THE LONDON SCHOOL OF ECONOMICS AND POLITICAL SCIENCE

Essays in Household Finance and Banking

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Declaration

I certify that the thesis I have presented for examination for the PhD degree of the London School of Economics and Political Science is solely my own work other than where I have clearly indicated that it is the work of others (in which case the extent of any work carried out jointly by me and any other person is clearly identified in it).

I warrant that this authorization does not, to the best of my belief, infringe the rights of any third party.

I declare that my thesis consists of approximately 58,000 words.

Statement of Conjoint Work

I certify that chapters 2 and 3 of this thesis were co-authored. Chapter 2 is co-authored with Davide Fantino, while Chapter 3 is coauthored with Philippe Bracke and Nic Garbarino. I contributed 50% of the work in chapter 2, and 33% of the work in chapter 3.

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My highest educational achievement is

for my first and most important teachers:

Mum and Dad

Abstract

This thesis consists of three chapters that belong to the realm of household finance and banking.

The first essay develops a structural model of mortgage demand and lender competition to study how leverage regulation a 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 interest rate by 10 percent for the average mortgage product. 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 buyers, thereby affecting risk.

The second essay, co-authored with Davide Fantino, exploits an allocation rule by the ECB for Targeted Long-Term Refinancing Operations on banks' borrowing limit as an instrument to identify the effects of an expansion in banks' funding availability on the cost of credit. Using transaction-level data from the Italian credit register and a difference-in-difference identification strategy, we show that treated banks decrease loan rates to the same firm by approximately 20 basis points relative to control banks. We then study how the effects of the liquidity injection vary with competition in the banking sector, exploiting the local nature of bank-firm lending relationships and exogenous variation from the historical development of Italian cities during the Renaissance. Our results suggest that banks' market power can significantly impair the effectiveness of unconventional monetary policy, especially for safer and smaller firms.

The third essay, co-authored with Philippe Bracke and Nic Garbarino, presents new evidence that lenders use down payment size to price unobservable borrower risk. We exploit the contractual features of a UK scheme that helps home buyers top up their down payments with equity loans. A 20 percentage point smaller down payment is associated with a 22 basis point higher interest rate at origination, and a higher ex-post default rate. Lenders see down payment as a signal for unobservable borrower risk, but the relative importance of this signal is limited, as it accounts for only 10% of the difference in interest rates between standard mortgages with 5% relative to 25% down payment.

Chapter 1

Leverage Regulation and Market Structure: An Empirical Model of the UK Mortgage Market

1.1 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., 2016a; 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 (Hanson et al., 2011; Admati and Hellwig, 2014; Kisin and Manela, 2016; Dagher et al., 2016). Following the financial crisis, policy makers allowed lenders to invest in internal rating-based models to tie capital requirements to asset classes with different risks. Large lenders adopted internal rating-based models, while the vast majority of small lenders opted for the standard regulatory approach. As a result, a two-tier system prevails to calculate risk-weighted capital requirements. This heterogeneity across different lenders and asset classes can have unintended consequences, such as potential regulatory arbitrage and reduced competition in the market (Acharya et al., 2013; Behn et al., 2016b; 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 of all mortgages offered by a lender results in a 0.25 percent decrease in loan demand and a 17 percent market share decline for the average lender.

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 risk-weighted capital requirement increases the marginal cost by 11 percent and the interest rate by 10 percent for the average mortgage product.

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

Finally, I explore with the estimated model possible interactions between capital requirements and limits to household leverage that have recently been discussed and implemented in some countries (Consumer Financial Protection Bureau, 2013; Bank of England, 2014; DeFusco et al., 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; Berry et al., 1995; Hendel, 1999; Thomassen et al., 2017). The characteristics approach captures rich heterogeneity in household preferences and product availability along several dimensions, which are otherwise hard to model together. The discrete-continuous approach allows me to decompose the impact of interest rates on households' choice of the lender, leverage and house size, which I could not achieve with a purely reduced form strategy. Within the household finance literature, my paper is 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 one of the first to apply similar techniques to the mortgage market and to study the implications of leverage regulation for consumers and market structure. Most notably, while previous studies focused on a "representative" product for each provider and only model the choice across providers, I exploit more granular variation in risk weights *within* a lender across asset classes to identify the elasticity of demand and the impact of leverage regulation.

Finally, my paper contributes to the growing literature assessing the effectiveness of new macro-prudential regulation both theoretically (Freixas and Rochet, 2008b;

Rochet, 2009; Vives, 2010; Admati and Hellwig, 2014) and empirically (Hanson et al., 2011; Acharya et al., 2014; Behn et al., 2016a; DeFusco et al., 2016) and the role of lenders' market power for the transmission of policy interventions (Scharfstein and Sunderam, 2014; Drechsler et al., 2017; Agarwal et al., 2017). 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; Corbae and D'Erasmo, 2017).

The rest of the paper is organized as follows. Section 1.2 describes the data sources and provides motivating evidence and empirical facts in the UK mortgage market. Section 1.3 develops the demand and supply model. Section 1.4 describes the estimation approach and the identification strategy. Section 1.5 discusses the results. Section 1.6 describes the estimates from the counterfactual exercises. Finally, Section 3.5 concludes.

1.2 Data and Setting

1.2.1 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]

[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.

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.

Panel A of Table 1.1 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

[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).

[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

Table 1.1: 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

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.

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 1.1 I show summary statistics for lenders' capital require-

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.

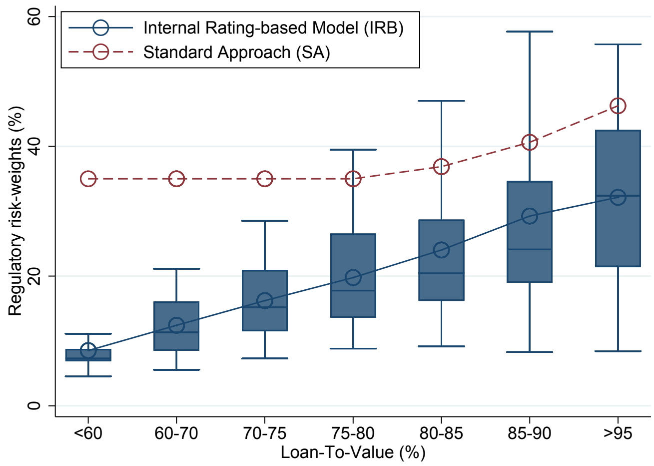
ments, risk weights and branches. The capital requirement includes both minimum requirements under Basel II (Pillar I, or 8 percent of RWAs) as well as lender-specific supervisory add-ons (Pillar II). Total capital resources include all classes of regulatory capital, including Common Equity Tier 1, Additional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

1.2.2 Institutional Background

Since 2008 two approaches to calculate capital requirements coexist: the standard approach (SA) and the internal rating-based approach (IRB). Figure 1-1 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

Figure 1-1: Risk-weights across lenders and loan-to-values



The figure 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 × IQR of the upper/lower quartiles. SA includes all lenders in the sample that adopt the standardized approach. For the latter group the risk weights are set by the regulator in a homogeneous manner across bank and varies between 35 percent and 45 percent based on the loan-to-value of the loan.

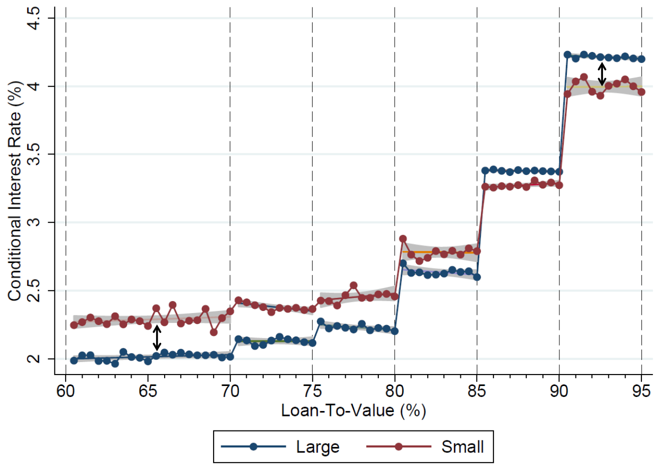
Basel II. Medium and small lenders, with very few exceptions, opted for the standard approach, mostly because of the large fixed compliance cost associated with internal rating-based models (Competition and Markets Authority, 2015; Benetton et al., 2016).

1.2.3 Facts

In this section, I document some stylized facts about the UK mortgage market on pricing, originations and performances that guide both the empirical model and the identification strategy. I start with two definitions for the key variables in my analysis: market and product.

In my setting a market is a borrower type-quarter combination. I define a borrower type based on the purpose of the transaction: refinancing an existing property (remortgager), buying a property (home mover), or buying a property for the first

Figure 1-2: Choice-set



The figure shows a snapshot from `https://www.moneysupermarket.com/mortgages/` of the cheapest five mortgages offered in a market after filling information about the value of the property and the loan amount.

time (first-time buyer).[5] A product is a combination of brand, interest rate type and maximum loan-to-value (e.g., Barclays, two year fixed rate, 90 percent maximum loan-to-value). In Figure 1-2 I show a snapshot from a popular search platform for mortgages in the UK after filling information on the value of the property and the loan amount. The key mortgage characteristics are the provider of the loan, the type of interest and the maximum loan-to-value. The market and the chosen product determine jointly the borrower monthly cost.

