Leverage Regulation and Market Structure:

An Empirical 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 variation in risk-weighted capital requirements across lenders and across mortgages with differential loan-to-values, I show that a one-percentage-point increase in risk-weighted capital requirements increases the marginal cost of lending by 25 basis points on average. The estimated model implies that heterogeneous leverage regulation increases the concentration of mortgage originations, as large lenders exploit a regulatory cost advantage. Counterfactual analyses uncover potential unintended consequences of policies regulating household leverage, since banning the highest loan-to-value mortgages may reduce large lenders' equity buffers, thereby affecting risk.

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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., 2016; DeFusco et al., 2016; Jiménez et al., 2017). Despite the growing importance of leverage regulations, there is scarce empirical evidence on their costs and 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 (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., 2016; Greenwood et al., 2017).

In this paper I develop an empirical model to quantify the cost of risk-weighted capital requirements and to study the equilibrium impact of heterogeneous leverage regulation on credit access, risk-taking and market structure. 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 across lenders and 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 can disentangle the separate effects of higher rates on substitution across mortgage products and aggregate deleveraging. I identify the demand side with two exclusion restrictions. First, I assume that local branch presence affects the probability of choosing a mortgage but not the conditional loan demand. This exclusion restriction allows the separation of the discrete and continuous parts of the demand model. Second, I assume that the risk-weighted capital requirements are uncorrelated with the unobservable demand shocks and use them as instruments to identify the demand elasticity to the endogenous interest rate. I find that a 10 basis points increase in the interest rate decreases loan demand by 0.25 percent and the market share of the product by approximately 20 percent.

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 and refinancing to back out unobservable marginal costs at the product level. I estimate the supply side with a difference-in-difference identification strategy that exploits variation in risk-weighted capital requirements across lenders and across leverage levels. This strategy allows me to identify the shadow value 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 capital requirement increases the marginal cost of issuing a mortgage by about 25 basis points.

I use the estimated structural parameters, together with exogenous variation from changes in capital requirements and leverage limits, 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 new regulation as well as for changes in their competitors' behavior. Motivated by proposals to reform capital requirements (Basel Committee on Banking Supervision, 2016b,a), 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 lenders. Overall, removing the policy-driven difference in risk weights reduces concentration in the market by between 20 and 30 percent.

The policy-driven comparative advantage that I identify with my counterfactuals affects lenders' market power and competition in the sector, with possible unintended implications for the transmission of policy interventions to mortgage rates (Scharfstein and Sunderam, 2014; Drechsler et al., 2017; Agarwal et al., 2017). Specifically, I study the pass-through of a one-percentage-point increase in risk-weighted capital requirements in three different competitive scenarios: 1) the full pass-through that some previous studies assume (See Firestone et al. (2017) among others); 2) the benchmark market structure that I have estimated with my empirical model; and 3) an intermediate case in which I limit market power by removing differences in brand value and branch network, but retain product differentiation. I find that the pass-through is approximately 5 percent larger when there is imperfect substitution across mortgages than in the standard case. As I reduce market power, the pass-through moves toward the benchmark case.

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., 2016). 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 can have 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.

Related literature. 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., 2015; 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; 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 the first to also account for lenders' response to demand preferences with a structural equilibrium model.

Second, my work contributes to recent papers that employ structural techniques to understand competition in financial markets, like retail deposits (Egan et al., 2017), insurance (Koijen and Yogo, 2016), corporate lending (Crawford et al., 2015) and pensions (Hastings et al., 2013). To the best of my knowledge, this paper is the first to apply similar techniques to the mortgage market and study the implication 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, my paper contributes to the growing literature assessing the effectiveness of new macro-prudential regulation both theoretically (Freixas and Rochet, 2008; Rochet, 2009; Vives, 2010; Admati and Hellwig, 2014) and empirically (Acharya et al., 2014; Behn et al., 2016; DeFusco et al., 2016). 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. 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, thus providing a building block for a more general equilibrium analysis of macro-prudential regulation (Justiniano et al., 2015; Greenwald, 2016; Begenau and Landvoigt, 2016).

The rest 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. Finally, Section 7 concludes.

2 Data and Setting

2.1 Data

My 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 the information about 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 in June 2016. Second, I exploit data on lenders' capital requirement and resources from the historical regulatory databases held by the Bank of England (Harimohan et al., 2016; De Ramon et al., 2016); 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' house with geographical information on both the distance from the lenders' headquarters and the house price index at the postcode level from the ONS statistics database.

[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]This information 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 details in Benetton et al. (2016).

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] he 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 variables at the lender level. 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.

2.2 Setting and Facts

In this section, I document some stylized facts about the UK mortgage market on regulation, pricing, originations and performances that guide both the empirical model and the identification strategy.

[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. (2014) 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 (%)	1155079	2.65	0.81	1.24	5.19
Fee (£)	1155079	631.50	602.25	0.00	2381.00
Fix 2 years	1155079	0.64	0.48	0.00	1.00
Fix 5 years	1155079	0.22	0.42	0.00	1.00
Loan value (£.000)	1155079	177.89	93.94	47.99	631.29
LTV (%)	1155079	77.60	12.16	50.00	95.00
LTI (%)	1155079	3.32	0.89	1.09	5.00
First-time buyers (%)	1155079	0.34	0.47	0.00	1.00
Home movers (%)	1155079	0.32	0.47	0.00	1.00
Remortgagers (%)	1155079	0.32	0.47	0.00	1.00
Maturity (Years)	1155079	25.69	6.64	5.00	40.00
Gross income (£.000)	1155079	57.08	30.86	16.79	233.72
Age (Years)	1155079	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

Notes: the table reports 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.

2.2.1 Mortgage Product

Figure 1 (a) shows a snapshot from a popular UK search platform for mortgages. 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] In my setting a market is a borrower type-time combination. In Figure 1 (b) I show the second snapshot from the same search platform 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. I define a product

[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.

Figure 1: Choice-set

(a) Borrower types

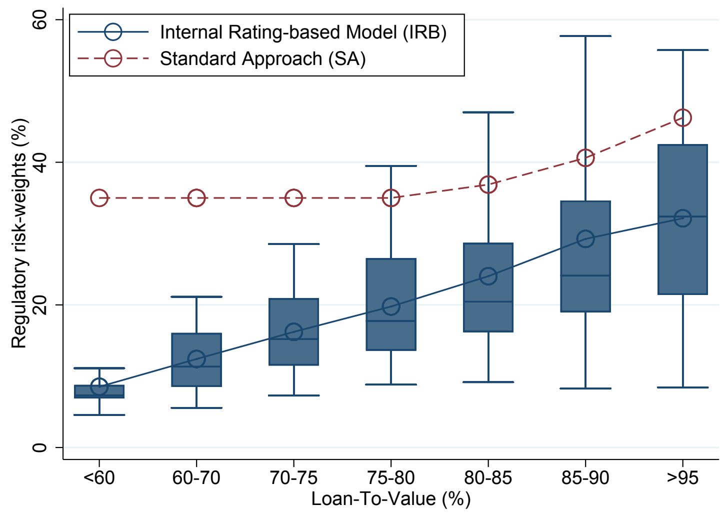
Provider	Initial monthly cost	Initial rate	Type of mortgage	Max LTV
HSBC	£ 635.05	1.99% then 3.94%	Fixed for 25 months	90%
The Loughborough Building Society	£ 639.44	2.05% then 4.99%	Discounted Variable for 24 months	90%
Yorkshire Building Society	£ 641.64	2.08% then 4.99%	Fixed for 25 months	90%
Yorkshire Building Society	£ 641.64	2.08% then 4.99%	Fixed for 25 months	90%
Leek United Building Society	£ 642.37	2.09% then 5.19%	Fixed for 27 months	90%

(b) Products

Notes: Panel (a) shows a snapshot from a search of mortgages in https://www.moneysupermarket.com/mortgages/. Panel (b) shows a snapshot after filling some information about the borrower and the property. In the empirical setting I account for all the product characteristics in Panel (b): type of mortgage, lender, maximum loan-to-value and initial interest rate.

as a combination of all of the above characteristics (e.g., Barclays, two year fixed rate, 90 percent maximum loan-to-value).

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



Notes: The chart shows the 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 homogenous manner across bank and varies between 35 percent and 45 percent based on the loan-to-value of the loan.

2.2.2 Capital Regulation

Since 2008 two approaches to calculate 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 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).

2.2.3 Mortgage Rates Setting

The price of the loan 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.[6] I test this claim in Appendix A and 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.[7]

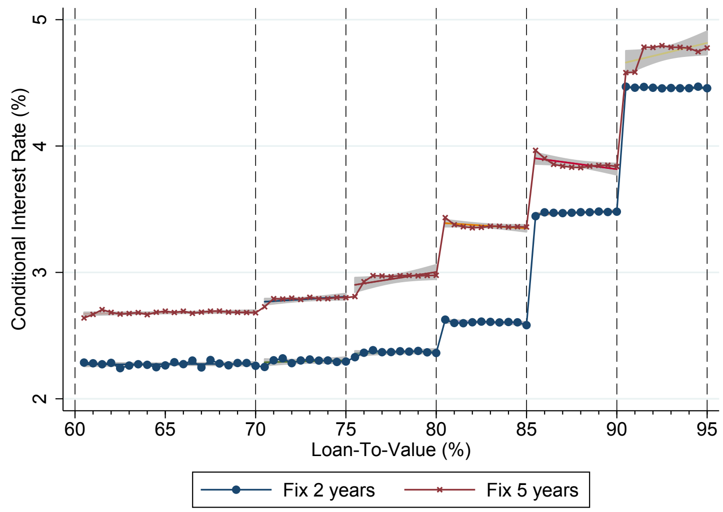
Figure 3 explores the variation in rates across maximum loan-to-values. I show the mean predicted interest rates, from a regression including mortgage and borrowers controls, as a function of the loan-to-value. I see that the lenders set the interest rate as a increasing schedule of the loan-to-value, which captures default risk (Schwartz and Torous, 1989; Campbell and Cocco, 2015), with discrete jumps at certain maximum loan-to-value thresholds (Best et al., 2015). I also explore the heterogeneity in pricing by loan-to-value according to the interest rate type. Both mortgage types show an increasing step-wise schedule with longer fixed rate mortgages always more expensive than shorter ones. This is due to the higher refinancing risk embedded in a contract with a longer fixed duration (Deng et al., 2000; Rose, 2013; Beltratti et al., 2017).

In Figure 3 (b) I study the effect of regulation and I compare a 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

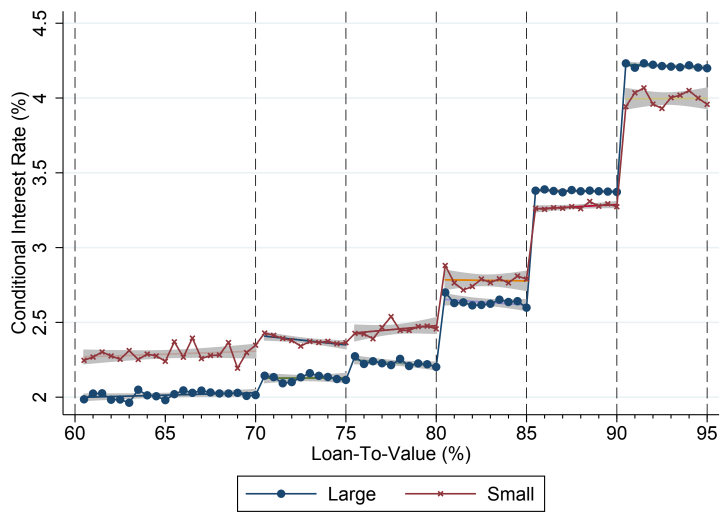
[6] Moneyfacts reports: "A personal Annual Percentage Rate is what you will pay. For a mortgage this will be the same as the advertised APR, as with a mortgage you can either have it or you can't. If you can have the mortgage, the rate doesn't change depending on your credit score, which it may do with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

[7] 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.

Figure 3: Pricing



(a) Default and Refinancing Risk



(b) Capital Regulation

Notes: the charts show the 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. Chart (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. Chart (b) reports the schedule for a representative large lender adopting the internal model and a representative small lender opting for the standardized approach.

start increasing as shown in Figure 2. The large lender offers a more competitive interest for low leverage mortgage. The gap in prices closes for intermediate leverage and even reversed for products with a loan-to-value above 85 percent.

2.2.4 Originations

The UK mortgage market is concentrated in terms of products. In Appendix A I report 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. 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.

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. Figure 4 (a) shows that 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. Home movers 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.

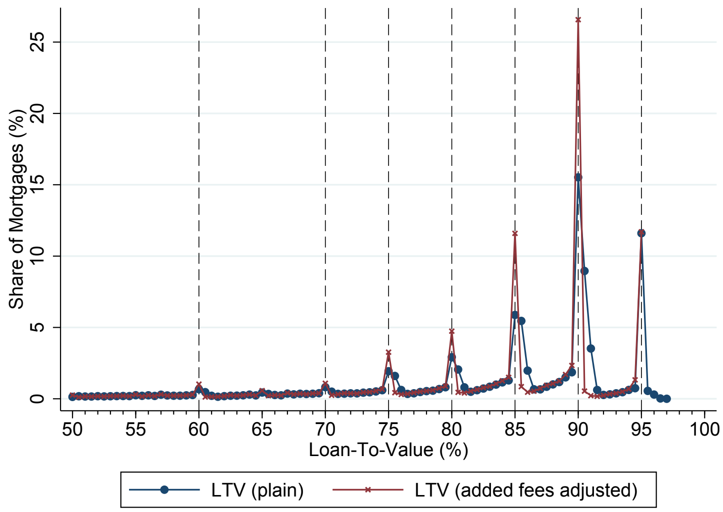
When we look at lenders, the largest six lenders account for about 70% of new mortgage originations. In the estimation I focus on the most popular mortgage types offered by the largest 13 lenders, and group other mortgages in a representative product.[8] In Figure 4 (b) I explore further the lender choice, by looking at the price and market share for two mortgage products with the same maximum loan-to-value (60 percent) and interest rate type (2 years fixed), 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 will account for factors (e.g., brand value) that can explain this effect.[9]

Finally, I look at specialization in mortgage lending across products and geographical areas, along the lines of Paravisini et al. (2015) for corporate lending. Figure 5 (a) shows the

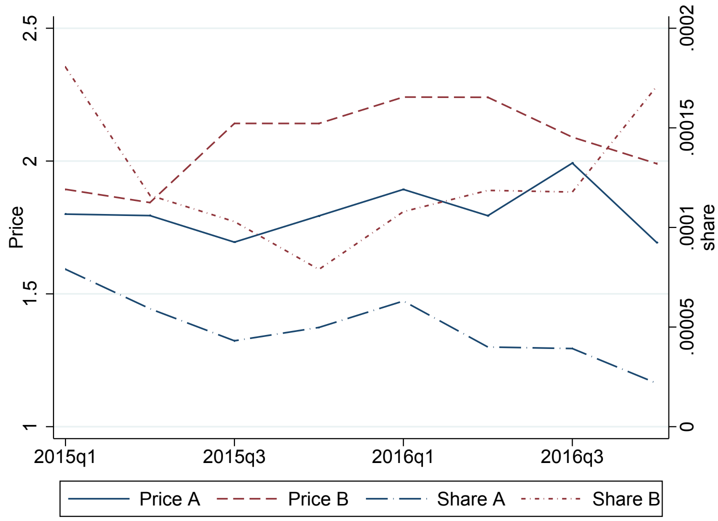
[8] In Goeree (2008) the outside option captures non-purchase, purchased of a used PC and purchase of a new PC not in the firms included; Egan et al. (2017) also consider the outside good all the banks outside the top sixteen. I further restrict the choice set by including in the representative product mortgages with a market share below 0.3%.

[9] An alternative explanation also comes from the supply side, with the low price - low market share products only approved to some customers. Due to data limitation 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 decide the best alternative. To limit concern 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. (2015).

