. Small lenders include challengers and building societies. Value is the actual value in the benchmark and counterfactuals; Δ is the absolute change of the value in the counterfactual relative to the benchmark.



(a) Counterfactual I: Homogenous Capital Requirement + 90% LTV Limit



(b) Counterfactual II: Heterogeneous Capital Requirement + 90% LTV Limit

Figure A12: Interaction of different leverage regulations

Note: Risk-weighted capital requirements for different counterfactuals at different loan-to-value levels. Panel a shows at the top the case in which all banks have a capital requirement of 8 percent and a risk-weight of 50 percent, as in the Basel I regime; Panel b shows at the top the risk-weighted capital requirement in the current system, averaging across banks with both internal model and standardized approach. The bottom panels show the two cases after removing mortgages with a loan-to-value above 90 percent.