The UK mortgage market has been historically very innovative, with a large number of products offered (Cocco, 2013). However, the market is concentrated in terms of both lenders and interest rate types. The largest six lenders account for about 70% of new mortgage originations and the most popular product is the fixed rate for two years, which accounts for more than 60% of originations to first-

[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 1.4.1 I describe in details how I construct the borrower specific choice set.

time buyers and more than 50% to home movers and remortgagers.[6] In terms of the maximum loan-to-value there is more heterogeneity depending on the borrower type. First-time buyers take higher leverage mortgages, with almost 60 percent borrowing more than 80 percent of the value of the house. Home movers 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.

Pricing

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.[7] I test this claim in Appendix A.1 in which I show the results of a regression of the loan-level interest rate on product fixed effects and additional controls. My product definition based on the type of mortgage, the lender and the maximum loan-to-value captures more than 70 percent of the full variation in the loan-level rate. The R^2 reaches 85 percent when I interact the product dummies with time dummies, and more than 90 percent when I also include dummies for the origination fees. Adding dummies for the location of the house and borrower level controls (age, income, house value, joint application, employment status) does not explain the residual variation in the rate.[8]

[6]In Appendix A.1 I report the market shares of prime residential mortgages originated in 2015-2016. The products that I consider, account for more than 80% of originations for first-time buyers, and more than 70% for home movers and remortgagers.

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

[8]The remaining variation is due to two possible reasons. First, unobservable product characteristics. Even if I control for the main factors affecting price, there can be some other product characteristics that lenders use to segment the market. Second I observe the date when the borrower gets a mortgage, but I do not know when exactly the deal was agreed. The time dummies

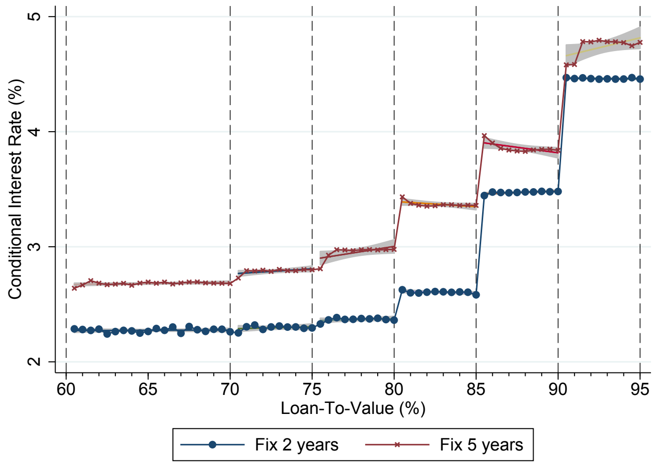
Figure 1-3 explores the variation in rates across different product characteristics and lenders. First, I show the mean predicted interest rates from a regression including mortgage and borrowers controls as a function of the loan-to-value. I see that the lenders set the interest rate as a increasing 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 as already documented by Best et al. (2015).

Second, I 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).

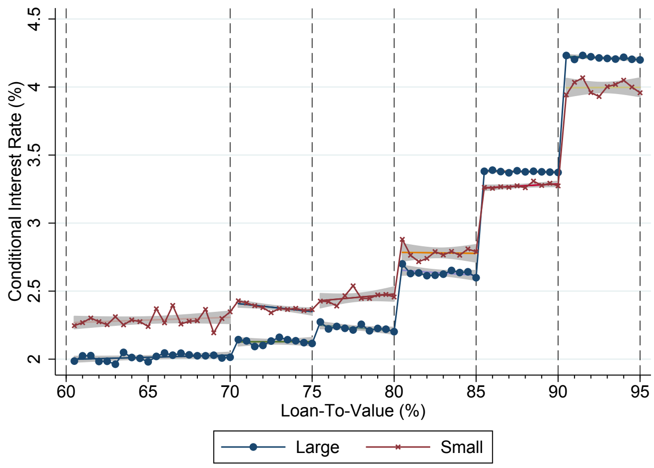
Third, I study the effect of regulation on risk-weights for mortgage rates and in Figure 1-3 (b) I compare a representative large lender adopting an internal model with a small lender using the standardized approach. The rate schedule of the large lender shows clear discontinuous jumps at maximum loan-to-values, while the small lender increases the rate only for loan-to-values above 80 percent, when risk weights start increasing as shown in Figure 1-1. The large lender offers a more competitive interest for low loan-to-value mortgages. The gap in prices closes for intermediate loan-to-value mortgages and even reverses for products with a loan-to-value above 85 percent, consistent with the shrinking gap in the risk weights between internal model and standardized approach.

capture the variation in the price imperfectly. I also replicate the exercise for origination fees, also reported in Appendix A.1. The product market fixed effects explain only about 35 percent of the loan-level variation, adding dummies for interest rate increases the R^2 to about 65 percent, and adding location and demographics bring it to about 70 percent. The larger dispersion that we find in the loan-level fees can by attributable to the same unobservable attributes that could affect the rate. Moreover, while the interest rates are not negotiated, there can be more flexibility with respect to fees. For example, borrowers have the opportunity to roll-over the fees on their loans and this option is often used.

Figure 1-3: Pricing



(a) Default and Refinancing Risk



(b) Capital Regulation

The figures 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. Panel (a) shows the average schedule in the first-time buyers market for products with the two most popular products: fixed rate mortgages for 2 and 5 years. Panel (b) reports the schedule for a representative large lender adopting the internal model and a representative small lender opting for the standardized approach.

Originations

Figure 1-4 explores equilibrium loan-to-values. Figure 1-4 (a) shows the loan-to-value choice of first-time-buyers. The vast majority of first-time buyers are concentrated at high maximum loan-to-values, with more than 25 percent borrowing (almost) exactly 90 percent of the value of their house.[9]. This behavior allows me to model the leverage choice as a discrete choice. Figure 1-4 (b) shows the portfolio share of a large lender adopting the internal rating based model and a small lender with the standardized approach. The large lender portfolio is evenly distributed across all leverage levels, while the small lender issues most mortgages at high loan-to-values, where the risk-weight gap with the large lender is lower and its pricing is more competitive (see Figures 1-1 and 1-3 (b), respectively).

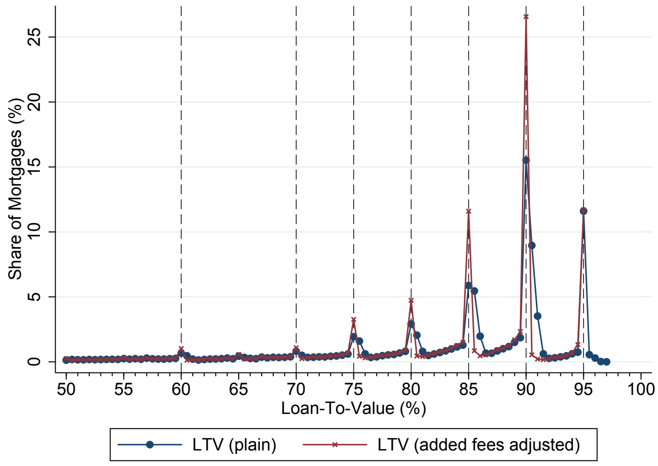
Figure 1-5 explores the lender choice. Figure 1-5 (a) shows the price and market share for two mortgage products with the same maximum loan-to-value (60 percent), interest rate type (2 years fixed), and loan size (£140-160.000) but offered by two different lenders. The mortgage with the higher price has the higher market share for the whole period under analysis. In my empirical model I account for factors (e.g., brand value) that can explain this counter-intuitive effect and I explore with the available data the role of lenders' branch network in affecting borrowers' choices.[10] Figures 1-5 (b) and (c) show that areas in which a lender has a large share of branches, the same lender originates more mortgages.[11] Accounting for

[9]Best et al. (2015) show a similar but less pronounced pattern for remortgagers.

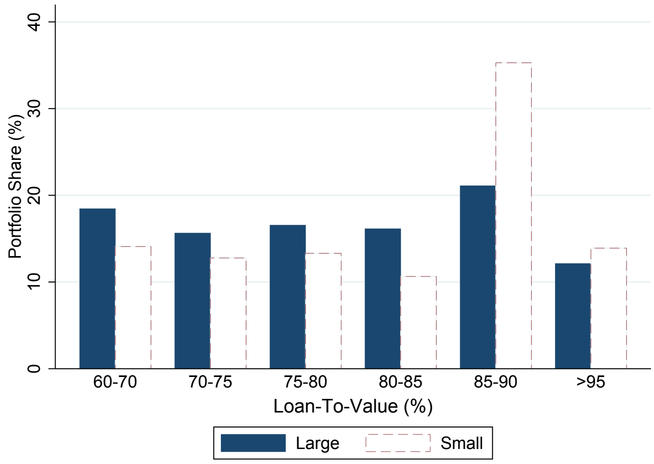
[10]A possible explanation also comes from the supply side, with the low price - low market share products only approved to some customers. Due to data limitations I cannot test this hypothesis, but given the low leverage (60 percent), rejections are less likely to be a concern. I do not have information on the lenders approval decision, so I need to assume that all borrowers of a certain type have access to the advertised rate and take the best alternative. To limit concerns about rejection, I restrict the choice set based on observable borrowers characteristics and affordability criteria as explained in Section 1.4.1. 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).