Figure 4: Household Choice



(a) Leverage



(b) Lender

Notes: the charts show the share of mortgages originated at different loan-to-value bins. Each bin is 0.5pp wide. Panel (a) shows originations for first-time buyers, while the lower panel shows originations for home-movers. 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 price and market shares for two products for first-time buyers offered by two different lenders with the same initial period (2 years) and the same maximum loan-to-value (70 percent). 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.

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). Figures 5 (b) and (c) show that areas in which a lender has a large share of branches, the same lender originates more mortgages. 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. 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 continue to play an important role even in modern lending markets (Becker, 2007; Scharfstein and Sunderam, 2014).

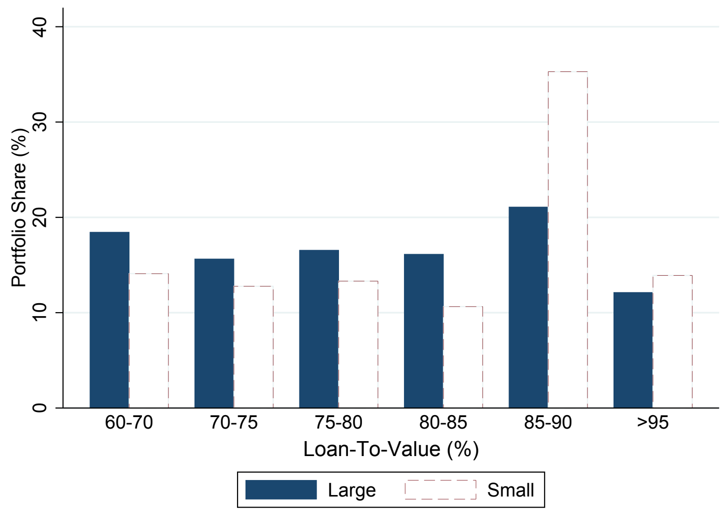
2.2.5 Performances

In Table 2 I show 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 1.5 percent. Building societies have less than 1 percent mortgages in arrears, followed by the big six lenders, at about 1.7 percent, and by challengers banks at almost 2 percent. The fraction of arrears increase monotonically with the maximum loan-to-value. This pattern is reflected in the pricing schedules of Figure 3.[10]

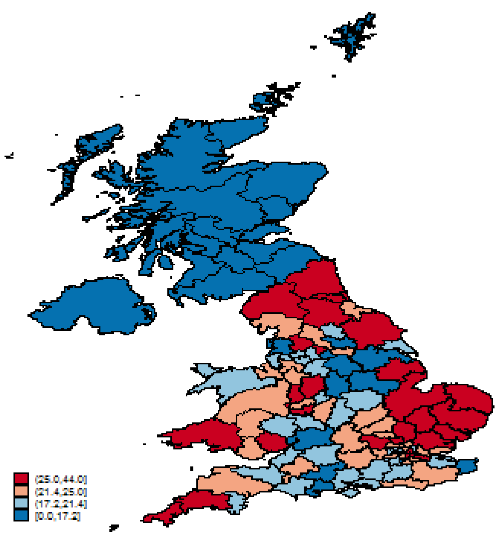
To capture refinancing risk, I consider for each product the fraction of outstanding mortgages in 2016 that are on a standard variable rate (SVR) out of the total mortgages in the lenders' balance sheet. In the UK mortgage market the SVR is the reset rate that borrowers

[10] 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.

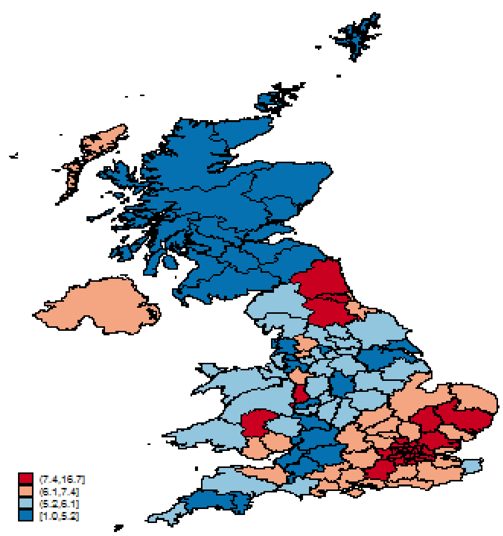
Figure 5: Specialization



(a) Portfolio Share



(b) Branch Share



(c) Mortgage Share

Notes: Panel (a) shows the portfolio shares for a representative large lender adopting the internal model and a representative small lender opting for the standardized approach. 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.

pay at the end of the initial fixed or discounted period. The refinancing variable is defined as one minus the share paying the SVR. 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 similar across lender types, while it seems to decrease with loan-to-value.

Table 2: Performances

	Arrears (1)	Refinancing (2)	SVR (3)
Full sample	1.5	78.5	3.8
Lender			
Big six	1.7	79.9	3.7
Challenger	1.9	78.7	4.0
Building society	0.8	76.1	4.0
Max LTV			
50-60	0.7	83.5	3.8
60-70	0.9	79.9	3.9
70-75	1.0	78.8	4.0
75-80	1.0	78.2	4.0
80-85	1.4	76.7	4.0
85-90	1.5	77.2	3.8
90-95	4.2	75.0	3.7

Notes: the table reports the fraction of mortgages in arrears, the fraction of borrowers paying the standard variable rate and the median standard variable rate for different categories of product and borrower type.

Finally, column (3) of Table 2 shows the SVR. The standard variable rate is always around 4 percent. Challenger lenders and building societies have an average 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 (Best et al., 2015).

3 A Structural Model of the UK Mortgage Market

In this section I develop a structural model of mortgage demand and pricing and in Section 4 I use exogenous variation in capital regulation to estimate it. The structural model allows me to: 1) decompose the effect of changes in interest rates between substitution across products and aggregate mortgage demand; 2) estimate the effect of capital requirements and leverage limits on lenders costs and products supply; 3) study how the competitive environment affects the pass-through of capital 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 accounts for the key features of the UK mortgage market and for leverage regulation, as 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. Building on Dubin and McFadden (1984), I assume that 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 the income of household i; D_i are other household demographics (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; 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 a market; ε_{ijm} is an idiosyncratic a taste shock; θ_i collect the demand parameters that I allow to vary across household.

The indirect utility in equation (1) captures 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. We enrich the standard framework to account for the non-linearities in the pricing schedules described in Section 2, by allowing the initial interest rate to depend on the maximum loan-to-value. The evidence in Section 2.2 support my assumption that in the UK mortgage market lenders set national prices, which do not vary geographically or based on borrowers' demographics.

The variables in X_j allow for horizontal differentiation at the type, leverage and lender level, thus capturing in a realistic way substitution patterns across products. A further dimension of horizontal differentiation at the transaction level is the number of branches of the lender in the postcode area of borrowers' house ($A_{ij(l)}$). In this way I account for borrowers' costs associated to the application and the formation of the choice set, along the lines of Hastings et al. (2013). 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).[11] Higher branch presence can also increase the utility for households, because they generate spatial differentiation. For example, a large branch presence allows the household to walk in a branch when needed, thus lowering transaction costs.

I impose an additional restriction to the choice set of the household based on affordability and liquidity constraints. 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). 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.[12]

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 product at a time. The constrained problem is:

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

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 the representative product with the chosen maximum loan-to-value as the outside option. An individual chooses product

[11] 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. See Basten and Koch (2015) and Michelangeli and Sette (2016) among possible exceptions.

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

j if $V_{ijm} > V_{ikm}$, $\forall j \in J_i$.

At the chosen product, the borrower decide the optimal quantity (q_{ijm}), which I obtained using Roy identity:

$$q_{ijm} = -\frac{\frac{\partial V_{ijm}}{\partial r_{jm}}}{\frac{\partial V_{ijm}}{\partial Y_i}} = q_{ijm}(Y_i, D_i, X_j, r_{jm}, \zeta_i, \xi_{jm}; \theta_i). \tag{2}$$

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 us to study issues related to the timing of the purchase, refinance or default. This will complicates the analysis, given that the timing will be affected by many additional factors not limited to the mortgage (e.g., housing and labor markets). 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 2.2.5 and Best et al. (2015)). Furthermore, strategic default is unlikely to be present 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. In my model of lenders' optimal pricing I account for default and refinancing risks.

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.[13] My focus is on acquisition pricing: initial rate and origination fees; I consider indirectly retention pricing, via the reset rate, including it as a product characteristic.[14] I assume the main source of revenue for lenders is the net interest

[13] 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.

[14] 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. As already mentioned in Section 2.2.5 the vast majority of borrowers refinance their mortgage at the time their initial rate expires. As a result, the initial rate and fees is likely to be a major source of revenues for lenders. However, a fraction of borrowers may not refinance at all or

income from the monthly payments. The present value of net interest income from a risk-free mortgage with fixed rate r_{jm} until maturity T_i is given by:

$$PV(q_{ijm}, r_{jm}, T_i) = q_{ijm} \sum_{k=1}^{T_i} \left[\frac{r_{jm}(1+r_{jm})^T}{(1+r_{jm})^T - 1} - \frac{c_{jm}(1+c_{jm})^{T_i}}{(1+c_{jm})^{T_i} - 1} \right], \tag{3}$$

where q_{ijm} is the quantity and c_{jm} is the marginal cost of borrowing for the lender when issuing product j, which I assume to be constant over time. The marginal cost of borrowing will be a function of the cost of debt, given by a spread over the risk-free rate; the cost of swapping a fixed payment for a variable payment; and the cost of capital.

Equation (3) 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. (2015). 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.[15]

For long maturity, equation (3) with refinancing and default risks becomes:

$$PV(q_{ijm}, r_{jm}, t_j, d_j) \approx q_{ijm} t_j (r_{jm} - c_{jm}) - d_j q_{ijm} t_j r_{jm} = q_{ijm} t_j r_{jm} (1 - d_j) - q_{ijm} t_j c_{jm}, \tag{4}$$

where t_j is the initial period and d_j is the average expected default probability for product j. 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 (4), I can write the problem

not exactly at the end of the initial period. This will make the reset rate a potentially profitable source of revenues for lenders, given that the reset rates are always much higher than the introductory rates (see Tables 11 and 2).

[15] In Appendix B I allow for a more flexible specification in which some borrowers fail to refinance at the end of the initial period and pay the reset 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. This is consistent with previous evidence, showing that the vast majority of borrowers that remortgage do it in a window around the end of the initial period.

of the lender as:

$$\max_{r} \Pi_{lm}(r_{jm};\theta_i) = \sum_{j\in J_{lm}} \Pi_{jm}(r_{jm};\theta_i) =$$
$$\sum_{j\in J_{lm}} \sum_{i\in I_m} s_{ijm}(r_{jm}, X_j, r_{-jm}, X_{-j};\theta_i) \times PV(q_{ijm}, r_{jm}, X_j;\theta_i) =$$
$$\sum_{j\in J_{lm}} \sum_{i\in I_m} s_{ijm} \times q_{ijm} \times \left[t_j r_{jm}(1-d_j) - t_j c_{jm}\right]. \tag{5}$$

θ_i collects all the demand parameters and the individual demographics and J_{lm} are the products offered by lender l in market m. I sum over the expected demand (s_{ijm}) coming from the product choice of all borrowers in market m. The demand parameters also affect the present value because they have an impact on the monthly payment through the quantity choice. Note that the price and characteristics of other products enters 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 (we remove the market subscript m for simplicity):

$$\frac{\partial \Pi_j}{\partial r_j} = S_j Q_j (1-d_j) t_j + S_j \frac{\partial Q_j}{\partial r_j}\left[t_j r_j (1-D_j) - t_j c_j\right]$$
$$+ \sum_{k\in J_l} \frac{\partial S_k}{\partial r_j} PV_k - S_j Q_j \frac{\partial D_j}{\partial r_j}(t_j r_j) = 0, \tag{6}$$

where 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 initial interest rate gives:

$$r_j^* = \overbrace{\frac{c_j}{(1-D_j) - \frac{\frac{\partial D_j}{\partial r_j}}{\frac{\partial S_j}{\partial r_j}\frac{1}{S_j} + \frac{\partial Q_j}{\partial r_j}\frac{1}{Q_j}}}}^{\text{Effective marginal cost}} - \overbrace{\frac{1}{\frac{\partial S_j}{\partial r_j}\frac{1}{S_j} + \frac{\partial Q_j}{\partial r_j}\frac{1}{Q_j} - \frac{\partial D_j}{\partial r_j}\frac{1}{1-D_j}}}^{\text{Full mark-up}}$$
$$- \underbrace{\sum_{k \neq j \in J_l} \frac{\frac{\partial S_k}{\partial r_j} PV_k}{t_j \left(\frac{\partial S_j}{\partial r_j} Q_j (1-D_j) + S_j \frac{\partial Q_j}{\partial r_j}(1-D_j) - S_j Q_j \frac{\partial D_j}{\partial r_j} \right)}}_{\text{Other products}}. \tag{7}$$

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 (7) collapses to the standard mark-up pricing formula: $r_j^* = c_j - \frac{S_j}{\frac{\partial S_j}{\partial r_j}}$. Equation (7) characterizes the optimal interest rate for lenders in the absence of regulatory constraints, but in reality lenders set rates accounting for regulatory constraints. 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 sheet 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 to the share of mortgage with a loan-to-income above 4.5, along the lines of Goldberg (1995) for cars' import.[16] The problem for constrained lenders becomes:

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

[16]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 section 6.2.

where K_{lm} are the time varying capital resources; $\underline{\mathrm{K}}_{lm}$ is the time varying lender specific minimum capital requirement; ρ_{jm} are the risk weights; and $\mathbb{I}[LTI > 4.5]$ is an indicator for mortgages with a loan-to-income greater than 4.5. The Lagrangian multipliers associated with the constraints represent the shadow value of leverage regulations. The equilibrium in the market is characterized by lenders optimal pricing subject to the leverage regulations.

4 Estimation and Identification

In this section I discuss the estimation of the model. 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 estimate the model using data from first-time buyers.[17] Different borrower types represent separate markets, in which lenders may offer different products. The purpose of the transaction is predetermined and restricts borrowers' choice set. I proceed in two steps to determine the products available in borrowers' choice set. First, I classify borrowers into groups based on income, age, region and quarter when they took the mortgage. I construct the choice set for borrower i including all products sold in the group g to which borrower i belongs. The rationale for this is that borrowers with similar observable characteristics consider similar alternatives.[18] 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 put an upper bound on households leverage, while unobservable differences in wealth can put a lower bound. As a result, two households in the same group may shop at different maximum loan-to-values.

I address these additional constraints in a second step, in which I further restrict the

[17] I follow the taxonomy that I show Figure 1 (a) and I also estimate the model separately for home movers, to account unobservable differences in shopping ability and experience of the mortgage market, that I do not model explicitly. The estimates for home movers are available upon request. Consistent with previous works and my reduced-form evidence in Appendix E leverage regulation has a lower impact for borrowers with already more equity in their houses.

[18] In a recent paper Crawford et al. (2016) describe the use of the choice set of similar consumer as the interpersonal logit model.

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.[19] In this way I allow borrowers to shop locally in terms of the down-payment decision, consistent with the bunching behavior from Figure 4 (a).

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 portfolio 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 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, via the branch network of the lender.

4.2 Estimation

I estimate the demand and supply side separately.[20] My model 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 parameters in each group, thus allowing for observable heterogeneity for all parameters in the model according to region, income and age.

Demand. I estimate the demand model described in Section 3.1 with two assumptions on the structural unobservables error terms. First, 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:

$$Pr(i\ chooses\ j) = p_{ijm}(\zeta_i) = \frac{exp(\bar{V}_{ijm})}{\sum_{k=0}^{J_i} exp(\bar{V}_{ikm})}, \tag{8}$$

and the unconditional probability can be found by integrating out the borrowers unobserv-

[19] As a robustness we perform all our analysis when we stop at the first step of the choice set definition, thus enlarging the choice set.

[20] I have also done a robustness exercise described in Appendix D, in which I estimate in a second step jointly the demand moments at the market level with the supply side moment. The results are very similar and the coefficient on the interest rate is shown in Appendix D.

able:

$$s_{ijm} = \int_{\zeta} p_{ijm}(\zeta_i) dF(\zeta_i). \tag{9}$$

Second, I assume that the unobservable borrower heterogeneity follows a normal distribution with variance σ ($\zeta_i \sim N(0, \sigma)$). I also make a parametric assumption on the indirect utility $\bar{V}_{ijm}$ (Train, 1986):

$$\bar{V}_{ijm} = \frac{\gamma}{1-\phi} Y_i^{1-\phi} + \mu \exp(-\alpha r_{jm} + \beta X_j + \xi_{jm} + \eta D_i + \zeta_i) + \lambda A_{ij(l)}. \tag{10}$$

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

$$\ln(q_{ijm}) = \ln\left(-\frac{\frac{\partial \bar{V}}{\partial r}}{\frac{\partial \bar{V}}{\partial y}}\right) = \phi \ln(Y_i) + \ln(\frac{\mu\alpha}{\gamma}) - \alpha r_{jm} + \beta X_j + \xi_{jm} + \eta D_i + \zeta_i. \tag{11}$$

From equation (11) and the normal distribution assumption, the probability of the conditional loan demand is:

$$\begin{aligned} f(\ln(q_{ijm})|j, j \neq 0) = \frac{1}{\sqrt{2\pi\sigma^2}} \times \exp\Bigg[-\frac{1}{2\sigma^2}\Bigg(\ln(q_{ijm}) \\ -(\phi \ln(Y_i) + \ln(\frac{\mu\alpha}{\gamma}) - \alpha r_{jm} + \beta X_j + \xi_{jm} + \eta D_i)\Bigg)^2\Bigg]. \end{aligned} \tag{12}$$

To account for the simultaneous nature of the choice of the mortgage and the loan amount I estimate the joint likelihood in one step. The joint log likelihood for individual i to buy product j and borrow an amount q_{ijm} is given by:

$$\ln(L_i) = \sum_{j=0}^{J_i} d_{ijm} \left[\ln(s_{ijm}) + \ln(f(\ln(q_{ijm})|j, j \neq 0))\right], \tag{13}$$

where d_{ijm} is an dummy equal to one if borrower i chooses product j and zero otherwise. In this way I address the simultaneity bias that can arise if I do not account for the discrete product choice, when I estimate the continuous quantity choice. 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. I estimate the joint likelihood (13) with product-market fixed effects and recover the impact of the interest rate and other product characteristics in a second step with standard instrumental variable techniques, using the estimated fixed effects as dependent variable. I rewrite equation (10) as:

$$\bar{V}_{ijm} = \frac{\gamma}{1-\phi} Y_i^{1-\phi} + \mu \exp(\delta_{jm} + \eta D_i + \zeta_i) + \lambda A_{ij(l)}. \tag{14}$$

The choice probability conditional on ζ_i will be as above with $\bar{V}_{ijt}$ given by the previous expression. The probability of the conditional loan demand (equation (12)) becomes :

$$f(\ln(q_{ijm})|j, j \neq 0) = \frac{1}{\sqrt{2\pi\sigma^2}} \times \exp\left[-\frac{1}{2\sigma^2}\left(\ln(q_{ijm}) - (\phi \ln(Y_i) + \ln(\frac{\mu\alpha}{\gamma}) + \delta_{jm} + \eta D_i)\right)^2\right]. \tag{15}$$

In the first step I estimate the joint maximum likelihood 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 use the δ_{jm} from the first step and estimate the parameters α and β with instruments that I discuss in Section 4.3:

$$\hat{\delta}_{jm} = -\alpha r_{jm} + \beta X_j + \xi_{jm}. \tag{16}$$

Supply. The estimation of the supply side parameters is based on the optimal pricing formula derived in Section 3.2. Using the estimated parameters from the demand side, additional information from lenders' balance sheets and Equation (7), I back out the effective marginal costs. I then regress the estimated costs on products characteristics and leverage regulation. I obtain a two-step estimator of the cost parameters at the product level with the following linear specification:

$$Emc_{jm} = \tau_X X_j + \tau_c c_{jm} + \tau_R \underline{\mathrm{K}}_{lm} \rho_j + \tau_m + \kappa_{jm}, \tag{17}$$

where the dependent variable (Emc_{jm}) is the effective marginal costs; X_j are the same product characteristics that affect borrower demand (rate type, maximum loan-to-value, lender); c_{jm} is the marginal borrowing cost for lender l when issuing mortgage j in market m; $K_{lm}\rho_j$ is the risk-weighted regulatory capital requirement; τ_m are market fixed effects; and κ_{jm} is a structural error term capturing unobservable cost determinants (e.g., advertising, screening).

To estimate the full lender pricing equation I need information on the average expected default rate and on the increase in defaults as a result of changes in the interest rate. I estimate a reduced form relation between interest rate and default, with a linear probability model:

$$d_{ijt} = \gamma_t + \gamma_j + \beta r_{jt} + \alpha LTI_i + \eta X_i + \epsilon_{ijt}, \tag{18}$$

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. The key parameter is β, which captures the causal effect of the interest rate on arrears and enter the optimal pricing formula (equation (7)). To isolate the effect of the interest rate at origination on arrears I control for product fixed effects (γ_j), year-quarter of origination (γ_t) and borrower level demographics (X_i). I use the estimated parameters from equation (18) 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 (18), and an indirect impact via both the discrete mortgage choice and the continuous quantity choice. Changes in interest rates will affect the loan demand and, assuming no changes in income, borrowers' loan-to-income will be affected.

4.3 Identification

I deal with endogeneity concerns, coming from both 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 (13). In this way I solve the bias that can arise if I do not account for the discrete product choice, when I estimate the continuous quantity choice. To achieve the separate identification of the discrete and continuous choices, I assume that the lenders' local branch presence affects the choice of the lender, but does not have an impact on the choice of the quantity.[21] Since I estimate

[21] Smith (2004) studies supermarket choice in the UK and assumes that car parking and distance affect the store choice, but not the number of groceries purchased; Dubois and Jódar-Rosell (2010) focus on

the model in each group separately and I control for lender fixed effects, this 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. 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 the time-invariant characteristics (X_j), but I allow for unobservable attributes that can affect demand (e.g. advertising, screening, cash-back). The identification of preferences for product characteristics comes from variation in product characteristics and lenders market shares. The key endogenous variable is the time-varying 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 our 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 for a specific product and at the same time increases the interest rate on that product. Screening effort is not observable, thus entering the error term (ξ_{jm}) and may be corrected with the interest rate, such that $E\left[\xi_{jm}|X_j, r_{jm}\right] \neq 0$). As a result, I may see borrowers still buying the product and mistakenly conclude that they are not responding to the higher interest rate, while the effect of the higher price has been countervailed by differential screening effort.

I tackle the endogeneity in interest rates in two ways. 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 supply side instruments 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 2.2.2, to construct supply-side instruments at the *product* level. I assume that the interest rate is a function of the exogenous supply side

supermarket choice in France and exclude from the expenditure decision distance between household and retailers, outlet size and number of competing retailers within 3 kilometers.

shifters and other unobserved factors:

$$r_{jm} = f(X_j, Z_{jm}; \tau) + \kappa_{jm}, \tag{19}$$

where $Z_{jm} = \underline{\mathrm{K}}_{lm}\rho_{jm}$ are exogenous supply-side shifters affecting costs (e.g., risk-weighted capital requirements); τ are cost parameters; κ_{jm} is a structural error term that captures unobservable cost shifters (e.g. advertising, screening). The identification assumption for the demand parameters is:

$$E\left[\xi_{jm}|X_j, Z_{jm}\right] = 0. \tag{20}$$

Equation (20) 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 lenders 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.[22] 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 value 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 shadow value of relaxing the

[22]In a recent paper Behn et al. (2016) 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.

constraint only with variation within lender across products. My identification strategy for the shadow value 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 value of leverage regulation across lenders, by interacting the constraints with the lender type and the equity buffer. Finally, to address any concern about endogeneity in the regulation and omitted variable bias 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. Table 3 shows the estimated demand parameters averaged across all groups. The main parameter of interest is α, which captures the effect of interest rate on indirect utility. As expected the coefficient is negative and this results is robust to different cuts of the data.[23] 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 B. I find an average loan demand elasticity of 0.08 and a product demand elasticity of 6.4.[24] 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 I can compute elasticities at various levels. In Table 4 (a) I show the average loan demand

[23] Appendix C 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. I present the instrumental variable estimates using the regulatory instruments and I show results from alternative specifications in Appendix D.

[24] The loan demand elasticity is consistent with previous studies using bunching techniques (Best et al., 2015; DeFusco and Paciorek, 2017) and survey data (Fuster and Zafar, 2015). The product demand elasticity is higher than what Crawford et al. (2015) 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
Fixed effects						
Lender	Yes	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes	Yes
F stat	178	178	178	178	178	178
N likelihood	609,878	609,878	609,878	609,878	609,878	609,878
N second stage	773	773	773	773	773	773
N borrowers	370,575	370,575	370,575	370,575	370,575	370,575

Notes: the table shows the 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 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. The loan demand and product demand elasticities follows from assumption on the indirect utility and are described in appendix B. The F stat is the average F statistics for the excluded 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.

and own product demand elasticity across different mortgage characteristics. The largest six lender 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 lower elasticity, followed by the largest six lenders. Challengers banks face the highest elasticities of mortgage demand. As a result for the same percentage increase in interest rate challenger banks both loose 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 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 whose elasticities are 0.6 and 4.8, respectively.[25]

In Table 4 (b) 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 1 percent increase in the interest rate decrease the market share of the mortgage by 3-7 percent, while the shares of other mortgages increase by 0.01-0.07 percent.

[25] Best et al. (2015) also find elasticities of demand that are larger at higher loan-to-value notches.

Table 4: Elasticities

	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

(a) Loan demand and own 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

(b) Own and cross product demand

Notes: The tables report the interest rate elasticities for a random subsample of first-time buyers. In Panel (a) I show the loan demand and own product demand elasticities. The elasticities are computed using the structural parameters from Table 3 and the formulas (24) and (25) in Appendix B. We report the average elasticities for all products and by different product characteristics: lender type, maximum LTV and fix period. In Panel (b) I show the own and cross product demand elasticities for the ten most popular products in a market.

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., 2014). 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.[26] Finally, the fraction of branches in the postcode where

[26]Even if in the UK mortgage market the vast majority of the product has an interest rate fixed for a

households have their houses has a positive impact on average, as captured by the parameter λ.

So far I focused on average effects, but the estimated model allows for rich heterogeneity, 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 (11)) 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 household even within my narrowly defined groups and controlling for observable demographics within group.

In Appendix C I explore further heterogeneity across groups that can be important to evaluate the distributional effect of alternative leverage regulations. I find that lower income households are more sensitive to the interest rate and prefer mortgages with higher maximum leverage. This result can be due to richer households having already more savings and thus being less affected by the requirement. In the case of interest rate, the lower sensitivity can be attributable to less incentives to shop around, as a result of the lower incidence of the monthly payment on their available income. Households in London are more sensitive to the interest rate and value more high leverage products. The former can be due to households in London shopping more for better deals; the latter can be driven by the higher cost of properties in London relative to households available income. Income elasticity is higher for lower income households, who are more likely to be credit constrained. Interestingly the elasticity is highest in London, where households have higher income, but face higher house prices. Unobservable heterogeneity seems to be more important for lower income and younger borrowers and for borrowers living in London.

Finally, the effect of branches is significantly stronger for borrowers with a lower income and for older people. This heterogeneity in the effect of local branches on the choice probability is consistent with the household finance literature about financial literacy. Even if we don't have a proper measure of financial literacy, income and age are often used as a proxy (**?**). We find that a larger share of local branches have a stronger effect on the less financially literate borrowers. I find that younger borrower are less affected by local branches, as they are probably more likely to use the Internet to search for the best deal on the market. The effect of branches on rich people is not significantly different from zero. I also find that

period of two years, and there are few products with a fixed rate for more than five years, I can still explore the preference to for a longer duration by comparing mortgages fixed for two versus five years.

Table 5: Model fit

	mean	sd	p10	p50	p90
Loan value					
Data	136.4	64.6	75.0	121.7	212.2
Model	135.3	64.5	76.3	119.7	213.8
LTI					
Data	3.5	0.8	2.3	3.6	4.6
Model	3.5	0.9	2.4	3.5	4.6
Shares					
Data	1.2	2.1	0.1	0.4	3.0
Model	1.2	2.4	0.1	0.4	2.9
LTV					
Data	80.7	11.2	62.5	84.8	90.0
Model	83.4	5.4	74.8	85.1	88.8

Notes: The table shows the fit of the estimated demand model. 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.

branches have a positive effect on the probability to choose a product in West Midlands and Scotland, but no effect in London. This result again in consistent with a financial sophistication story. Households in London may shop around more than borrowers in more deprived and less populated areas.

5.1.1 Fit and Robustness

I now briefly comment on the fit of the model and report on several robustness checks. Both are discussed more in detail in Appendix C and D, respectively. Table 5 looks at the ability of the model to predict some key variables of interest on the demand side, namely loan demand, loan-to-income and 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.

Table 13 in Appendix C shows the baseline markup of a discrete only model, the markup from the discrete-continuous choice model, and the effective markup that also exploits information on arrears. The average markup is about 0.53 percentage points in the full sample. Adding loan demand decreases the markup to just below 0.5, while adding default risk only has a minor impact. The markup I estimate is about 18 percent of the average interest rate in the data.[27]

There is variation in markups across lender types and other product characteristics. The markup in percentage points is on average higher for challenger banks, similar for building societies and lowest for incumbent lenders. With respect to leverage I observe an increasing pattern when I look at markups in percentage points. Mortgages with a maximum loan-to-value below 70 have a markup of about 0.47 percentage points, while products with a leverage above 85 have markups almost 0.10 percentage points larger. However, this relation is reversed when we look at markups relative to the initial interest rate. High leverage products have a lower relative markup, around 15 percent, while low leverage products' markups reach on average 20 percent of their respective interest rates. Markups on two and five years fixed products have similar patterns. The markup in percentage points is higher for products with longer duration, but the relative price is even higher. As a result mortgage with a two year fixed period have on average a 20 percent markup over the initial rate, while this ratio for mortgages with a five year fixed period is around 15 percent.

Finally, in Appendix D I report the results of 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 (16)) simultaneously with the supply side (equation (17)) using generalized method of moments. My results are robust to these different instruments, variable definitions and estimation methods.

5.2 Supply Parameters and The Cost of Capital Regulation

In this section I describe the results of the estimation of the supply parameters. I obtain the marginal cost inverting equation (7) and solving for the effective marginal costs as a function of the observed interest rates and the estimated mark-ups. In Appendix C I show the estimated marginal costs, distinguishing four cases: 1) no default and refinancing risk; 2)

[27] Button et al. (2010) perform a decomposition of new lending rate for 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.

only default risk; 3) only refinancing risk; 4) both default and refinancing risks. The average marginal cost in the sample is 2.41 percentage points and it increase by 2 basis points on average when we account for default risk. When we account for the add-on effect the marginal cost almost doubles.[28] I find that building societies have the lowest costs, followed by the big six and challengers banks. When I account for the add-on effects, large lenders' costs increase the most since they have a larger back-book of customers. As expected, high leverage and longer duration mortgages have higher costs. The effect of accounting for default risk is strongest for high leverage products for which I see an increase by more than 4 basis points, while cost for products with a maximum loan-to-value below 80 increase by only 1 basis point.

I use the estimated effective marginal cost as a dependent variable in equation (17), to decompose the effect of product characteristics and identify the cost of 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 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 1 percentage point higher risk-weighted capital requirement increases the marginal cost of lending to first-time buyers by about 57 basis points.

In column (2) 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 1 percentage point higher risk-weighted capital requirement increases the cost of lending to first-time buyers by approximately 20 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. The risk weights capture the residual variation within a certain leverage across lenders, as Figure 2 displays.