[11]This relation is not driven by smaller lenders (e.g. building societies). In Appendix A.1 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.

Figure 1-4: Leverage



(a) Market share



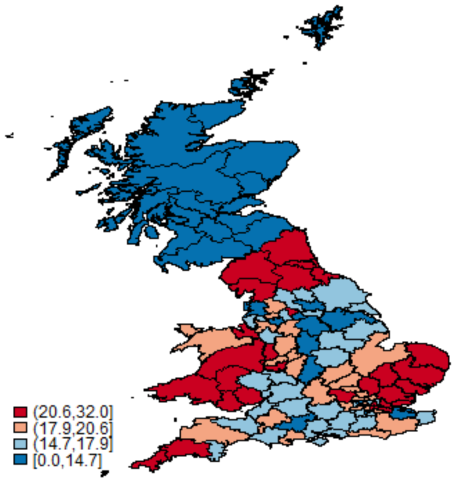
(b) Portfolio share

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

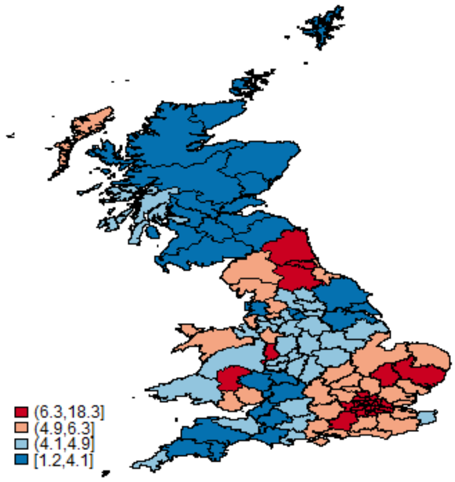
these features in the demand model is important to capture factors that can affect the demand elasticity (e.g. limited substitution due to local shopping), as the distance between the borrower and the lender continues to play an important role even

Figure 1-5: Lender

(a) "Dominated" products



(b) Branch Share



(c) Mortgage Share

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

in modern lending markets (Becker, 2007; Scharfstein and Sunderam, 2014).

Table 1.2: 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 lenders and maximum loan-to-values.

Performances

Finally, in Table 1.2 I study some patterns in default and refinancing for different lenders and maximum loan-to-values. I capture the default risk by looking at mortgages originated since 2005, that are in arrears in 2016. Column (1) of Table 1.2 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 increases monotonically with the maximum loan-to-value. This pattern is reflected in the pricing schedules of Figure 1-3.[12]

To capture refinancing risk, I consider for each product the fraction of outstand-

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

ing 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 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 1.2 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.

Finally, column (3) of Table 1.2 shows the SVR. The standard variable rate is always around 4 percent. Challenger lenders and building societies have a higher SVR, while the SVR does not seem to vary across loan-to-values, in a way similar to the origination rate. The SVR is almost always larger than the origination rate, giving a strong incentive to refinance the mortgage at the end of the initial period (Best et al., 2015).

1.3 A Structural Model of the UK Mortgage Market

In this section I develop a structural model of mortgage demand and pricing to study the equilibrium implications of changes in leverage regulation. First, I specify household utility as a function of product characteristics and derive both product and loan demand. Then, I develop a pricing equation that incorporates capital requirements and the empirical facts described in Section 1.2.3.

1.3.1 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:

$$V_{ijm} = \bar{V}_{ijm}(Y_i, D_i, X_j, r_{jm}, A_{ij(l)}, \zeta_i, \xi_{jm}; \theta_i) + \varepsilon_{ijm}, \tag{1.1}$$

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

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

The constrained problem becomes:

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

where J_m is the total number of products available in a given market m. In the standard case the borrower has access to all products, so that $J_i \equiv J_m$. I implement affordability constraints by: 1) restricting the choice set of the borrower to products with the chosen maximum loan-to-value and only one step above and below; and 2) considering a representative product with the chosen maximum loan-to-value as the outside option. An individual chooses product j if $V_{ijm} > V_{ikm},\ \forall j \in J_i$. I assume that ε_{ijm} in equation (1.1) is identically and independently distributed across households and mortgage products with a type I extreme value distribution. Then, the demand by borrower i in market m for product j is given by:

$$s_{ijm} = \frac{\exp(\bar{V}_{ijm})}{\sum_{k=0}^{J_i} \exp(\bar{V}_{ikm})}. \tag{1.2}$$

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

$$q_{ijm} = -\frac{\frac{\partial V_{ijm}}{\partial r_{jm}}}{\frac{\partial V_{ijm}}{\partial Y_i}} = q_{ijm}(Y_i, D_i, X_j, r_{jm}, \zeta_i, \xi_{jm}; \theta_i). \tag{1.3}$$

The demand model jointly described by equations (1.2) and (1.3) captures in a

[13] I discuss in detail the construction of the borrower specific choice set in Section 1.4.1.

flexible ways several factors that are likely to affect households' mortgage choice. First, the sensitivity to the interest rate r_{jm}, which I allow to vary across different products consistent with the non-linearities in the pricing schedules from Section 1.2.3.[14] In this way I capture a standard intertemporal trade off between consumption today and consumption tomorrow (Brueckner, 1994). A higher leverage (i.e., a larger maximum loan-to-value captured in the X_j) implies a higher repayment burden in the future, thus lowering consumption via a larger monthly payment.

Second, additional characteristics such as the interest type and brand in X_j allow for horizontal differentiation and the number of branches of the lender in the postcode area of borrowers' house ($A_{ij(l)}$) allows for spatial differentiation. In this way I account for borrowers' costs associated with the application process and the formation of the choice set, along the lines of Hastings et al. (2013). Higher branch presence can increase the utility for households, because they generate spatial differentiation. For example, a large branch presence allows the household to walk in to a branch when needed, thus lowering transaction costs. However, more branches can make the lender more salient to the borrower, by increasing the probability that the borrower will consider it. Moreover, in the absence of data on borrowers' assets, the local share of branches can proxy for pre-existing relations between the borrower and the lender (e.g., current account).[15]

Third, I allow for unobservable product heterogeneity (ξ_{jm}) to affect the household mortgage and quantity choice. In the case of mortgage products the unobservable term can capture "quality" as in standard IO models (Berry et al., 1995;

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

[15]In the UK mortgage market borrowers search for mortgage products and apply via branches, intermediaries and on-line comparison website. The application process is long and can be very costly. Ideally I would like to observe the true household choice set when applying for mortgages, but this information is not available in most settings. See Basten and Koch (2015) and Michelangeli and Sette (2016) for examples of settings in which the choice sets are observable.

Nevo, 2001). Even if I observe the most relevant mortgage characteristics, lenders can offer optional services and contracts can include additional features (e.g., cash back, payment holidays) that may increase the "quality" of the product, coeteris paribus. Advertising plays an important role in the mortgage industry and could also justify the inclusion of unobservable product heterogeneity (Goeree, 2008; ?).[16]

Two remarks are in order. First, I fix the interest rate set at origination, which implies that borrowers expect future interest rates to reflect current interest rates. This assumption holds for fixed rate mortgages until the end of the initial period and is reasonable for variable rate mortgages, given the short horizon before remortgaging. Second, I develop a static model, which does not allow us to study issues related to the timing of the purchase, refinance or default. This will complicate 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 1.2.3 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.[17]

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

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

1.3.2 Lender Pricing

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

$$PV(q_{ijm}, r_{jm}, c_{jm}, T_i) = q_{ijm} \sum_{k=1}^{T_i} \left[\frac{r_{jm}(1+r_{jm})^{T_i}}{(1+r_{jm})^{T_i}-1} - \frac{c_{jm}(1+c_{jm})^{T_i}}{(1+c_{jm})^{T_i}-1} \right], \qquad (1.4)$$

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

Equation (1.4) does not account for the two key risks in the mortgage market: default and refinancing. First, default risk raises the expected cost for the lender to issue a mortgage. I assume that lenders setting interest rate do not forecast the probability of default in each period, but consider an average expected probability of default, as in Crawford et al. (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.[19]

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

[19] In Appendix A.2 I allow for a more flexible specification in which some borrowers fail to refinance at the end of the initial period and pay the standard variable rate until maturity. Even if borrowers can refinance the mortgage in any month, I capture this risk in a simpler way by allowing one remortgaging opportunity at the end of the initial period. As already mentioned in Section 1.2.3 the vast majority of borrowers refinance their mortgage at the time their initial rate expires. Furthermore, in the period I analyze there is almost no variation over time in the standard variable rate, so that it is captured by the lender dummies.