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,

[28] This strong effect is driven by two forces. First, as I show in Section 2.2.5 a relative larger fraction of borrower pays the standard variable rate. Second, I assume that borrowers who do not refinance at the end of the fix period pay the standard variable rate until maturity.

Table 6: Structural supply estimates

	Main			Heterogeneity	
	(1)	(2)	(3)	(4)	(5)
RW Capital Req (%)	0.570***	0.202***	0.262***	0.426***	0.305***
	(0.025)	(0.029)	(0.024)	(0.032)	(0.041)
High LTV		1.113***	1.032***	0.900***	1.024***
		(0.046)	(0.042)	(0.049)	(0.045)
Fix 5		0.686***	0.684***	0.709***	0.686***
		(0.022)	(0.026)	(0.021)	(0.027)
RW Capital Req (%)					
x Challenger				-0.272***	
				(0.034)	
x Building Society				0.172**	
				(0.081)	
x High buffer					-0.079**
					(0.040)
Market F.E.	Yes	Yes	No	No	No
Lender F.E.	Yes	Yes	No	No	No
Market-Lender F.E.	No	No	Yes	Yes	Yes
R^2	0.46	0.80	0.82	0.85	0.83
Observations	1070	1070	1070	1070	1070

Notes: the table shows the 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 LTV above 85. Max LTV is the maximum LTV the mortgage product. Fix 5 is a dummy for mortgages with a fix period of 5 years. Robust standard errors in parenthesis.

ruling out concerns of 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 are 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.

5.3 Default Parameters

My last set of results concern default behavior. I estimate a reduced form relation of the effect of mortgage and households characteristics on defaults. I run a linear probability model in which the dependent variable is a dummy equal to one if the borrower is at least 3 months late in the mortgage payment in June 2016. Table 7 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 0.08 percentage points. I also study how loan-to-income and loan-to-value at originations affect the probability of default. Mortgages with loan-to-income below 3 and loan-to-value below 75 are always less likely to fall in arrears. Estimates for mortgages with an loan-to-income above 4.5 and a loan-to-value above 85 are less precise.

To explore this further, 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 one percentage point, while the effect is ten times smaller for mortgages issued after the crisis. Mortgages will lower loan-to-income and loan-to-value are less 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. High loan-to-income mortgages are significantly less likely to default before the crisis, while there is no significant difference with mortgages with a loan-to-income between 3 and 4.5 originated after the crisis. 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 than mortgages with a leverage between 75 and 85. A possible explanation for the latter result can be the increase in supply side restrictions and affordability checks after the crisis, which lead to an overall low volume of originations at high leverage to a selected pool of low risk households.

Two caveats are in order here. First, I am looking at the effect of variable at originations on ex-post outcomes. As some variables will change over time (income, value of the house, and even interest rate if variable) a better specification will 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 will play an important role for pricing of the *expected* probability of arrears. Second, to use the parameters from the default model in the counterfactual analysis

Table 7: Default estimates

	Full sample		Pre-crisis		Post-crisis	
	(1)	(2)	(3)	(4)	(5)	(6)
	Arrears	Arrear 5 Y	Arrears	Arrear 5 Y	Arrears	Arrear 5 Y
Interest (%)	0.0008***	0.0013***	0.0107***	0.0070***	0.0010***	0.0005***
	(0.0003)	(0.0003)	(0.0028)	(0.0019)	(0.0002)	(0.0001)
LTI < 3	-0.0015***	-0.0004***	-0.0040***	-0.0004	-0.0006***	-0.0005***
	(0.0003)	(0.0001)	(0.0008)	(0.0002)	(0.0002)	(0.0001)
LTI > 4.5	-0.0009*	0.0000	-0.0062***	0.0002	-0.0005	-0.0004
	(0.0005)	(0.0002)	(0.0012)	(0.0003)	(0.0003)	(0.0002)
LTV < 75	-0.0053***	-0.0012***	-0.0144***	-0.0010***	-0.0020***	-0.0013***
	(0.0010)	(0.0002)	(0.0006)	(0.0002)	(0.0004)	(0.0002)
LTI > 85	0.0002	-0.0005*	0.0069***	-0.0005	-0.0014***	-0.0005***
	(0.0007)	(0.0002)	(0.0014)	(0.0006)	(0.0003)	(0.0002)
Time F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Lender F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Rate type F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Postcode district F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2717174	2717174	552506	552506	2164633	2164633

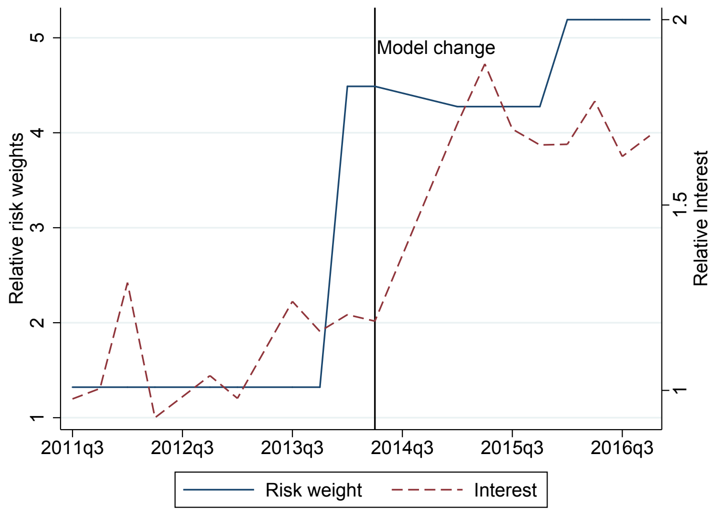
Notes: the table shows the default estimates from equation (18). The dependent variable is a dummy equal to one if a mortgage originated between 2005 and 2015 is in arrear in June 2016. We define arrears as being at least 3 months late in servicing the monthly payment. Column (1) and (2) use the full sample. Columns (3) and (4) focus on mortgages originated before 2008, while columns (5) and (6) look at mortgages originated after 2008. Interest is the interest rate at origination expressed in percentage terms. Loan-to-income is a dummy for the loan to income at originations and loan-to-value is a dummy for the loan to value at origination. The excluded dummies are one for loan-to-income between 3 and 4.5 and one for loan-to-value between 75 and 85. Borrowers controls include type of borrower, employment status, income, age, maturity and property value.

in Section 6 I need to assume that the change in the regulation does not change the relation between interest rate and default.

6 Counterfactual Leverage Regulations

In this section I use the estimated model to study alternative leverage regulations and their equilibrium impact on interest rates, credit access market structure and risk. In Section 6.1 I eliminate the risk-weight gap between large and small lenders, as Figure 2 displays. I study a first counterfactual in which all lenders calculate risk-weighted capital requirements using the standardized approach and a second counterfactual in which also small lenders adopt an internal model. In Section 6.2, I analyze the interactions between risk-weighted capital requirements and regulation limiting household leverage. I impose a maximum loan-to-value limit by removing from households' choice set all mortgages with a leverage above 90

Figure 6: MODEL CHANGE



Notes:The chart shows the 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 an IRB model.

percent and study the effect of this policy both in a counterfactual market with homogeneous capital requirements, as was the case before the crisis, and in the current regime with risk-weighted capital requirements.

6.1 Equilibrium Effects of Risk-Weighted Capital Requirements

The reduced form evidence from Section 2.2 suggests that risk-weighted capital requirement affect pricing and specialization.[29] Figure 6 explores this relation further by exploiting 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. In this way I address potential concerns about differences across lenders and selection into treatment. I compare the relative risk weight and relative interest rate for the same lender for mortgages with a maximum loan-to-value of 95 percent relative to those with a maximum of 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

[29]In Appendix E I explore further the reduced form relation between risk weights and interest rates.

leverage regulation. Furthermore, contemporaneous changes in market power and business models (e.g., securitization) can confound the effects of regulation. To address these issues, I explore with the estimated model the equilibrium impact of changes in risk-based capital requirements. 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).[30] The two policies are illustrated in Figure 7.

To illustrate the mechanism consider two mortgages 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. From (7), the difference in prices between the two lenders for product j will be given by:

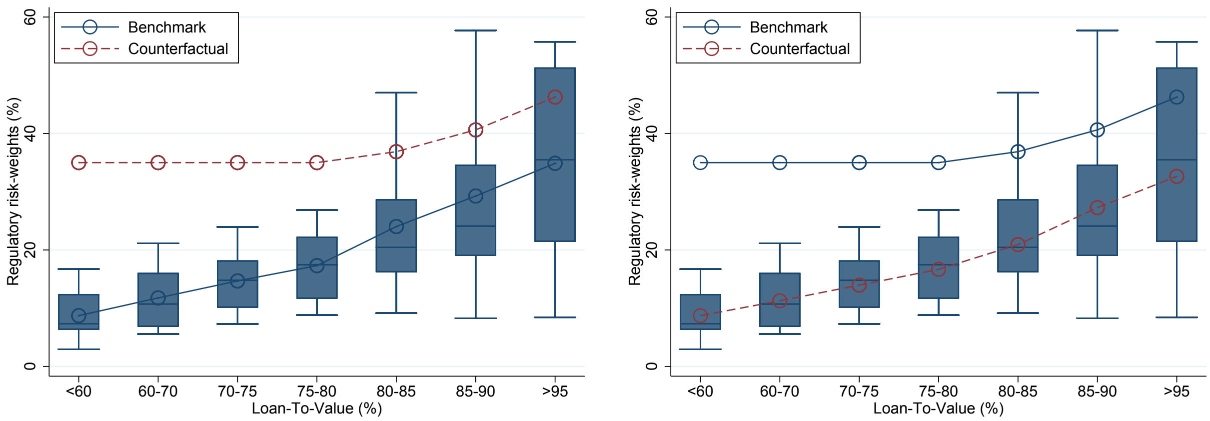
$$r_{j,small} - r_{j,large} = \underbrace{\rho_{j,small} - \rho_{j,large}}_{\text{Regulatory advantage}} - \underbrace{\left[\frac{1}{\frac{\partial Q_{j,small}}{\partial r_{j,small}} \frac{1}{Q_{j,small}}} - \frac{1}{\frac{\partial Q_{j,large}}{\partial r_{j,large}} \frac{1}{Q_{j,large}}} \right]}_{\text{Incumbent advantage}} \tag{21}$$

The higher risk weights for the small lender translate into higher rates, coeteris 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. I explore the consequences of changing the regulatory advantage in equation (21). Table 8 shows the results for several variables of interest in a random subset of the first-time buyer market.

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. As a result of the abolition of internal models the market becomes more competitive. Large lenders lose the regulatory advantage (first element in equation (21)) 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, which become now more attractive. The share of the largest six lenders drops from almost

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

Figure 7: Counterfactual risk-weighted capital requirements



(a) I: All standard approach

(b) II: All internal approach

Notes: the charts show the 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 standardized 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 standardized approach.

85 percent to about 60 percent. The adoption of internal models for small lenders also has a pro-competitive effect on the market.[31] I find that the Herfindahl index declines from 15 percent to about 12 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 counterfactual I, according to both measures.

Panels B and C of Table 8 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 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

[31] In a recent paper Buchak et al. (2017) show that regulatory arbitrage can account for about 55 percent of the increase in shadow banks after the crisis. In this paper I study a different form of regulatory arbitrage, that favors the large banks and impairs competition.

Table 8: 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	141.51	-52.74	9.92
Panel D: Risk			
Default:			
Naive	1.47	0.16	-0.05
Full	1.47	-0.02	-0.04
Buffer:			
All	2.21	2.57	-0.06
Top six	1.86	2.29	-0.01
Others	4.32	1.36	-1.34

Notes: the table shows the baseline estimate of the model and two counterfacuals in a market for first-time buyers. In the first counterfactual scenario, we impose all lenders to adopt the standardized approach for setting the risk weights. In the second counterfactual we 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 is the total number of borrowers; Utility is the log sum of the indirect utility of a representative consumer (see appendix B); Profits is the sum of lenders profits; Welfare is the sum of consumers' utility and lenders' profits; Specialization index measures the relative different of lenders across leverage relative to the average (see appendix B); Default is the average number of defaults in percentage points. Small lenders include challengers and building societies; Low risk mortgages have a maximum LTV below 80; Rich indexes consumers with income above the median. Value is the actual value in the benchmark and counterfactuals; %Δ is the change of the value in the counterfactual relative to the benchmark divided by the benchmark value.

of consumer surplus based on the sum of indirect utilities (see Appendix B for derivation and references). In counterfactual I, as a result of overall higher prices, average consumer surplus decreases by more than 30 percent, while in counterfactual II the lower prices increase consumer surplus.

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 8, I first look at borrowers' default. I report both the naive effect, which accounts only for the mechanical price change, and the full effect after both lenders and borrowers adjust their behavior to the new regulatory regime. 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 2.2.5. With the abolition of internal models I observe an increase in the average default in the system, as higher prices make it harder for borrowers to serve their monthly payments. However, as leverage and demand adjust the overall default rate decreases. In the second counterfactual lower prices and relative small changes in credit access translate into lower defaults, which decrease by approximately 0.04 percentage points.

In Panel D of Table 8 I also report a measure of resilience for the overall mortgage market, based on the extra equity buffer relative to expected default for each mortgage. Expected losses come from equation (18) after lenders and borrowers re-optimize in reaction to the new risk-weighted capital requirements; lenders' equity is given by the endogenous loan size multiplied by the lender specific capital requirement and the counterfactual risk weights. Both are expressed in pounds. Abolishing internal models almost doubles the excess capital buffer in the system, as large lenders are now forced to hold extra capital even for low risk mortgages. In the second counterfactual there is 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 institutions 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.

I find that heterogeneous capital regulation accounts for between 20 and 30 percent of the concentration in the market. The abolition of internal model addresses the imbalance between large and small lenders in terms of capital requirements, but the higher capital reduces demand and affects 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.

6.1.1 Implications for Transmission Mechanism of Capital Requirements

The competitive structure of the market affects the transmission mechanism of monetary policy, leverage regulations and other policy interventions (Scharfstein and Sunderam, 2014; Drechsler et al., 2017; Agarwal et al., 2017). In Section 6.1, I have shown that heterogeneous leverage regulation shapes market structure, thus altering the effectiveness of changes in capital regulation. In this section I study how an increase in capital requirements is transmitted into mortgage rates under alternative market structures.

I use the estimated model to simulate a one percentage point increase in risk-weighted capital requirements in three cases: 1) full pass-through; 2) the estimated market structure; 3) an intermediate case in which I remove the effect of the branch network and lender brand on the mortgage choice, thus increasing competition by reducing market power. To isolate the effect of market power from confounding factors (e.g., heterogeneous risk weights), I compute the equilibrium when all lenders have the same risk-weighted capital requirements, as shown in Figure 18 in Appendix E.

Table 9 shows the results on mortgage rates when I increase the risk-weighted capital requirements by one percentage point for all lenders. Column (1) shows the full pass-through case, in which a one percentage point increase in marginal costs translate into a one-to-one increase in interest rates. The 26 basis points increase follows directly from the supply side estimates of the shadow value of capital regulation in Table 6. Column (3) of Table 9 shows the change in mortgage rates when I allow lenders to adjust their markups after the policy change. I find that the pass-through is larger when there is imperfect substitution across mortgages than in the standard case by approximately 1.25 basis points, or 5 percent of the baseline increase in rates. I explore the mechanism by looking at heterogeneity across products. The largest increase in rates comes from large lenders and low leverage mortgages. Large lenders exploit their incumbent advantage and pass-on more of the cost increase to borrowers than smaller competitors. The pass-through is also larger for mortgages with a low loan-to-value, as borrowers taking these products are less price sensitive.

Finally, to validate how market power changes the transmission mechanism within my model, I study an intermediate case in column (2) of Table 9. I eliminate differences in market power across lenders (second element in equation (21)) removing the effect of lender brand and branch network on borrowers' choice. As I reduce market power, I find no differences in the pass-through between large and small lenders and the transmission mechanism moves

Table 9: TRANSMISSION MECHANISM OF CAPITAL REQUIREMENTS

	MARKET POWER		
	NONE	LIMITED	FULL
	(1)	(2)	(3)
ALL	26.00	26.91	27.26
LENDER TYPE			
LARGE	26.00	26.91	27.33
SMALL	26.00	26.91	27.20
LOAN-TO-VALUE			
≤ 80	26.00	26.82	27.28
> 80	26.00	26.96	27.25
FIXED PERIOD			
2 YEARS	26.00	26.91	27.28
5 YEARS	26.00	26.90	27.24

Notes: the table shows the interest rate for mortgages after a 1 percentage point increase in risk-weighted capital requirements in three scenario. All of them assume a common capital requirement of 8 percent and a risk-weight of 50 percent. Column (1) is the case with full pass-through. Column (3) is the estimated model in the new equilibrium after the markup adjustment. Column (2) is the case with the estimated parameters, but without market power coming from differences across lenders. The numbers are in basis points.

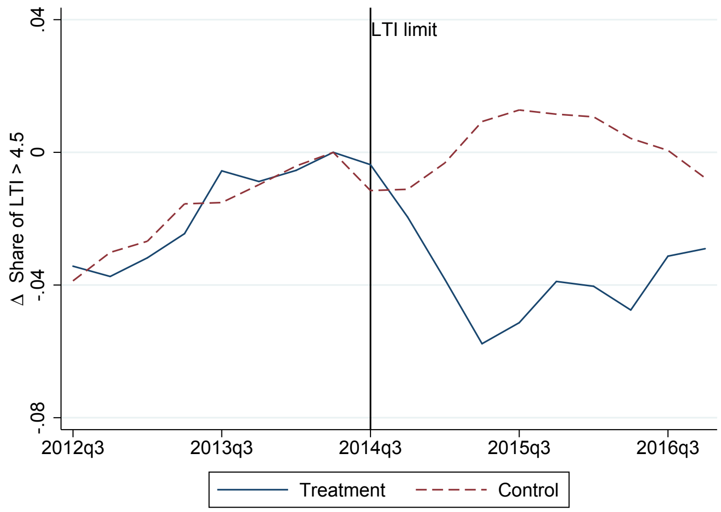
toward the full pass-through baseline. I borrow from the macro literature studying the costs and benefits of higher capital requirements in general equilibrium to convert the basis points difference into actual GDP losses (see Firestone et al. (2017) for a recent analysis and a review of previous studies). A 1.25 basis point higher pass-through as a result of market power translates into an additional 3 basis points decrease in long-run GDP.[32] My results shows that accounting for the equilibrium effect of market power on the transmission mechanism can significantly change the cost of capital regulation for the real economy.

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., 2016). In this section I study two of such

[32] I assume that mortgage loans are approximately 40 percent of bank assets and use the conversion rate from Firestone et al. (2017): "a 1 basis point increase in lending rates implies a decrease in the level of GDP of approximately 1.07 basis points".

Figure 8: Loan-to-income limit and originations



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

policies: actual loan-to-income and counterfactual loan-to-value limits.

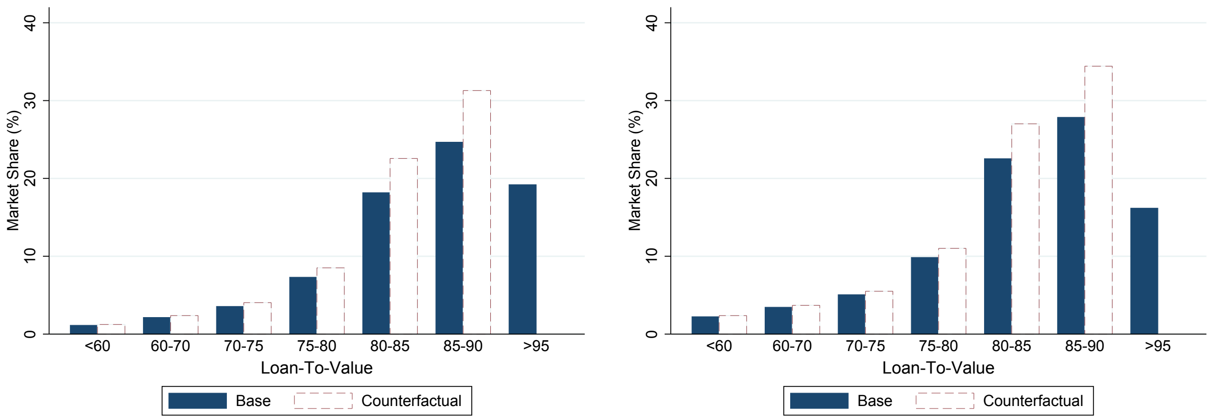
I exploit exogenous variation coming from a recommendation by the Financial Policy Committee (FPC) in June 2014 that limited mortgage originations with a loan-to-income (LTI) above 4.5 to 15 percent of the total number of new mortgage loans (Bank of England, 2014).[33] I divide lenders in two groups 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 8 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 after the event. Lenders in the treatment group reduce more new high loan-to-income mortgages relative to the control group.[34]

I use the model to evaluate the equilibrium effects of a policy that limits household

[33] 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."

[34] In Appendix E I explore further the effect of the FPC recommendation on high loan-to-income originations.

Figure 9: Counterfactual leverage limits



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

Notes: the charts show of 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.

leverage to 90 percent of the value of their house, thereby excluding all products with a maximum loan-to-value above 90 percent from borrowers' choice sets. I study the interaction of this policy with the capital requirement regime in place. In the first case, I compute the counterfactual 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 crisis during the Basel I regime. In a second case, I compute the equilibrium with the actual risk-weighted capital requirements. Figure 9 shows the distribution of market shares by loan-to-value for the two cases in the baseline and after the elimination of mortgages with a leverage above 90 percent. As expected mortgages with loan-to-values close to 90 percent experience the largest increase, but as prices adjust also other products are affected in equilibrium.

Table 10 shows the quantification of costs and benefits, and explores potential unintended consequences due to the interaction of leverage regulations. The marginal cost of lending in the market goes down, as a result of eliminating high leverage-high cost mortgages, 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 10 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

Table 10: 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	513,548	-210,929	827,071	-252,934
LENDER PROFITS	299,065	-106,348	346,260	-108,398
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

Notes: the table shows the baseline estimate of the model and two counterfacuals 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 B); profits is the sum of lenders profits; welfare is the sum of consumers' surplus and lenders' profits; Value is the actual value in the benchmark; Δ is the change of the value in the counterfactual relative to the benchmark

between 4 to 7 percent.[35]. 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 more than 30 percent, as the regulation removes a profitable segment of the market.

Panel C of Table 10 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

[35]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 5 our model slightly under-predicts mortgages with a maximum loan-to-value above 90 percent with respect to the data.

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 equity buffer in the market, as the high risk - high capital mortgages are removed from the market. 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.

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. (2016), 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 better understand 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 UK mortgage market that accounts for several features characterizing borrowers' demand and lenders' competition, and estimate it exploiting variation in risk-weighted capital requirements across lenders and loan-to-values. Using *within* lender variation in capital regulation I provide new estimates of the demand elasticity to the interest rate and decompose it into an extensive margin (product demand) and intensive margin (loan demand). I quantify the cost of capital regulations for lenders and evaluate the costs and benefits of alternative capital requirements and limits to households' leverage.

My model and counterfactual simulations have important implications for policy, most notably regarding the interplay between leverage regulation and competition, which go well beyond the specific context of my analysis. Optimal leverage regulation should consider the impact on the transmission mechanism to the real economy of mortgage market characteristics, such as competition and households' choices. Regulation of the financial sector should take into account potential trade-offs between financial stability and consumer welfare and unintended consequences on market structure.

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. In this work 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-foundations for leverage regulation and a fully fledged quantification of the trade-offs. Finally, a more general equilibrium approach requires house prices to adjust as well. This would create feedback effects and dynamic consideration both on the demand side, affecting for example the timing of housing choice across the life cycle, and on the supply side via foreclosure externalities.

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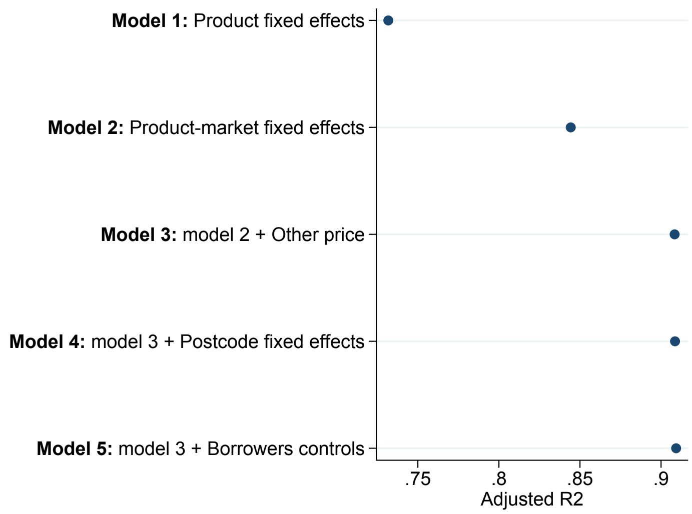
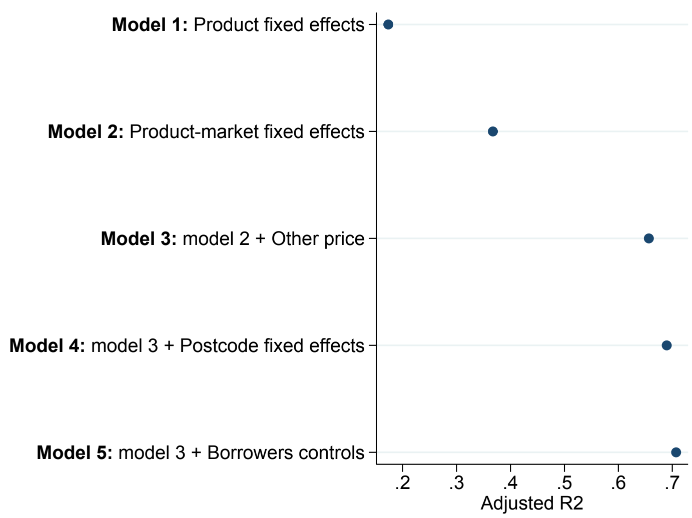
A Facts: Additional Material

Figure 10: Pricing: mortgage supermarket



(a) Interest



(b) Fee

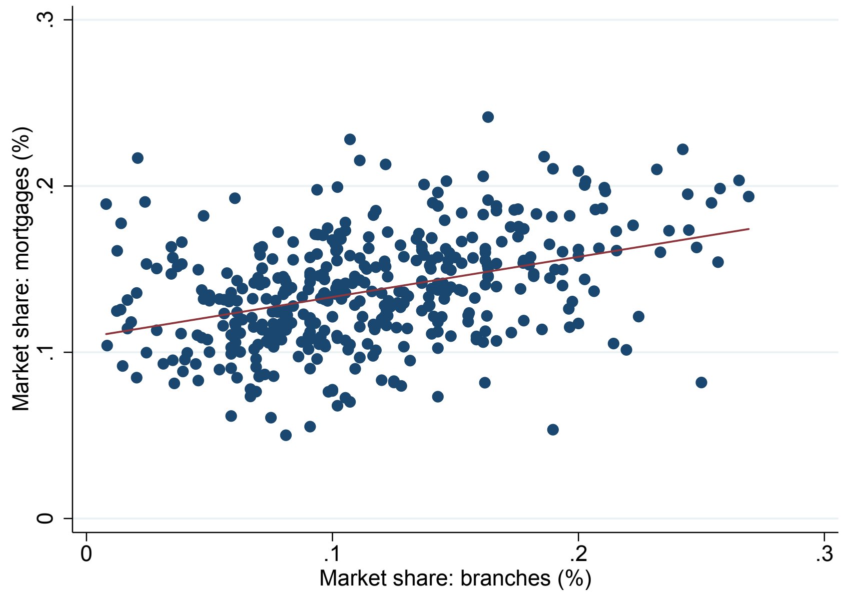
Notes: the chart reports the ajusted R^2 of regressions of borrower level interest rates and fees (r_{ijm} and f_{ijm}) on a set of dummy variables. Model (1) includes only dummy for the product, defined by the interaction of mortgage type, lender and loan-to-value band. Model (2) adds dummies for the 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).

Table 11: Market shares

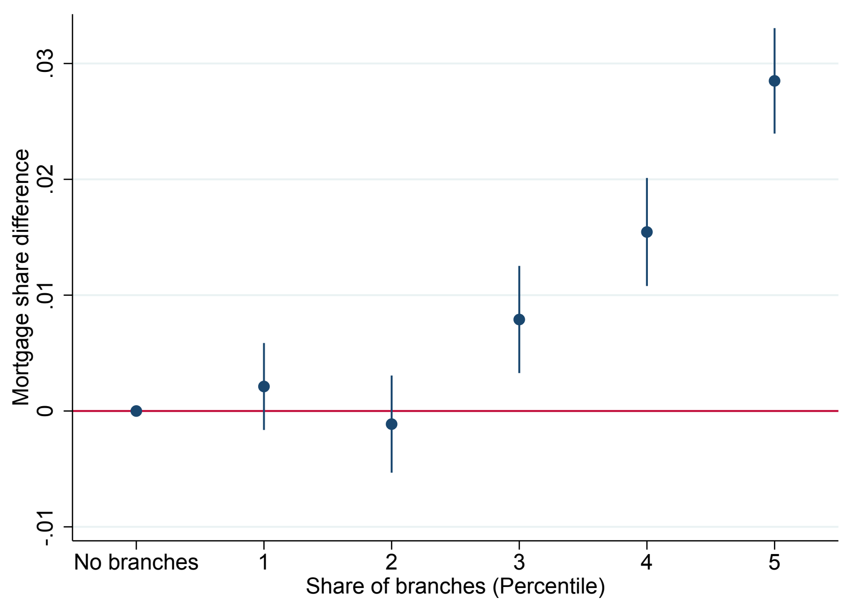
	FTB	HM	RMGT
Full sample	81.5	72.5	72.5
Type			
Fix 2 years	61.7	52.8	50.7
Fix 5 years	19.9	19.7	21.8
Max LTV			
50-60	4.2	9.4	17.8
60-70	5.0	9.9	17.2
70-75	5.8	9.3	13.3
75-80	7.7	9.8	10.8
80-85	15.8	14.2	8.9
85-90	29.8	16.6	4.4
90-95	13.3	3.2	
Lender			
Big six	69.9	58.5	55.6
Challenger	4.9	5.7	7.4
Building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

Notes: the table reports the 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 exclude mortgages from the smaller lenders and product with a market share below 0.03%.

Figure 11: Origination: branches



(a) Correlation



(b) Difference-in-difference

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

B Formula

In this section I derive some of the results in the main text and show additional results of the model.

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

$$\epsilon^q_{ijm} = \frac{\partial q_{ijm}}{\partial r_{jm}} \frac{r_{jm}}{q_{ijm}} = \frac{\partial \ln(q_{ijm})}{\partial r_{jm}} r_{jm} = -\alpha r_{jm} \tag{22}$$

$$\begin{aligned} \epsilon^d_{ijm} &= \frac{\partial s_{ijm}}{\partial r_{jm}} \frac{r_{jm}}{s_{ijm}} = -\mu \exp(-\alpha r_{jm} + \beta X_j + \xi_{jm} + \eta D_i + \zeta_i) s_{ijm}(1 - s_{ijm}) \times \frac{r_{jm}}{s_{ijm}} \\ &= -\alpha\mu \exp(-\alpha r_{jm} + \beta X_j + \xi_{jm} + \eta D_i + \zeta_i)(1 - s_{ijm}) r_{jm} \end{aligned} \tag{23}$$

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

$$\epsilon^q_{jm} = \frac{1}{N_{jm}} \sum_{i=1}^{N_{jm}} \frac{\partial q_{ijm}}{\partial r_{jm}} \frac{r_{jm}}{q_{ijm}} \tag{24}$$

$$\epsilon^d_{jm} = \frac{1}{N_{jm}} \sum_{i=1}^{N_{jm}} \frac{\partial s_{ijm}}{\partial r_{jm}} \frac{r_{jm}}{s_{ijm}} \tag{25}$$

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

$$\begin{aligned} PV(q, r, R, t, T) = q \sum_{k=1}^{t} \left[\frac{r(1+r)^T}{(1+r)^T - 1} - \frac{c(1+c)^T}{(1+c)^T - 1} \right] + \\ \gamma b \sum_{k=t+1}^{T} \left[\frac{R(1+R)^{T-t}}{(1+R)^{T-t} - 1} - \frac{c(1+c)^{T-t}}{(1+c)^{T-t} - 1} \right], \end{aligned} \tag{26}$$

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. Note that Equation (**??**) nests the simpler mortgage contract with fixed rate r until maturity (Equation (3)).