For long maturity, equation (1.4) with refinancing and default risks becomes:

$$PV(q_{ijm}, r_{jm}, c_{jm}, t_j, d_{ijm}) \approx q_{ijm}t_j(r_{jm}-c_{jm})-d_{ijm}q_{ijm}t_jr_{jm} = q_{ijm}t_jr_{jm}(1-d_{ijm})-q_{ijm}t_jc_{jm}, \tag{1.5}$$

where t_j is the initial period and d_{ijm} is the expected default probability for borrower i taking product j in market m, which I allow to also be a function of the interest rate.[20] 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 (1.5), I can write the problem of the lender as:

$$\begin{aligned} \max_r \Pi_{lm}(r_{jm}) &= \sum_{j \in J_{lm}} \Pi_{jm}(r_{jm}) = \\ &= \sum_{j \in J_{lm}} \sum_{i \in I_m} s_{ijm}(r_{jm}, r_{-jm}) \times PV(r_{jm}) = \\ &= \sum_{j \in J_{lm}} \sum_{i \in I_m} s_{ijm}(r_{jm}, r_{-jm}) \times q_{ijm}(r_{jm}) \times [t_jr_{jm}(1-d_{ijm}) - t_jc_{jm}] \,. \end{aligned} \tag{1.6}$$

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

[20] Equation (1.5) assumes that the remaining interest payment is lost upon default. In the case of collateralized lending, such as mortgage lending, the lender may be able to recover some fraction of the balance from the house sale and further actions against the defaulted borrower. Adding a positive recovery rate in case of default would increase the complexity of the model requiring lenders to form expectation on future house price values, but would not affected the cross-sectional nature of regulation and competition which is the focus of this paper.

derivative of the profits with respect to the price of product j is given by:

$$\begin{aligned}\frac{\partial \Pi_j}{\partial r_j} &= S_j Q_j (1-D_j) t_j + S_j \frac{\partial Q_j}{\partial r_j}\left[t_j r_j (1-D_j) - t_j c_j\right] \\ &+ \sum_{k \in J_l} \frac{\partial S_k}{\partial r_j} PV_k - S_j Q_j \frac{\partial D_j}{\partial r_j}(t_j r_j) = 0,\end{aligned} \tag{1.7}$$

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

$$\begin{aligned} r_j^* = & \overbrace{\frac{c_j}{(1-D_j) - \frac{\frac{\partial D_j}{\partial r_j}}{\frac{\partial S_j}{\partial r_j}\frac{1}{S_j} + \frac{\partial Q_j}{\partial r_j}\frac{1}{Q_j}}}}^{\text{Effective marginal cost}} - \overbrace{\frac{1}{\frac{\partial S_j}{\partial r_j}\frac{1}{S_j} + \frac{\partial Q_j}{\partial r_j}\frac{1}{Q_j} - \frac{\partial D_j}{\partial r_j}\frac{1}{1-D_j}}}^{\text{Full mark-up}} \\ & - \underbrace{\sum_{k \neq j \in J_l} \frac{\frac{\partial S_k}{\partial r_j} PV_k}{t_j \left(\frac{\partial S_j}{\partial r_j} Q_j (1-D_j) + S_j \frac{\partial Q_j}{\partial r_j}(1-D_j) - S_j Q_j \frac{\partial D_j}{\partial r_j}\right)}}_{\text{Other products}}. \end{aligned} \tag{1.8}$$

Note that if there is no default risk ($\frac{\partial D_j}{\partial r_j} = 0$ and $D_j = 0$), all lenders offer only one product and all households make only the discrete product choice ($Q_j = 1$), then equation (1.8) collapses to the standard mark-up pricing formula: $r_j^* = c_j - \frac{S_j}{\frac{\partial S_j}{\partial r_j}}$.

Equation (1.8) 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 sheets have other assets than mortgages, I assume that when they set rates for mortgages they behave so that they account for the capital requirement constraint. Second, I embed in the model regulation on household leverage, along the lines of recently implemented policies in the US and the UK (Consumer Financial Protection Bureau, 2013; Bank of England, 2014). I achieve that by imposing a 15 percent quota on the share of mortgages with a loan-to-income above 4.5, along the lines of Goldberg (1995) for cars' import.[21] The problem for constrained lenders becomes:

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

where K_{lm} is actual capital resources; $\underline{\mathrm{K}}_{lm}$ is the lender-specific minimum capital requirement; ρ_{jm} is the risk weight for mortgage product j; and $\mathbb{I}[LTI > 4.5]$ is an indicator for 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 mortgage market is characterized by lenders optimal pricing subject to the leverage regulations and borrowers optimal mortgage choice.

[21]The 15 percent limit comes from a recommendation by the Financial Policy Committee of the Bank of England in June 2014. For more details see Bank of England (2014) and section 1.6.2.

1.4 Estimation and Identification

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

1.4.1 Counterfactual Choice Set

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

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

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.,

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

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

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 market-group may shop at different maximum loan-to-values. I address these additional constraints in a third step, in which I further restrict the number of products available to household i by limiting the choice set to all products in household i group with a maximum loan-to-value equal to the one chosen by i or just above and below.[24] In this way I allow borrowers to shop locally in terms of the down-payment decision, consistent with the bunching behavior from Figure 1-4 (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 portfolios widespread across the UK, and even products from smaller lenders, with a more local business model, can be sold nationally via Internet, phone and brokers. Ruling out products from households' choice sets based on their 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.

1.4.2 Estimation

Demand. My demand model in Section 1.3.1 predicts for every household mortgage demand and loan size as a function of observable household characteristics, random preferences, products attributes and a vector of parameters to be estimated. I estimate the demand model described with two assumptions on the structural unobservables error terms. I assume that ε_{ijm} in equation (1.1) is identically and

[24]As a example a household buying in equilibrium a product with a maximum loan-to-value of 90 percent will have in the choice set mortgage with a maximum loan-to-value of 90, 85 and 95 percent. As a robustness I redo my analysis when I stop at the first step of the choice set definition, thus enlarging the choice set.

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:

$$Pr(i\ chooses\ j) = p_{ijm}(\zeta_i) = \frac{\exp(\bar{V}_{ijm})}{\sum_{k=0}^{J_i} \exp(\bar{V}_{ikm})}, \tag{1.9}$$

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

$$s_{ijm} = \int_{\zeta} p_{ijm}(\zeta_i) dF(\zeta_i). \tag{1.10}$$

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

$$\bar{V}_{ijm} = \frac{\gamma}{1-\phi} Y_i^{1-\phi} + \mu \exp(-\alpha r_{jm} + \beta X_j + \xi_{jm} + \eta D_i + \zeta_i) + \lambda A_{ij(l)}. \tag{1.11}$$

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

$$\ln(q_{ijm}) = \ln\left(-\frac{\frac{\partial \bar{V}}{\partial r}}{\frac{\partial \bar{V}}{\partial y}}\right) = \phi \ln(Y_i) + \ln(\frac{\mu\alpha}{\gamma}) - \alpha r_{jm} + \beta X_j + \xi_{jm} + \eta D_i + \zeta_i. \tag{1.12}$$

From equation (1.12) and the normal distribution assumption for ζ_i, the probability of the conditional loan demand is:

$$
\begin{aligned}
f(\ln(q_{ijm})|j, j \neq 0) = \frac{1}{\sqrt{2\pi\sigma^2}} \times \exp\Bigg[-\frac{1}{2\sigma^2}\Bigg(\ln(q_{ijm}) \\
-(\phi\ln(Y_i) + \ln(\frac{\mu\alpha}{\gamma}) - \alpha r_{jm} + \beta X_j + \xi_{jm} + \eta D_i)\Bigg)^2\Bigg].
\end{aligned} \tag{1.13}
$$

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, by estimating both choices in one step. The joint log likelihood for individual i to buy product j and borrow an amount q_{ijm} is given by:

$$
\ln(L_i) = \sum_{j=0}^{J_i} \mathbb{I}_{ijm}\left[\ln(s_{ijm}) + \ln(f(\ln(q_{ijm})|j, j \neq 0))\right], \tag{1.14}
$$

where $\mathbb{I}_{ijm}$ is an dummy equal to one if borrower i chooses product j and zero otherwise. I also take explicitly into account a possible correlation between the interest rate (r_{jm}) and unobservable product characteristics (ξ_{jm}). Let $\delta_{jm} = -\alpha r_{jm} + \beta X_j + \xi_{jm}$ be the product-market fixed effects. In the first step, I estimate the joint likelihood (1.14) with product-market fixed effects and obtain the utility parameters (ϕ, η, λ), the scaling factors (σ, μ), and the product-market fixed effects (δ_{jm}). In the second step, I recover the impact of the interest rate and other product characteristics using the estimated fixed effects as dependent variable, as follows:

$$
\hat{\delta}_{jm} = -\alpha r_{jm} + \beta X_j + \xi_{jm}. \tag{1.15}
$$

To account for endogeneity in the interest rate I estimate the second step with instruments that I discuss in Section 1.4.3:

Supply. The estimation of the supply side parameters is based on the optimal pricing formula derived in Section 1.3.2. To compute the full mark-up and isolate the marginal costs I need information on the average expected default rate and on the increase in defaults as a result of changes in interest rates. I back out the latter using a cross-section of data about mortgage performances as of June 2016 and a linear probability model:

$$d_{ijt} = \beta r_{jt} + \eta X_i + \gamma_t + \gamma_j + \epsilon_{ijt}, \tag{1.16}$$

where d_{ijt} is a dummy equal to one if borrower i who took product j in period t is in arrear in June 2016; X_i are borrower characteristics at origination; γ_t and γ_j are cohorts and product fixed effects. The key parameter is β, which captures the direct effect of the interest rate on arrears. To identify it I control for product and cohort fixed effects and borrower level demographics. Equation (3.3) estimates the effect of variables at originations on ex-post outcomes. As some variables will change over time (e.g. income, house value) a fully specified model should control for the actual value of these variables. Unfortunately I do not have a panel that will allow me to do that. However, variables at origination play an important role for pricing of the *expected* probability of arrears, which is the object of interest in the pricing function.[25]

Using the estimated parameters from the demand side and additional information about mortgage performances, I compute the marginal cost inverting equation (1.8). I then obtain a two-step estimator of the cost parameters with the following model:

$$c_{jm} = \psi \underline{\mathrm{K}}_{lm} \rho_{jm} + \tau X_j + \gamma_m + \gamma_{j(l)} + \kappa_{jm}, \tag{1.17}$$

[25] I use the estimated parameters from equation (3.3) 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 (3.3), and an indirect impact via both the discrete mortgage choice and the continuous quantity choice. To use the parameters from the default model in the counterfactual analysis I need to assume that the change in the regulation does not change the relation between interest rate and default.

where the dependent variable is the estimated marginal cost at the product-market level; $\underline{\mathrm{K}}_{lm}\rho_{jm}$ is the risk-weighted regulatory capital requirement; X_j are the same product characteristics that affect borrower demand (rate type, maximum loan-to-value, lender); γ_m and $\gamma_{j(l)}$ are market and lender fixed effects; and κ_{jm} is a structural error term capturing unobservable cost determinants (e.g., advertising, screening).

1.4.3 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 (1.14). 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 borrower's choice of the lender, but does not have an impact on the conditional choice of the quantity. Since I estimate the model in each region separately and I control for lender fixed effects, my assumption requires that within a region, a larger branch presence of a lender in a postcode area does not differentially affect the loan demand of borrowers choosing that lender.[26] I exploit variation in the branch network together with variation on the location of the borrowers' houses at the postcode level to identify application costs ($A_{ij(l)}$).

I consider exogenous time-invariant characteristics (X_j), such as lender, interest rate type and maximum LTV, but I allow for time-varying unobservable attributes that can affect demand (e.g. advertising, screening, cash-back) to be correlated

[26]This exclusion restriction is supported by the empirical evidence. In Appendix A.1 I regress market shares and loan amounts on quartiles of branches, controlling for differences across lenders and postcodes with fixed effects. I find that a higher branch presence affect the lenders' market share, but has no differential effect on loan amounts. Furthermore, my assumption resembles previous studies estimating discrete-continuous supermarket choice models (Smith, 2004; Dubois and Jódar-Rosell, 2010).

with the interest rate. The price setting decision of the lender can be taken as exogenous from the point of view of the borrower, and I can also rule out reverse causality from the "atomistic" individual borrower to the lender. However, the use of individual data does not solve the endogeneity problem, as unobservable attributes at the product level can be correlated with interest rates, thus biasing my results. As an example consider a lender that relaxes screening 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 correlated 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 choosing 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 the differential screening effort.

To account for endogeneity in the interest rate I include dummies for markets and lenders. In this way I control non-parametrically for time-invariant average unobservable differences across lenders and I identify the interest rate elasticity from the within lender variation across products and over time. Even in this difference-in-difference setting, unobservable (to the econometrician) attributes can affect borrower utility and be correlated with interest rates. I instrument interest rates using variation in risk-weighted capital requirements that affects the cost for lenders of issuing a particular product. Differently from previous papers that develop cost-shifters at the *firm* level (Egan et al., 2017; Koijen and Yogo, 2016), I exploit the institutional features of the leverage regulation in place in the UK, that I described in Section 1.2.2, to construct cost-shifters at the *product* level. The identification assumption for the demand parameters is:

$$E\left[\xi_{jm}|X_j, Z_{jm} = \underline{\mathrm{K}}_{lm}\rho_{jm}\right] = 0. \tag{1.18}$$

Equation (1.18) says that regulation is uncorrelated with demand shocks, conditional on observable characteristics. The reason behind this assumption is the following exclusion restriction: the only way through which risk-weighted capital requirements affect borrowers utility for a particular mortgage is via their effect on interest rates. Endogeneity in the regulatory instrument that is correlated with unobservable household preferences can pose a threat to my identification strategy. However, my identification assumption is conditional on product characteristics, which include lender fixed effects, thus requiring a *differential* change in risk weights across loan-to-values *within* lender, as an average change will be captured by the fixed effects. Furthermore, changes in the internal models need to be approved by the regulators, thus limiting lenders' discretion in setting them.[27] Finally, I extend the intuition in Berry et al. (1995) to instrument prices with exogenous characteristics of competitor products and I exploit the regulation of other lenders as an instrument for interest rates.

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

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

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.

1.5 Estimation results

1.5.1 Demand Parameters

In this section I present the results from the estimation of the structural model, using data from first-time buyers.[28] Table 1.3 shows the estimated demand parameters averaged across all groups.[29]

The main parameter of interest is α, which captures the effect of interest rate on the indirect utility. As expected the coefficient is negative and this results is robust to different cuts of the data. 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 A.2. I find an average loan demand elasticity of 0.08 and a product demand elasticity of 6.4.[30] 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

[28] Consistent with previous work and my reduced form evidence in Appendix A.5, leverage regulation has a larger impact on interest rates and credit access for borrowers with higher leverage, while home movers and remortgagers may already have accumulated equity in their houses.

[29] Appendix A.3 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 A.4.

[30] 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 more important roles.

Table 1.3: 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

Notes: the table shows the structural demand estimates of the econometric demand model of section 1.4.2. The model is estimated separately in each group (income-age-region) and the table reports the average point estimate and standard error in each group. The total number of borrowers is 370,575 and the average number of product-market observations is 773. The standard error for the parameters in the first stage are computed by the inverse of the information matrix; the standard errors for the mortgage attributes estimated in the second stage are computed by bootstrapping. All estimates include lender and market fixed effect.

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

In Table 1.4 (b) I report the estimated own- and cross-product demand interest

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

Table 1.4: 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 1.3 and the formulas in Appendix A.2. I 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.

rate elasticities for the ten most popular products in the first-time buyer market. A one-percent increase in the interest rate decreases the market share of the mortgage by 3-7 percent, while the shares of other mortgages increase by 0.01-0.07 percent.

In Table 1.3 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.[32] Finally, the fraction of branches in the postcode where households have their houses has a positive impact on average.

So far I focused on average effects, but the estimated model allows for rich heterogeneity, both observable and unobservable. Table 1.3 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 (1.12)) and measures the elasticity of loan demand to income. I find a positive and significant elasticity around 0.7. I also find significant unobservable heterogeneity across households even within my narrowly defined groups and controlling for observable demographics within group. [33]

Fit and Robustness

Table 1.5 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. In Appendix A.3 I report additional statistics and distribution to test the fit of my model.

Finally, in Appendix A.4 I discuss several robustness checks. First, I instrument

[32]In the UK mortgage market the vast majority of products has an interest rate fixed for a period of two years, and there are few products with a fixed rate for more than five years. I explore the preference to for a longer duration by comparing mortgages fixed for two versus five years.

[33]In Appendix A.3 I explore further heterogeneity across groups that may be potentially important for evaluating the distributional effect of alternative leverage regulations.

Table 1.5: 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.

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 (1.15)) simultaneously with the supply side (equation (1.17)) using generalized method of moments. My results are robust to these different instruments, variable definitions and estimation methods.

1.5.2 Supply Parameters and The Cost of Capital Regulation

First, I show the results for the default model, whose estimates enter the calculation of the mark-ups and marginal costs. 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 1.6 shows the estimates. I find a statistically significant and robust positive relation between the interest rate and default: a 1 percentage point higher interest rate increases the probability of default by 0.15 percentage points. I also study how loan-to-income and loan-to-value at origination affect the probability of default. Mortgages with loan-to-income above 3.5 and loan-to-value above 85 are always more likely to default.

Given that the estimates pool together mortgages from different years in columns (2) and (3) of Table 1.6 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 with higher loan-to-income are more likely to default when originated both before and after the crisis. Some differences emerge for high leverage mortgages originated after relative to those originated before the crisis. High loan-to-value mortgages issued before the crisis are significantly more likely to default, while high loan-to-value mortgages issued after are less likely to default. A possible explanation for the latter result can be the increase in supply side restrictions and affordability checks after the crisis, which led to an overall low volume of originations at high leverage to a selected pool of low risk households.