Second, I allow for the possibility that borrowers default. This raise the cost of the lender to issue a mortgage. I follow Phillips (2013) and define $s_k = \prod_{r=1}^{k}(1-d_r)$ the probability that borrower will make payment k, where d_r is the probability of default in period r. Accounting for both default and prepayment risk, the present value of net interest income is given by:

$$PV(q,r,R,t,T) = q\sum_{k=1}^{t}\left[\frac{s_k r(1+r)^T}{(1+r)^T-1} - \frac{c(1+c)^T}{(1+c)^T-1}\right] + \gamma b\sum_{k=t+1}^{T}\left[\frac{s_k R(1+R)^{T-t}}{(1+R)^{T-t}-1} - \frac{c(1+c)^{T-t}}{(1+c)^{T-t}-1}\right]. \tag{27}$$

For long maturity T I can approximate (27) as:

$$PV(q,r,R,t,T) \approx \overbrace{q\left[t(r-c)+\gamma(T-t)(R-c)\right]}^{\text{“Risk-free” return}} + \underbrace{-(1-s_t)\frac{qr\sum_{k=1}^{t}(1-s_k)}{1-s_t} - \gamma(1-s_T)\frac{qR\sum_{k=t+1}^{T}(1-s_k)}{1-s_T}}_{\text{Probability of Default (PD)} \times \text{Loss Given Default (LGD)}}. \tag{28}$$

The first line captures the return, that is free from default risk, but already accounts for refinancing risk. The return from a non-defaulting borrower that refinances the mortgage at the end of the initial period is $qt(r-c)$; while the return from a borrower that pays the mortgage until maturity is approximately $q\left[t(r-c)+(T-t)(R-c)\right]$. The second line captures the default risk, which can materialize both during the initial period and afterwards. The probability that the loan defaults before (after) the end of the initial period is given by $1-s_t$ $(1-s_T)$ and the loss given default is equal to $\frac{qr\sum_{k=1}^{t}(1-s_k)}{1-s_t}$ $(\frac{qR\sum_{k=t+1}^{T}(1-s_k)}{1-s_T})$.

I assume 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. (2015). I assume a constant default probability in each period $d_r = d \; \forall r = 1, ..., T$.[36] In this case the net return given by Equation (4) simplifies to:

$$PV(q,r,R,t,T) \approx q\left[t(r-c)+\gamma(T-t)(R-c)\right] - dq\left[tr+\gamma(T-t)R\right] = q\left[tr+\gamma(T-t)R\right](1-d) - q\left[tc+\gamma(T-t)c\right]. \tag{29}$$

[36]In the data I do not observe at each point in time the probability that borrowers make each payment in each period, but only an average probability of default.

$$\max_r \Pi_{lm}(r;\theta_i) = \sum_{j\in J_{lm}} \Pi_{jm}(r_{jm};\theta_i) =$$
$$\sum_{j\in J_{lm}} \sum_{i\in I_t} s_{ijm}(r_{jm}, X_j, r_{-jm}, X_{-j};\theta_i) \times PV(r_{jm}, X_j;\theta_i) =$$
$$\sum_{j\in J_{lm}} \sum_{i\in I_m} s_{ijm} \times q_{ijm} \times \underbrace{[(t_j r_{jm} + \gamma_j(T_j - t_j)R_j)(1-d_j) - (t_j + \gamma_j(T_j - t_j))c_{jm}]}_{\chi_{jm}=\text{Effective mark-up}}. \tag{30}$$

θ_i collects all the demand parameters and the individual demographics and J_{lm} are the products offered by lender l in market m. I sum over the expected demand s_{ijm} coming from the product choice of all borrowers in market m. The demand parameters also affect the present value because they have an impact on the monthly payment through the quantity choice. Note that the price and characteristics of other products enters the product demand (s_{ijm}), but not the present-value (PV_{ijm}), which only depends on the conditional loan demand (q_{ijm}). 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):

$$\frac{\partial \Pi_j}{\partial r_j} = S_j Q_j (1-d_j) t_j +$$
$$S_j \frac{\partial Q_j}{\partial r_j} [(t_j r_j + \gamma_j(T_j - t_j)R_j)(1-D_j) - (t_j c_j + \gamma_j(T_j - t_j)c_j)] +$$
$$\sum_{k\in J_l} \frac{\partial S_k}{\partial r_j} PV_k - \frac{\partial D_j}{\partial r_j}(t_j r_j + \gamma_j(T_j - t_j)R_j) = 0, \tag{31}$$

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

$$r_j^* = \overbrace{\frac{c_j(t_j + \gamma_j(T_j - t_j))(\frac{\partial S_j}{\partial r_j}Q_j(1-D_j) + S_j\frac{\partial Q_j}{\partial r_j}(1-D_j))}{t_j\left(\frac{\partial S_j}{\partial r_j}Q_j(1-D_j) + S_j\frac{\partial Q_j}{\partial r_j}(1-D_j) - D_jQ_j\frac{\partial D_j}{\partial r_j}\right)}}^{\text{Effective marginal cost}} +$$

$$- \overbrace{\frac{S_jQ_j(1-D_j)}{\frac{\partial S_j}{\partial r_j}Q_j(1-D_j) + S_j\frac{\partial Q_j}{\partial r_j}(1-D_j) - S_jQ_j\frac{\partial D_j}{\partial r_j}}}^{\text{Full mark-up}}$$

$$- \underbrace{\gamma_j\frac{R_j(T_j - t_j)}{t_j}}_{\text{“Add-on” effect}} - \underbrace{\sum_{k\neq j\in J_l}\frac{\frac{\partial S_k}{\partial r_j}PV_k}{t\left(\frac{\partial S_j}{\partial r_j}Q_j(1-D_j) + S_j\frac{\partial Q_j}{\partial r}(1-D_j) - S_jQ_j\frac{\partial D_j}{\partial r_j}\right)}}_{\text{Other products}}. \tag{32}$$

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 borrowers demand one unit of loan ($Q_j = 1$), then Equation (7) collapses to the standard mark-up pricing formula: $r_j^* = c_j - \frac{S_j}{\frac{\partial S_j}{\partial r_j}}$.

I now derive the optimal interest rate and show the different cases. . The profits of the lender are given by:

$$\max_r \Pi_l(r;\theta_i) = \sum_{j\in J_l}\Pi_j(r_j;\theta_i) = \sum_{j\in J_l}\sum_{i\in I} s_{ij}\times PV_{ij} =$$

$$\sum_{j\in J_l}\sum_{i\in I} s_{ij}\times q_{ij}\times \underbrace{[(t_jr_j + \gamma_j(T_j - t_j)R_j)(1-d_j) - (t_j + \gamma_j(T_j - t_j))c_j]}_{\chi_j=\text{Effective mark-up}} \tag{33}$$

The deritivative with respect to the price of j from equation (33) is given by (I remove the market subscript for simplicity):

$$
\begin{aligned}
\frac{\partial \Pi_l}{\partial r_j} &= \sum_{i\in I}\left[s_{ij}q_{ij}\frac{\partial \chi_j}{\partial r_j} + s_{ij}\frac{\partial q_{ij}}{\partial r_j}\chi_j + \sum_{k\in J_l}\frac{\partial s_{ik}}{\partial r_j}\chi_k q_{ik}\right] = \\
&\frac{\partial \chi_j}{\partial r_j}\sum_{i\in I}s_{ij}q_{ij} + \chi_j\sum_{i\in I}s_{ij}\frac{\partial q_{ij}}{\partial r_j} + \sum_{k\in J_l}\chi_k\sum_{i\in I}\frac{\partial s_{ik}}{\partial r_j}q_{ik} = \\
&\frac{\partial \chi_j}{\partial r_j}\sum_{i\in I}s_{ij}q_{ij} + \chi_j\sum_{i\in I}s_{ij}\frac{\partial q_{ij}}{\partial r_j} + \chi_j\sum_{i\in I}\frac{\partial s_{ij}}{\partial r_j}q_{ij} + \sum_{k\neq j,\in J_l}\chi_k\sum_{i\in I}\frac{\partial s_{ik}}{\partial r_j}q_{ik} = \\
&\frac{\partial \chi_j}{\partial r_j}\sum_{i\in I}s_{ij}q_{ij} + \chi_j\left[\sum_{i\in I}(s_{ij}\frac{\partial q_{ij}}{\partial r_j} + \frac{\partial s_{ij}}{\partial r_j}q_{ij})\right] + \sum_{k\neq j,\in J_l}\chi_k\sum_{i\in I}\frac{\partial s_{ik}}{\partial r_j}q_{ik} = 0
\end{aligned}
$$

If $d_j = 0$, $\gamma_j = 0$ and $t_j = 1$, then we have the standard mark-up $\chi_j = r_j - c_j$. And $\frac{\partial \chi_j}{\partial r_j} = 1$. From the previous equation we get the optimal interest rate:

$$
r_j^* = \underbrace{c_j}_{\text{Effective marginal cost}} - \underbrace{\frac{\sum_{i\in I}s_{ij}q_{ij}}{\sum_{i\in I}(s_{ij}\frac{\partial q_{ij}}{\partial r_j} + \frac{\partial s_{ij}}{\partial r_j}q_{ij})}}_{\text{Mark-up}} - \underbrace{\frac{\sum_{k\neq j,\in J_l}\chi_k\sum_{i\in I}\frac{\partial s_{ik}}{\partial r_j}q_{ik}}{\sum_{i\in I}(s_{ij}\frac{\partial q_{ij}}{\partial r_j} + \frac{\partial s_{ij}}{\partial r_j}q_{ij})}}_{\text{Other products}} \tag{34}
$$

I can rearrange the previous expression to get:

$$
(r_j - c_j)\sum_{i\in I}s_{ij}\frac{\partial q_{ij}}{\partial r_j} + \sum_{k\in J_l}(r_k - c_k)\sum_{i\in I}\frac{\partial s_{ik}}{\partial r_j}q_{ik} = -\sum_{i\in I}s_{ij}q_{ij} \tag{35}
$$

Where the sum is now over all $k \in J_l$. This conditional hold for all products and for all firms. We can summarize in the following vector of equilibrium conditions:

$$
\begin{bmatrix}
(r_1 - c_1)\sum_{i\in I}s_{i1}\frac{\partial q_{i1}}{\partial r_1} + \sum_{k\in J_l}(r_k - c_k)\sum_{i\in I}\frac{\partial s_{ik}}{\partial r_1}q_{ik} = -\sum_{i\in I}s_{i1}q_{i1} \\
(r_2 - c_2)\sum_{i\in I}s_{i2}\frac{\partial q_{i2}}{\partial r_2} + \sum_{k\in J_l}(r_k - c_k)\sum_{i\in I}\frac{\partial s_{ik}}{\partial r_2}q_{ik} = -\sum_{i\in I}s_{i2}q_{i2} \\
... \\
(r_J - c_J)\sum_{i\in I}s_{iJ}\frac{\partial q_{iJ}}{\partial r_J} + \sum_{k\in J_l}(r_k - c_k)\sum_{i\in I}\frac{\partial s_{ik}}{\partial r_J}q_{ik} = -\sum_{i\in I}s_{iJ}q_{iJ}
\end{bmatrix} \tag{36}
$$

I can rewrite the vector in matrix form:

$$
\chi(SDQ + I \times DSQ \times I) = -SQ \tag{37}
$$

Where I is a block diagonal ownership matrix and:

$$\chi = \begin{bmatrix} (r_1 - c_1) \\ (r_2 - c_2) \\ ... \\ (r_J - c_J) \end{bmatrix} \tag{38}$$

$$SQ = \begin{bmatrix} \sum_{i \in I} s_{i1} q_{i1} \\ \sum_{i \in I} s_{i2} q_{i2} \\ ... \\ \sum_{i \in I} s_{iJ} q_{iJ} \end{bmatrix} \tag{39}$$

$$SDQ = \begin{bmatrix} \sum_{i \in I} s_{i1} \frac{\partial q_{i1}}{\partial r_1} & 0 & ... & 0 \\ 0 & \sum_{i \in I} s_{i2} \frac{\partial q_{i2}}{\partial r_2} & ... & 0 \\ ... & ... & ... & ... \\ 0 & 0 & ... & \sum_{i \in I} s_{iJ} \frac{\partial q_{iJ}}{\partial r_J} \end{bmatrix} \tag{40}$$

$$DSQ = \begin{bmatrix} \sum_{i \in I} \frac{\partial s_{i1}}{\partial r_1} q_{i1} & \sum_{i \in I} \frac{\partial s_{i2}}{\partial r_1} q_{i2} & ... & \sum_{i \in I} \frac{\partial s_{iJ}}{\partial r_1} q_{iJ} \\ \sum_{i \in I} \frac{\partial s_{i1}}{\partial r_2} q_{i1} & \sum_{i \in I} \frac{\partial s_{i2}}{\partial r_2} q_{i2} & ... & \sum_{i \in I} \frac{\partial s_{iJ}}{\partial r_2} q_{iJ} \\ ... & ... & ... & ... \\ \sum_{i \in I} \frac{\partial s_{i1}}{\partial r_J} q_{i1} & \sum_{i \in I} \frac{\partial s_{i2}}{\partial r_J} q_{i2} & ... & \sum_{i \in I} \frac{\partial s_{iJ}}{\partial r_J} q_{iJ} \end{bmatrix} \tag{41}$$

We can use the fact that $\frac{\partial s_{ik}}{\partial r_k} = s_{ik}(1 - s_{ik})\frac{\partial V_{ik}}{\partial r_k}$ and $\frac{\partial s_{ij}}{\partial r_k} = -s_{ik}s_{ij}\frac{\partial V_{ik}}{\partial r_k}$. Then DSQ becomes:

$$DSQ = \begin{bmatrix} \sum_{i \in I} s_{i1}(1 - s_{i1}) \frac{\partial V_{i1}}{\partial r_1} q_{i1} & \sum_{i \in I} -s_{i1} s_{i2} \frac{\partial V_{i1}}{\partial r_1} q_{i2} & ... & \sum_{i \in I} -s_{i1} s_{iJ} \frac{\partial V_{i1}}{\partial r_1} q_{iJ} \\ \sum_{i \in I} -s_{i2} s_{i1} \frac{\partial V_{i2}}{\partial r_2} q_{i1} & \sum_{i \in I} s_{i2}(1 - s_{i2}) \frac{\partial V_{i2}}{\partial r_2} q_{i2} & ... & \sum_{i \in I} -s_{i2} s_{iJ} \frac{\partial V_{i2}}{\partial r_2} q_{iJ} \\ ... & ... & ... & ... \\ \sum_{i \in I} -s_{iJ} s_{i1} \frac{\partial V_{iJ}}{\partial r_J} q_{i1} & \sum_{i \in I} -s_{iJ} s_{i2} \frac{\partial V_{iJ}}{\partial r_J} q_{i2} & ... & \sum_{i \in I} s_{iJ}(1 - s_{iJ}) \frac{\partial V_{iJ}}{\partial r_J} q_{iJ} \end{bmatrix} \tag{42}$$

And we now that: $\frac{\partial V_{ik}}{\partial r_k} = -\alpha\mu \exp(-\alpha r_k + \beta X_k + \xi_k + \eta D_i + \zeta_i)$.

Additional variables. Finally I report the formula that we use in the calculation of several variables and indexed in the counterfactual simulations of section 6. We calculate expected consumer surplus following Small and Rosen (1981). To convert the utility measure into money terms we 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. We adopt the representative consumer approach and compute welfare within each group type, thus allowing for observable heterogenenous 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:

$$E\left[\max_{j\in J^0} U(y, r_j^0, X_j, \epsilon_j)\right] = E\left[\max_{j\in J^0} U(y, r_j^1 - cv, X_j, \epsilon_j)\right] \tag{43}$$

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 we remove products from the choice set as a result of the leverage limit, is given by:

$$E\left[\max_{j\in J^0} U(y, r_j^0, X_j, \epsilon_j)\right] = E\left[\max_{j\in J^1} U(y, r_j^1 - cv, X_j, \epsilon_j)\right] \tag{44}$$

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

$$\Delta E[CS] = \frac{1}{\lambda}\left[\ln(\sum_{j=1}^{J^1} \exp(V_j^1)) - \ln(\sum_{j=1}^{J^0} \exp(V_j^0))\right] \tag{45}$$

With $\lambda = \frac{-\alpha\mu \exp(-\alpha r_j)}{q}$. We construct the specialization index as follows. For each product we compute the difference between the share in a lender portfolio (S_{jlm}) and the average share for all lenders offering that product in the market ($\bar{S}_{jm}$).

$$\Delta Spec_{jlm} = \left\|S_{jlm} - \bar{S}_{jm}\right\| \tag{46}$$

Then we aggregate the differences in each product type for each lender to measure specialization at the lender level:

$$Spec_{lm} = \sum_{j=1}^{J_{lm}} \Delta S_{jlm} \tag{47}$$

In the counterfactual analysis of section 6 we report the average specialization across lenders in each market $Spec_m = \frac{1}{L_m}\sum_{l=1}^{L_m} K_{lm}$.

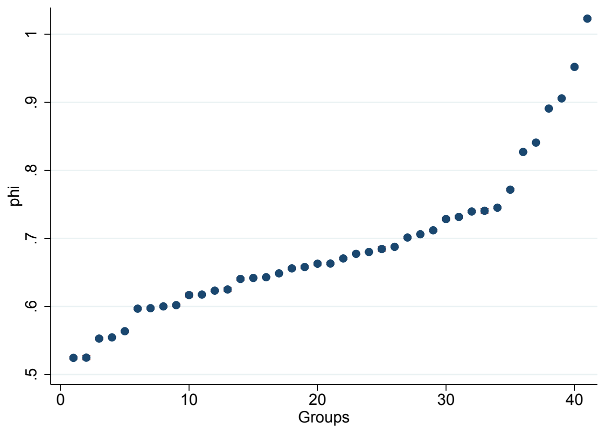
C Fit: Additional Material

Table 12: Structural demand estimates: heterogeneity

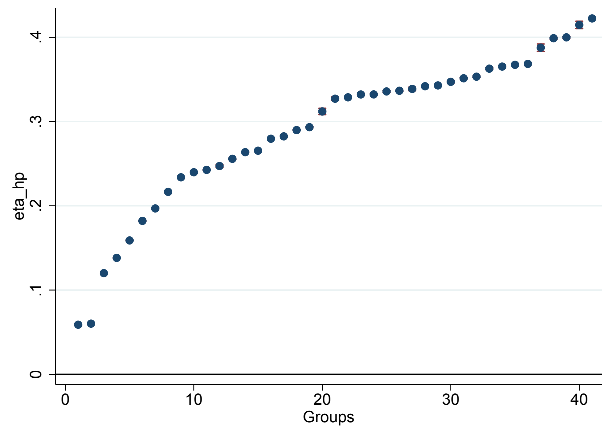
	All	Income		Age		Region		
		poor	rich	young	old	London	West Mid	Scotland
Demographics								
Income (ϕ)	0.7003	0.7342	0.6664	0.7005	0.7000	0.8298	0.6509	0.6849
	0.0007	0.0006	0.0008	0.0006	0.0008	0.0005	0.0007	0.0008
Age (η)	0.0003	-0.0011	0.0017	0.0040	-0.0052	0.0012	-0.0011	0.0012
	0.0001	0.0001	0.0001	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

Notes: the table shows the 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 B. 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.

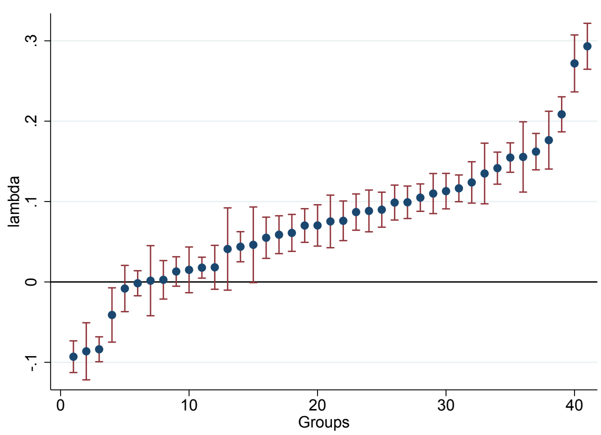
Figure 12: Demand parameters: first stage



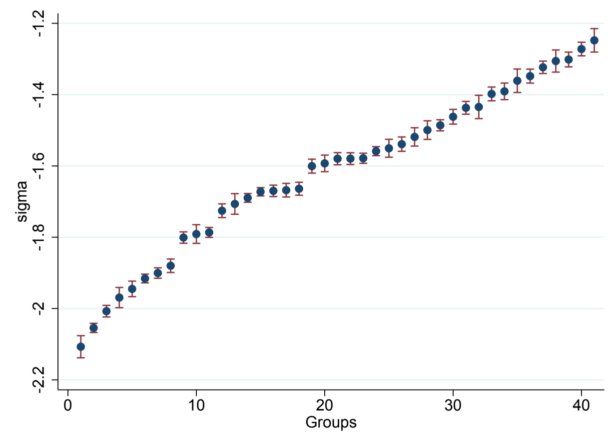
(a) Income (log)



(b) House prices (log)



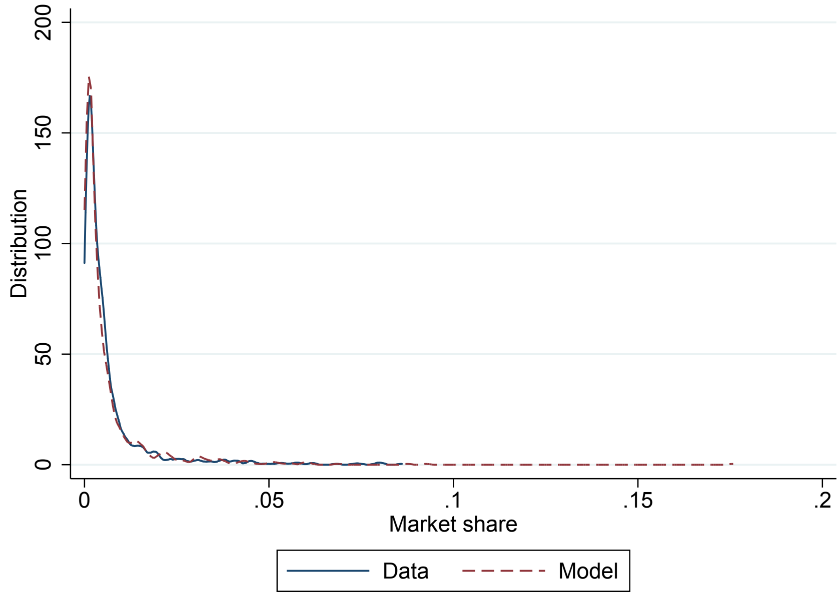
(c) Branches (log)



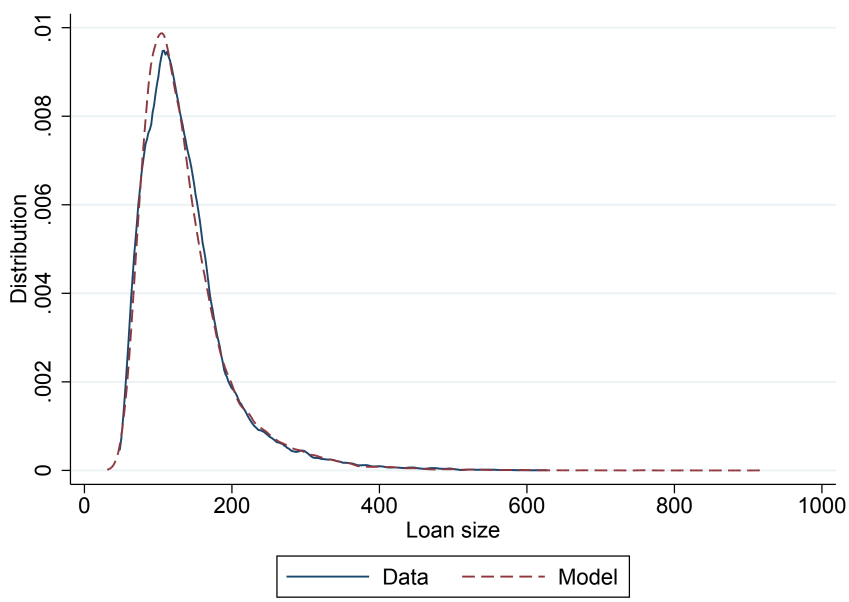
(d) Heterogeneity

Notes: the charts show some of the 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 dot represent the point estimate; the red bar the 95% confidence interval.

Figure 13: Model fit: product and loan demand



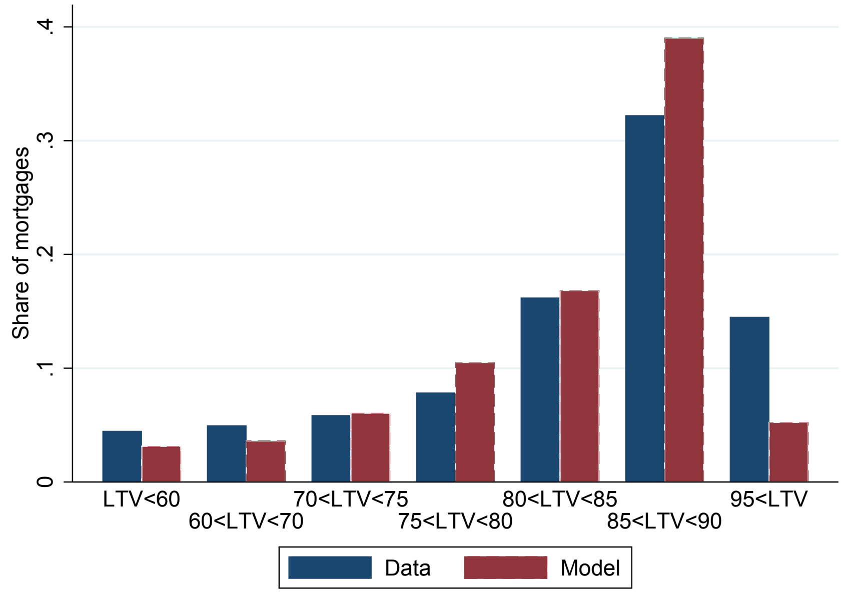
(a) Product share



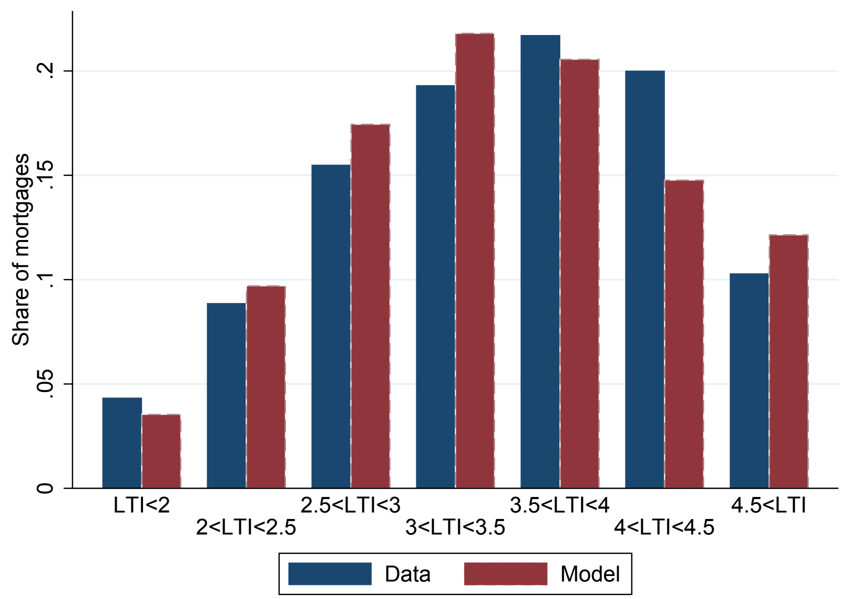
(b) Loan demand

Notes: the upper panel show the kernel density for the market share of all product. The lower panel show 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. We use a random subsample of 10% of the whole population.

Figure 14: Model fit: LTV and LTI



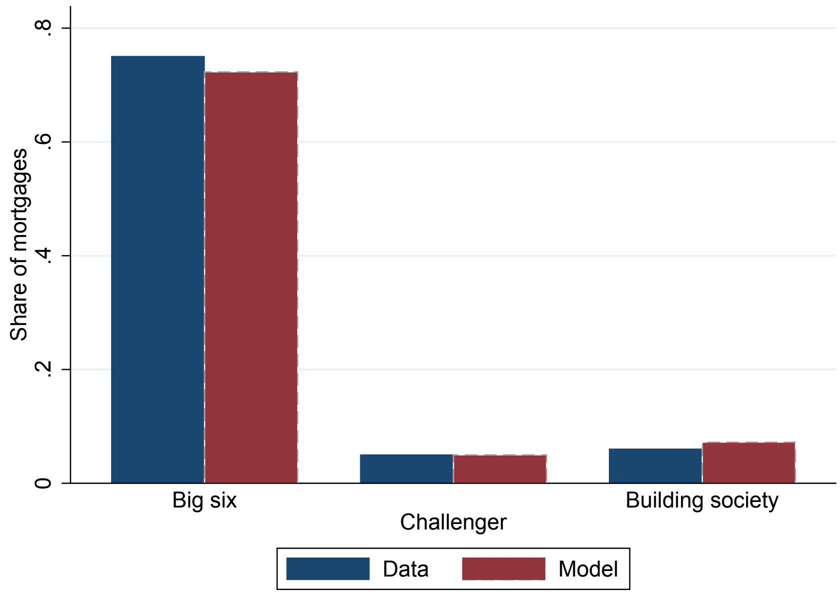
(a) Loan-To-Value



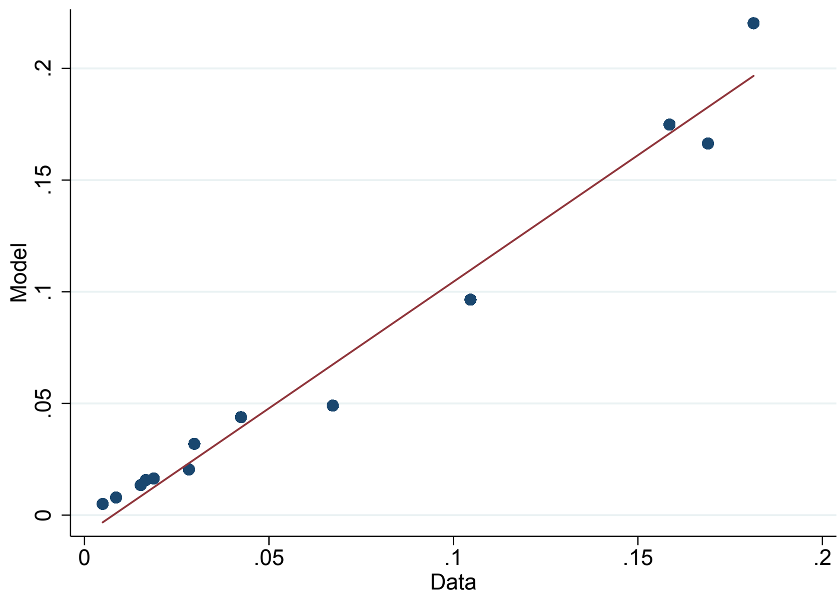
(b) Loan-To-Income

Notes: the upper panel show the percentage of borrowers in each LTV band. The lower panel show 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 13 and sum across maximum LTI. We use a random subsample of 10% of the whole population.