To address endogeneity concerns coming from omitted variables correlated to both the interest rate and the default probability, I show the result of an instrumental variable approach in column (4) of Table 1.6. I instrument the interest rate with the risk weight, following the same identification assumption from section 1.4.3 for demand parameters. The IV estimates are almost identical to the OLS estimates.

With the estimated demand and default parameters I compute the mark-ups

Table 1.6: Default estimates

	Full sample	Pre-crisis	Post-crisis	
	OLS	OLS	OLS	IV
	(1)	(2)	(3)	(4)
Interest (%)	0.0015***	0.0114***	0.0012***	0.0012***
	(0.0001)	(0.0006)	(0.0001)	(0.0004)
High LTI	0.0007***	0.0025***	0.0003*	0.0003**
	(0.0002)	(0.0006)	(0.0001)	(0.0001)
High LTV	0.0013***	0.0127***	-0.0010***	-0.0009**
	(0.0002)	(0.0008)	(0.0002)	(0.0004)
Time F.e.	Yes	Yes	Yes	Yes
Lender F.e.	Yes	Yes	Yes	Yes
Rate type F.e.	Yes	Yes	Yes	Yes
Postcode district F.e.	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes
Observations	2708046	551840	2156171	2082421

Notes: the table shows the default estimates from equation (3.3). The dependent variable is a dummy equal to one if a mortgage originated between 2005 and 2015 is in arrears in June 2016. We define arrears as being at least 3 months late in servicing the monthly payment. Column (1), column (2) focuses on mortgages originated before 2008, while columns (3) and (4) look at mortgages originated after 2008. Interest is the interest rate at origination expressed in percentage terms. High LTI is a dummy for mortgages with loan to income at originations above 3.5; High LTV is a dummy for mortgages with loan to value at origination above 85. Borrower controls include type of borrower, employment status, income, age, maturity and property value. In column (4) the excluded instrument for the interest rate is the mortgage risk weight.

and marginal costs. The average markup is about 0.53 percentage points in the full sample, which correspond to about 18 percent of the average interest rate in the data.[34] 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. 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 marginal cost as a dependent variable in equation (1.17), to

[34]Button et al. (2010) perform a decomposition of new lending rates for UK mortgages, into funding costs, capital costs and a residual. They find that after the financial crisis in 2008 the residual, which includes operating costs and markup, has risen. As operating costs are unlikely to have changed and if anything they may have decreased as results of consolidation, their finding is consistent with increasing markups.

Table 1.7: Structural supply estimates

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

Notes: the table shows the structural parameters of the supply model from equation (1.17). 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. Fix 5 is a dummy for mortgages with a fix period of 5 years. In column (6) the excluded instrument for the mortgage risk-weighted capital requirements is the closest risk weight for the same loan-to-value and rate type offered by another lender. Robust standard errors in parenthesis.

decompose the effect of product characteristics and identify the cost of capital regulation in the mortgage market. Table 1.7 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 1.7 shows the effect of capital regulation on effective marginal cost controlling for market and lender fixed effects. I find that a one-percentage-point higher risk-weighted capital requirement increases the marginal cost of lending to first-time buyers by about 65 basis points.

In column (2) of Table 1.7 I further control for other product characteristics that have an impact on the cost of issuing mortgages. As expected, we find that high leverage and longer fix rate mortgages have higher marginal costs. Once I control for these product attributes the coefficient on the risk-weighted capital requirements is reduced in magnitude, but the effect is still significant. A one-percentage-point higher risk-weighted capital requirement increases the marginal cost of lending to first-time buyers by approximately 27 basis points. The inclusion of the control for leverage, which captures the decrease in risk for mortgages with a lower leverage that is common across lenders, drives the decline in the effect.

In column (3) of Table 1.7 I add interacted market-lender fixed effects. In this way I only exploit the variation in risk-weighted capital requirement within a lender-time pair, ruling out concerns about other time-varying lender-specific factors affecting the cost of issuing mortgages. The coefficient that captures the impact of regulation on the cost of lending is still significant and the magnitude is larger than in column (2).

In columns (4) and (5) of Table 1.7 I explore the heterogeneity in the cost of risk-weighted capital requirements across lenders. Column (4) allows the effect of capital requirements to vary with the type of lender. The baseline is the largest six lenders. I find that the effect of capital regulation is stronger for building societies, whose business model is centered around mortgages, and weaker for challenger lenders, which have a more diversified portfolio. In column (5) I interact capital requirements with the lenders' capital buffer, defined as the difference between capital resources and capital requirements. I find that lenders with more capital relative to the requirement are less affected by the regulation.

Finally in column (6) of Table 1.7 I address possible concerns about endogeneity in the regulation and omitted variable bias. I exploit the regulation of other lenders as an instrument for own regulation. In particular, for each mortgage product I calculate the closest risk weight for the same loan-to-value and rate type offered by another lender and I use it as an instrument for the lender risk weight. The IV estimates are almost identical to the OLS estimates.

Magnitude

The baseline estimate in column (2) of Table 1.7 shows an increase in the marginal cost of about 27 basis points for a one-percentage-point increase in the risk-weighted capital requirement. Given an average marginal cost of 2.4 percent, marginal cost increases by approximately 10 percent for the average mortgage product. To put my estimates of the cost of capital regulation into context, I simulate an increase in capital requirement by 10-percentage-points, along the lines of previous studies (Hanson et al., 2011; Baker and Wurgler, 2015; Firestone et al., 2017).[35] Previous papers find a wide range of values going from 3 basis points (Kisin and Manela, 2016), to 25-45 basis points (Hanson et al., 2011), up until 60-90 basis points (Baker and Wurgler, 2015). I find that increasing capital requirement by 10-percentage-points increase marginal costs by about 60 basis points. This increase is on the upper end of previous estimates. My number can be interpreted as an upper bound to the cost of increasing capital requirements, as I allow lenders to adjust to the new regulation *only* by increasing mortgage rates. In reality lenders can lower deposit rates, issue new equity and retain earnings. These additional margins of adjustment will likely decrease the cost of increasing capital requirements (Elliott, 2009).

1.6 Counterfactual Leverage Regulations

In this section I use the estimated model to study alternative leverage regulations and their equilibrium impact on interest rates, market structure and risk. Section

[35] In Appendix A.5 I show the effect of a common increase in capital requirement by 10-percentage-points on marginal costs, rates and several additional variables of interest.

1.6.1 compares two alternative counterfactuals that remove the risk-weight gap between large and small lenders that I document in Figure 1-1. Section 1.6.2 analyzes the interactions between risk-weighted capital requirements and regulations limiting household leverage.

1.6.1 Equilibrium Effects of Risk Weights

The reduced form evidence from Section 1.2.3 suggests that risk weights affect pricing and specialization.[36] Figure 1-6 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 average risk weight and the average interest rate for the same lender for mortgages with a maximum loan-to-value of 95 percent relative to those with a maximum 70 percent. The relative risk weight of the lender jumps from slightly above one to more than four, as the lender adopts the internal model. At the same time the relative interest rate of the high leverage product increase from around one to approximately 1.5.

The adoption of an internal model by one lender is not enough to learn what would have happened in the mortgage market if all or some lenders are affected by changes in the leverage regulation. Furthermore, contemporaneous changes in market power and business models (e.g., securitization) can confound the effects of regulation. To address these issues, I explore with the estimated model the equilibrium impact of changing risk-based capital requirements keeping all else equal. First, I simulate an equilibrium without internal models for the calculation of capital requirements (Counterfactual I: All Standard). Second, I allow lenders adopting a

[36] In Appendix A.5 I explore further the reduced form relation between risk weights and interest rates.

Figure 1-6: 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.

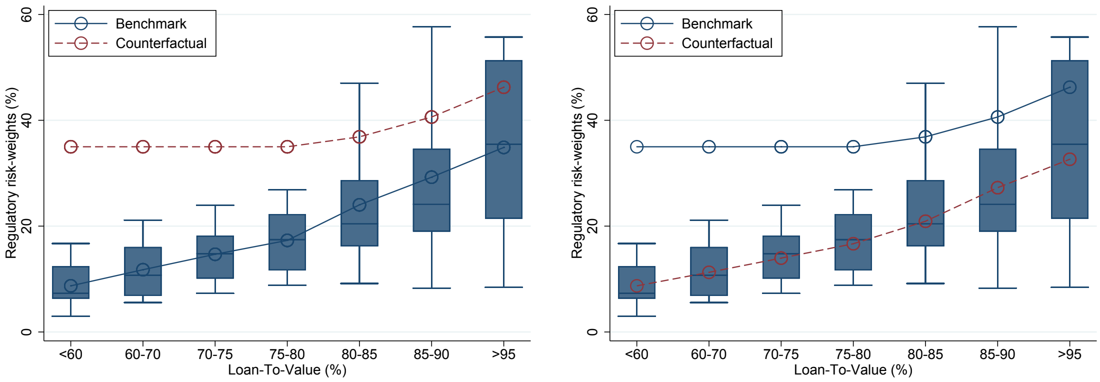
standardized approach to develop an internal model, with the average risk weights of large lenders (Counterfactual II: All Internal).[37] The two policies are illustrated in Figure 1-7.