Figure 15: Model fit: Lender



(a) Lender type



(b) Lender

Notes: the upper panel show the percentage of borrowers for each lender type. We 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. The lower panel show the correlation between the market share in the data and the market share predicted by the model. We use a random subsample of 10% of the whole population.

Table 13: 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

Notes: The tables report the 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 estimated in section 5.3. PP stays for percentage points, while % is then we divide the markup in percentage points by the interest rate, also in percentage points. We report the average elasticities for all products and by different product characteristics: lender type, maximum LTV and fix period.

Table 14: 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

Notes: The tables report the marginal costs for first-time buyers. The number of observations is given by the product-market pairs. Marginal cost indicate the case of equation (7) 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 estimated in section 5.3. Without add-on is the case of equation (7) 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. We report the average elasticities for all products and by different product characteristics: lender type, maximum LTV and fix period.

D Robustness

In this section we show the estimate with the joint second step demand and supply model. We construct demand moments from (16) in each group and supply moments using (17). The two set of moments are related by the markup formula (**??**).

$$
\begin{aligned}
E\left[\xi^g_{jm}(\alpha^g,\beta^g)\middle|\, z_{jm}\right] = 0, \quad g = 1,...,G \quad & \textit{Demand} \\
E\left[\kappa_{jm}(\alpha^1,...,\alpha^G,\tau)\middle|\, z_{jm}\right] = 0 \qquad\qquad & \textit{Supply}
\end{aligned}
\tag{48}
$$

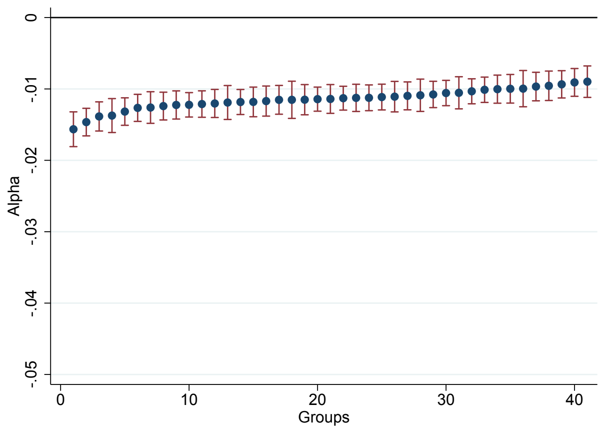
In the sample:

$$
m(\alpha,\beta,\tau) = \begin{bmatrix} \sum_m^M \sum_{j\in J_m} \left[\hat{\delta}^g_{jm} - (-\alpha^g r_{jm} + \beta^g X_j)\right] z_{jm} = 0, \quad g = 1,...,G \\ \sum_m^M \sum_{j\in J_m} \left[r_{jm} - (\tau_X X_j + \tau_c c_{jm} + \tau_R \underline{\mathrm{K}}_{lt}\rho_j + \tau_t) + \frac{\sum_{i\in I} s_{ij}q_{ij}}{\sum_{i\in I}(s_{ij}\frac{\partial q_{ij}}{\partial r_j} + \frac{\partial s_{ij}}{\partial r_j}q_{ij})}) \right] z_{jm} = 0 \end{bmatrix}
\tag{49}
$$

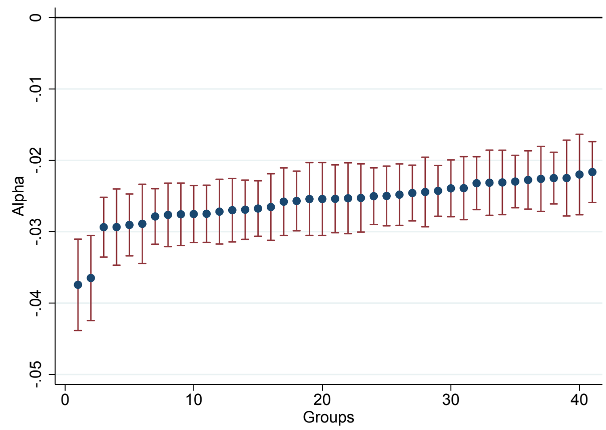
The method of simulated moments estimator is given by:

$$
(\hat{\alpha},\hat{\beta},\hat{\tau}) = \arg\max \left[\sum_{g=1}^{G} m(\beta^g,\alpha^g)'W^{-1}m(\beta^g,\alpha^g) + m(\tau,\alpha)'W^{-1}m(\tau,\alpha)\right] \tag{50}
$$

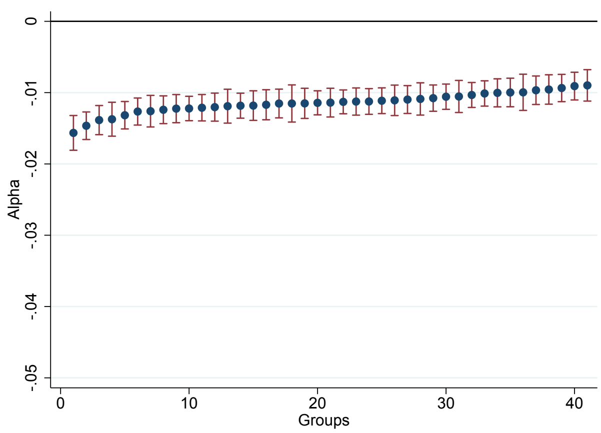
Figure 16: Demand parameters: second stage - robustness



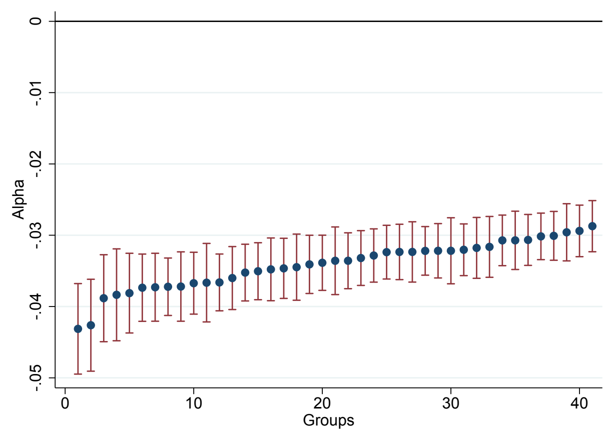
(a) OLS



(b) IV: Risk weights



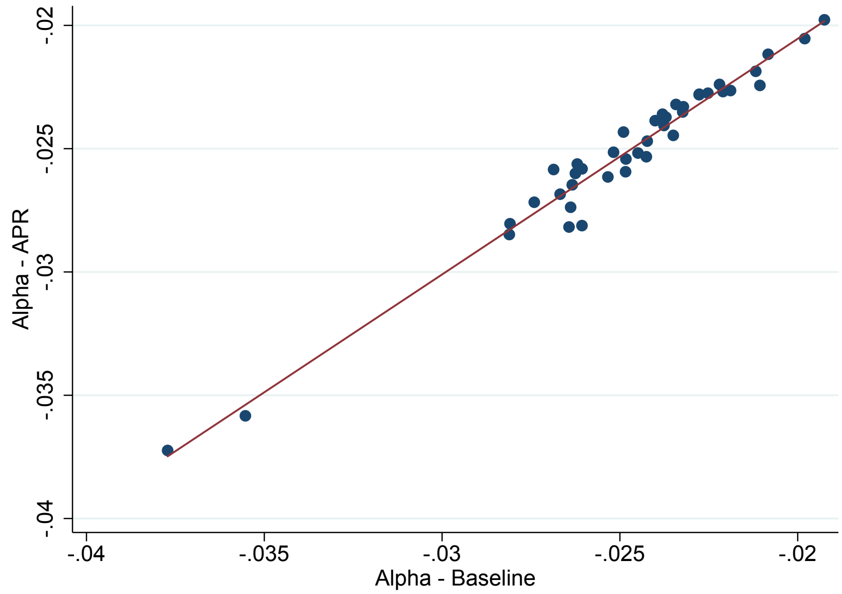
(c) OLS



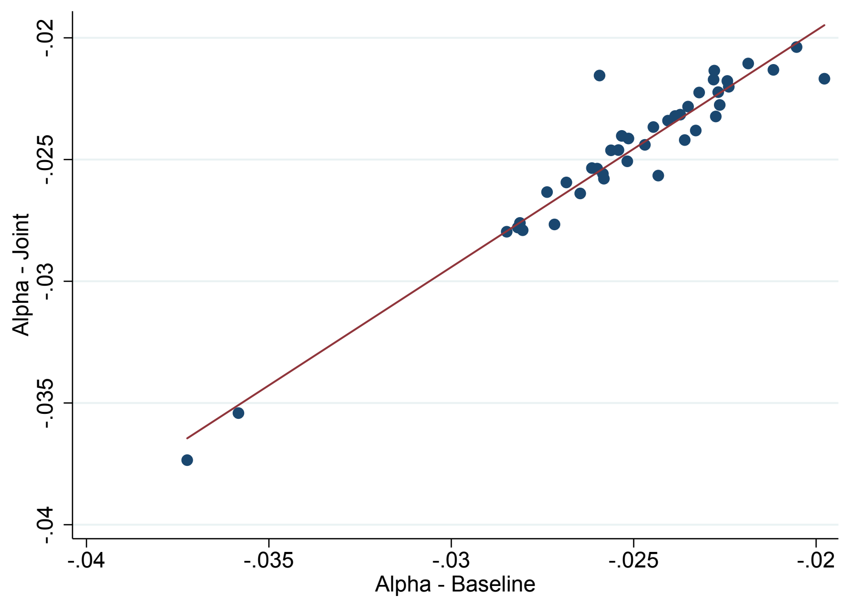
(d) IV: Risk weights (others)

Notes: the charts show the 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 estimate; the red bar the 95% confidence interval.

Figure 17: Demand parameters: second stage - further robustness



(a) Annual Percentage Rate (APR)



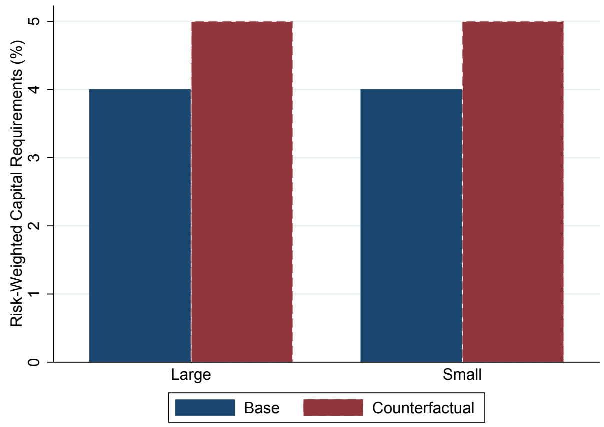
(b) Joint estimation

Notes: the upper panel shows the correlation between the alpha coefficient for our 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 andds a representative loan size, as advertised in https://www.moneysupermarket.com/mortgages/. The lower panel show the correlation .

E Counterfactuals: Additional Material

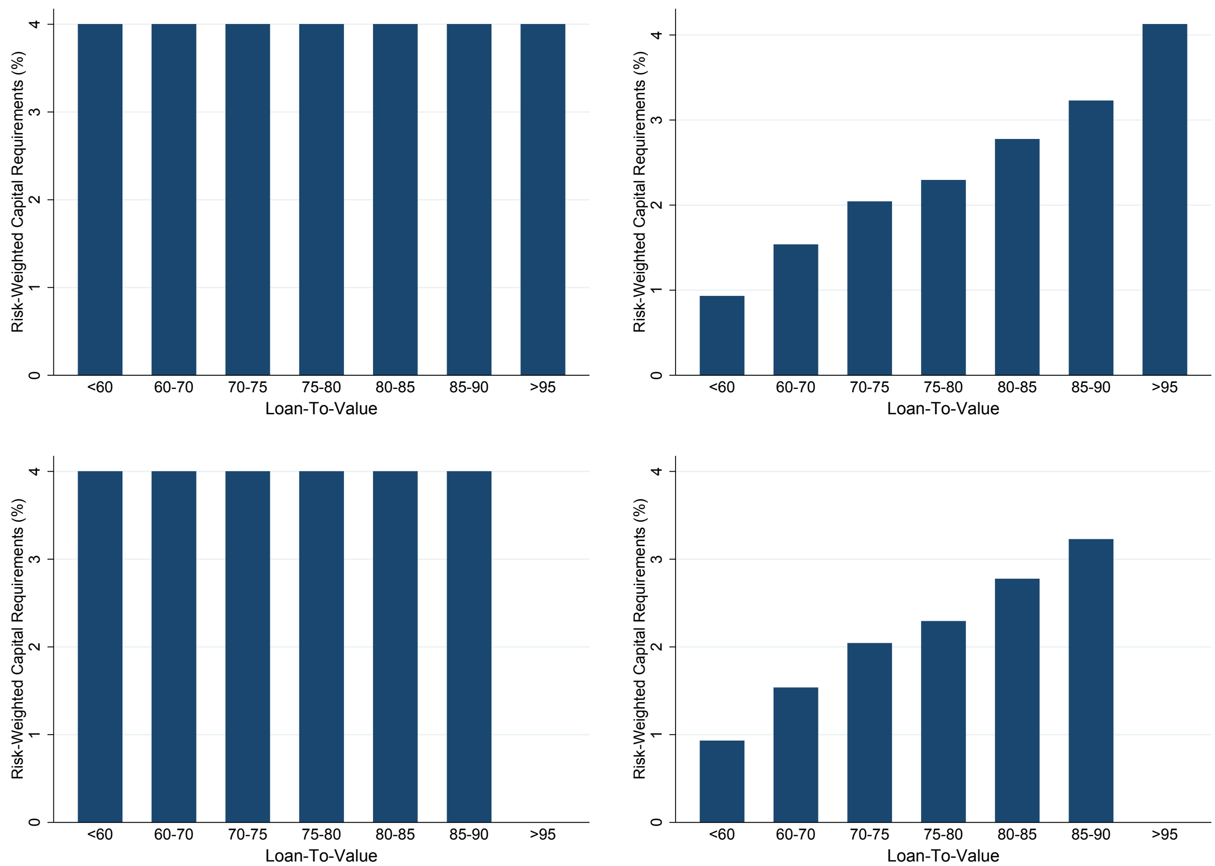
E.1 Extra Charts

Figure 18: Pass-through of risk-weighted capital requirement



Notes: the chart shows the risk-weighted capital requirements for large and small lenders. The blue bar denote 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. The red bar show the counterfactual risk-weighted capital requirement after an exogenous increase by 1 percentage point.

Figure 19: Interaction of different leverage regulations



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

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

Notes: the charts show.

E.2 Reduced-Form Evidence

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:

$$r_{jm} = \beta RW_{jm} + X_j + \gamma_m + \epsilon_{jm} \tag{51}$$

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 15 shows the results. I find that 1 percentage point higher risk weight lead 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 barely affected. In the remaining columns I run model (51) separately for the different borrower types. I find a strong and significant effect of risk-adjusted capital requirements for first-time buyers. A 1 percentage point higher risk-weight translate 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.

I estimate the effect of the FPC reccomandation with the following difference-in-difference model:

$$Share_{lm} = \beta_1 Treatment_l + \beta_2 Post_m + \beta_{12} Treatment_l \times Post_m + \epsilon_{lm} \tag{52}$$

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 16 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 4 percent 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

Table 15: Reduced form evidence: 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

Notes: The table shows the coefficients of regression (51). 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.

remaining columns of table 16 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.

Table 16: Reduced form evidence: 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

Notes: The table shows the coefficients of regression (52). 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.