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 (1.8), the difference in prices between the two lenders for product j will be given by:

$$r_{j,small} - r_{j,large} = \underbrace{\rho_{j,small} - \rho_{j,large}}_{\text{Regulatory advantage}} - \underbrace{\left[\frac{1}{\frac{\partial Q_{j,small}}{\partial r_{j,small}} \frac{1}{Q_{j,small}}} - \frac{1}{\frac{\partial Q_{j,large}}{\partial r_{j,large}} \frac{1}{Q_{j,large}}} \right]}_{\text{Incumbent advantage}} \tag{1.19}$$

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

Figure 1-7: 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 standard approach for setting the risk weights. In Figure (b) I show the second counterfactual, in which I compute the mean risk weight across lenders with the internal model and assign it to the small lenders with the standard approach.

The higher risk weights for the small lender translate into higher rates, ceteris paribus. If the elasticity of the product offered by the large lenders is lower, due to brand power, there is also an incumbent advantage, which further amplifies the price gap. I explore the consequences of changing the regulatory advantage in equation (1.19). Table 1.8 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 for mortgage originations. As a result of the abolition of internal models the market becomes more competitive. Large lenders lose the regulatory advantage (first element in equation (1.19)) and increase their prices following an increase in the regulatory capital they have to hold. As a result of the higher rates, large lenders loose market shares in favor of smaller lenders already adopting the standard regulatory approach. The share of the largest six lenders drops from almost 85 percent to about 60 percent.

The adoption of internal models for small lenders also has a pro-competitive effect on the market.[38] 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 1.8 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 (intensive margin) decrease by approximately £1.5K, which is slightly higher than one percent of the average baseline balance. In the second counterfactual, marginal costs in the mortgage market go down by about 13 basis points, as a result of lower capital requirements for small lenders. This fall translates into a reduction in prices by about 14 basis points and an increase in mortgage demand by slightly more than one percent. I use the model to compute a measure of consumer surplus based on the sum of indirect utilities (see Appendix A.2 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

[38]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 may impair competition.

Table 1.8: 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	1.12	-0.39	0.07
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, all lenders adopt the standard approach for setting the risk weights. In the second counterfactual I compute the mean risk weight across IRB lenders and simulate a scenario in which SA lenders develop and internal model that gives them the average risk weight of their IRB competitors. Cost is the marginal cost in percentage points; price is the interest rate in percentage points; demand (extensive) is the total number of borrowers; demand (intensive) is the loan amount; consumer surplus is the log sum of the indirect utility of a representative consumer (see appendix A.2); default is the average number of defaults in percentage points; buffer is the difference between the equity and the predicted loss. Small lenders include challengers and building societies. Value is the actual value in the benchmark and counterfactuals; Δ is the absolute change of the value in the counterfactual relative to the benchmark.

large systemic lenders. In Panel D of table 1.8, 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 1.2.3. With the abolition of internal models I observe an increase in the average default in the mortgage market, as higher prices make it harder for borrowers to service 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 1.8 I also report a measure of resilience for the overall mortgage market. I compute the equity buffer as the difference in pounds between lenders' equity and expected losses for each mortgage. Lenders' equity is given by the endogenous loan size multiplied by the lender-specific capital requirement and the counterfactual risk weights; expected losses come from expected default given by (3.3) after lenders re-optimize rates in reaction to the new risk-weighted capital requirements and borrowers adjust demand with the new prices. Abolishing internal models almost doubles the equity buffer in the mortgage market, 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 lenders in a crisis (Acharya et al., 2012; Akerlof et al., 2014; Bianchi, 2016), my second counterfactual suggests that the reduction of risk weights for small lenders will not threaten the stability of the system.

I find that heterogeneous capital regulation accounts for between 20 and 30 percent of the concentration in the market. The abolition of internal models addresses the imbalance between large and small lenders in terms of capital requirements, but the higher capital reduces demand and consumer surplus. The provision of a representative internal model to small lenders could also address the competitive distortion due to the differential regulatory treatment, but with limited impact on credit access, ex-post mortgage defaults and the resilience of large lenders.[39]

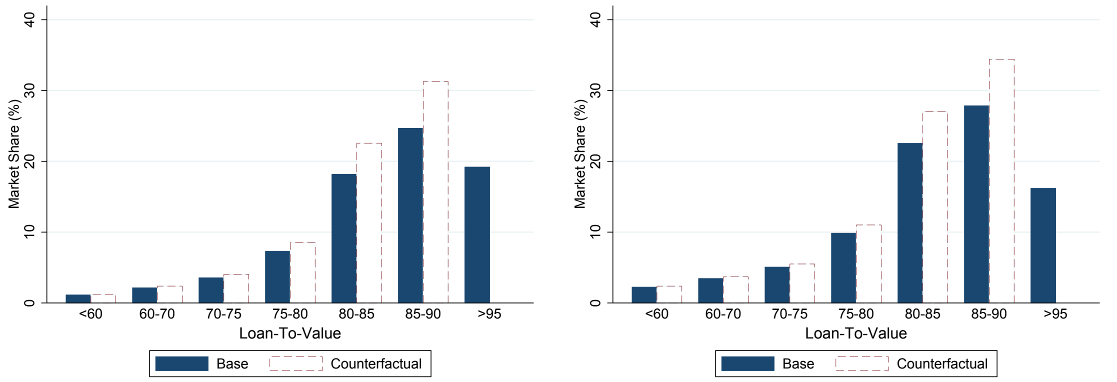
1.6.2 Limits of Leverage Limits

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). As an example, in the UK the Financial Policy Committee issued a recommendation in 2014 to limit new mortgage originations with a loan-to-income above 4.5 to no more than 15 percent of all new mortgage originations. In this section I use the model to evaluate the equilibrium effects of an alternative policy that limits household leverage via loan-to-value rather than loan-to-income limits. Most notably, I study the interaction of this policy with the capital requirement regime in place, which varies by loan-to-value as shown in Section 1.2.2. In this way I shed light on the equilibrium effects from jointly regulating both lenders' and borrowers' leverage.

Figure 1-8 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. Panel (a) shows the equilibrium with a common capital requirement of 8 percent and a risk-weight of 50 percent for all lenders, as was the cases before the crisis during the Basel I regime, while Panel (b) shows the equilibrium with the actual risk-weighted capital requirements. As expected mortgages with loan-to-values close to 90 percent experience the largest increase, but as prices adjust other

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

Figure 1-8: 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.

products are affected in equilibrium. Table 1.9 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 1.9 shows the effect on mortgage demand and profits. Despite the overall lower rates, there is a reduction in mortgage originations for first-time buyers, dropping between 4 to 7 percent.[40] 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

[40]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 1.5 our model slightly under-predicts mortgages with a maximum loan-to-value above 90 percent with respect to the data.

Table 1.9: Counterfactual leverage limits

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

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 A.2); profits is the average profit across lenders in thousand £; default is the average number of defaults in percentage points; buffer is the difference between the equity and the predicted loss. Value is the actual value in the benchmark; Δ is the change of the value in the counterfactual relative to the benchmark.

also by the positive valuation that households attach to high leverage mortgages, as I show in Table 1.3. Lenders' profits drop by more than 30 percent, as the regulation removes a profitable segment of the market.

Panel C of Table 1.9 shows that regulating household leverage with loan-to-value limits affects risk in the mortgage market. Specifically, the limit to high leverage mortgages decreases defaults, which drop by about 9-10 percent in both cases as a result of both lower prices and lower leverage. To capture the overall riskiness in the mortgage market I also look at lenders' equity buffers. In the counterfactual with homogeneous capital requirement there is almost no change in the buffer or even a slightly positive change, as lower prices reduce defaults. In the scenario with risk-weighted capital requirements there is a 10 percent decrease in the equity buffer in the market as a result of the ban on mortgages with the highest risk, but also the highest capital. According to my estimates, the decline in the buffer is even larger for the largest lenders, which experience a drop of about 13 percent, thus increasing their exposure to risk in the mortgage market.

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.

1.7 Conclusion

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

Chapter 2

Bank Competition and The Pass-Through of Unconventional Monetary Policy

2.1 Introduction

Since the global financial crisis central banks around the world have implemented unprecedented measures to counteract the credit crunch and sustain economic activity, such as quantitative easing, liquidity injections and policy announcements. These new tools have spurred the academic and policy debate about the role of the banking sector for their transmission to the real economy (Gertler and Karadi, 2011; Chodorow-Reich, 2014; Acharya et al., 2015; Di Maggio et al., 2016; Rodnyansky and Darmouni, 2017; Agarwal et al., 2017; Krishnamurthy et al., 2017).

Empirical studies of the effects of both conventional and unconventional monetary policy on credit supply faces two well-known identification issues: simultaneous causality between credit demand and supply, and selection into treatment as banks choose to borrow from the central bank (Kashyap and Stein, 2000; Jiménez et al., 2012, 2014). Furthermore, disentangling the role of the banking sector in the transmission mechanism poses an additional identification challenge due to non-random assignment of banks' market power, which can be correlated in the cross-section with other confounding factors (Scharfstein and Sunderam, 2014; Drechsler et al., 2017; Agarwal et al., 2018).

In this paper we provide causal evidence on the effect of targeted unconventional monetary policy on banks' credit supply to firms and on the role of competition in the banking sector for the transmission mechanism. We study a series of Targeted Longer-Term Refinancing Operations (TLTROs) by the ECB announced on the 5th of June 2014 with the goal to enhance the functioning of the monetary policy transmission mechanism by supporting lending to the real economy. We exploit an allocation rule by the policy together with a rich dataset on transaction-level bank-firm lending relationships and with exogenous variation in banks' local market power to address three identification challenges and shed light on the functioning of the transmission of unconventional monetary policy through the banking sector.

First, the dynamics of credit in the lending market are driven by both demand and supply. In equilibrium, borrowers' willingness to take new loans and accept different conditions as well as lenders' incentives to supply and reprice loans jointly determine the amount of credit and its price. Less risky borrowers may have a higher demand for the liquidity coming through TLTROs so that a decrease in lending rates comes from selection on the demand side, rather than from treatment on the supply side. To control for demand factors, we leverage on a panel of firms borrowing from multiple banks and estimate an empirical model with a full set of firm-time interacted fixed effects, thus only exploiting the variation within a firm across banks, as pioneered in Khwaja and Mian (2008).

A second identification challenge arises from selection into treatment. Even after controlling for demand factors, the supply side variation across banks that we use for identification may be endogenous because banks' use of TLTROs is a choice. To control for time-invariant bank level unobservables, we include in our empirical model bank fixed effect. However, time-varying differences across banks that affect both TLTROs borrowing and lending strategies, can still bias our results. We construct an instrumental variable (IV) for banks' treatment using a rule in TLTROs guidelines, that set the maximum amount that banks can borrow in the first two operations to 7% of their outstanding amount of eligible loans on April 2014. The threshold is set by the ECB for the whole euro area and is based on a variable that is fixed before the announcement of the policy. The differences in potential treatment across banks are therefore predetermined and orthogonal to unobservables than may affect loan supply in the period after TLTROs. The relevance of our instrument is ensured by the fact that in the first two TLTROs more than 90% of the banks actively participating to the operations borrowed at least 95% of their borrowing limit.

Third, to study how the transmission mechanism is affected by the structure of the banking sector we need exogenous variation in competition. We define local banking markets the Italian provinces, the equivalent of US counties, and we assume that each firm borrows in the same province where it has its headquarter.[1] We isolate the effect of competition on the pass-through of unconventional monetary policy by exploiting geographical variation in banks' market shares across provinces. As the latter may be correlated with other factors affecting the equilibrium in the local

[1] In our data we don't observe from which branch of the bank the firm borrows, but previous evidence for Italy (Bofondi and Gobbi, 2006; Felici and Pagnini, 2008; Crawford et al., 2018) and other countries (Petersen and Rajan, 1994, 1995; Mian, 2006) suggest that lending to firms has a local dimension. This choice is also motivated by the fact that provinces are the geographical units used by the regulator to approve branch openings. We use the structure of Italian provinces existing in 2005.

credit market, we design an IV strategy using variation in the presence of pawnshops across Italian cities during the Renaissance as an instrument for the level of local competition in the banking sector today.[2]

Our first set of results looks at the effect of unconventional monetary policy on credit supply for firms. We find that banks participating to TLTROs decrease their rates to the same firm by 20 basis points relative to banks that do not participate, when we instrument banks' borrowing choice using the exogenous allocation rule. This effect is significant and represents approximately 5 percent of the baseline cost of credit. We allow the pass-through to vary over time and find that treated banks start decreasing rates about two quarters after the first liquidity injection. Our IV estimates are significantly larger than the OLS estimates, where banks choosing to borrow from TLTROs decrease rate by about 5 basis points relative to banks choosing not to borrow.

Our second set of results examines the role of banks' market power for the transmission mechanism of unconventional monetary policy. We find that competition plays a significant role for the pass-through of unconventional monetary policy, limiting the sensitivity of the cost of corporate loans to the cost of bank funding. The magnitude of the result is significant: a one-standard-deviation increase in concentration reduces the impact of TLTROs on lending rates by approximately 14 basis points. This corresponds to a 32% decline in the transmission of unconventional monetary policy relative to the benchmark of perfect competition. Furthermore, we find that in provinces with low concentration lenders pass-on the lower rates to borrowers immediately, while in provinces with high concentration banks do not lower rates immediately after the policy change, but start after two quarters.

[2]Monte dei Paschi di Siena, the world's oldest surviving bank, was founded in Siena by the city magistrates as a pawnshop in 1472. Guiso et al. (2004) and Pascali (2016) show the importance of historical difference in access to credit for long-term financial development across region and provinces in Italy.

Finally, we explore heterogeneous effects in the transmission mechanism of TLTROs due to differences in firms' and banks' characteristics. Small firms and those with better credit rating borrowing from a bank using TLTROs experience a decrease in the cost of credit, while the reduction is not significant for the other firms of the same bank. Banks' local market power affects the pass-through for smaller and safer firms, but plays no role for larger and riskier firms. The differential effect on small firms is consistent with previous studies showing that small firms have less alternatives than large firms in raising funding and may be more affected by bank' competition (Berger and Udell, 1995; Beck et al., 2004). The differential effect on ex-ante safer firms is consistent with theories based on information asymmetries and hold-up problems (Sharpe, 1990; Rajan, 1992). Our heterogeneity analysis suggests a flight-to-quality within the corporate sector, with large banks competing to allocate the ECB liquidity toward smaller and ex-ante safer firms, especially in more competitive provinces.

Related literature Our paper is related to two main strands of literature. First, we contribute to the empirical macroeconomic literature about the transmission mechanism of monetary policy and how this is affected by financial imperfections, by studying how unconventional monetary policy affect the cost of credit for firms with an innovative research design.[3] The key empirical challenge is to identify how monetary policy affects supply side-factors, when there are confounding demand side effects (Kashyap and Stein, 2000). A stream of literature has used firm-time fixed effects to controls for unobservable demand factors, together with exogenous measures of exposure to a shock. This approach has been adopted to study the effect of supply-side liquidity shocks (Khwaja and Mian, 2008; Schnabl, 2012; Gambacorta

[3]Theoretical works on the topic go back to the seminal contributions by Bernanke and Blinder (1992) and Bernanke et al. (1999). After the global financial crisis new models have included an active financial sector (Gertler and Kiyotaki, 2010; Brunnermeier and Sannikov, 2014) and studied its implications in a general equilibrium setting (Gerali et al., 2010; Gertler and Karadi, 2011).

and Mistrulli, 2014), sovereign shocks (Bofondi et al., 2013; Albertazzi et al., 2014; De Marco, 2015), and the transmission mechanism of both conventional and unconventional monetary policy (Jiménez et al., 2012; Drechsler et al., 2016; Jiménez et al., 2014; Acharya et al., 2015; Carpinelli and Crosignani, 2017; Di Maggio et al., 2016).We are the first to study a new unconventional monetary policy which has been implemented with the explicit goal of increasing lending to the real economy, thus providing evidence on the value of setting a lending target for monetary policy effectiveness. Differently from most previous empirical studies that look at quantities our work focuses on the pass-through to interest rates, which have been less studied by the previous literature because of limited data availability on prices at the loan-level (Jiménez et al., 2014; Krishnamurthy et al., 2017). Most notably, in our setting we observe both actual and potential treatment based on an exogenous allocation rule, while previous studies generate cross-sectional variation in banks' exposure to a shock or a policy change using predetermined banks characteristics.

Second, our work contributes to the literature on the relation between competition and monetary policy. The industrial organization approach to banking literature has studied theoretically the link between competition and monetary policy (Freixas and Rochet, 2008a; Rochet, 2009), but the empirical evidence about the relationship between market power and pass-through is ambiguous (Berger and Hannan, 1989; Neumark and Sharpe, 1992; De Graeve et al., 2007). On the one hand, in more competitive market the pass-through of borrowing rate to lending rates can be larger, as a results of higher elasticities of firms' loan demand and absence of smoothing coming from relationship lending (Cottarelli et al., 1995; Van Leuvensteijn et al., 2013). On the other hand, the response of lending rate can be higher in more concentrated market, if banks pass-through cost efficiency or exploit market power from holdup situations to adjust their markups (Petersen and Rajan, 1995). We develop a new identification strategy to study empirically the effect of competition on the transmission mechanism of unconventional monetary policy to corporate lending, complementing recent studies that look at the effect of competition for the transmission of monetary policy in the US mortgage and deposit markets (Scharfstein and Sunderam, 2014; Drechsler et al., 2017). Our focus on targeted unconventional monetary policy has the unique advantage that the treatment is by design heterogeneous across lenders, which allows us to separate differences across banks from differences in market structure.

The rest of the paper is organized as follows. Section 2.2 describes the institutional background of TLTROs and the Italian banking system; Section 2.3 summarizes the data; Section 2.4 explains the identification strategy; Section 2.5 presents our results and Section 2.6 concludes.

2.2 Institutional Setting

2.2.1 Targeted Longer-Term Refinancing Operations

On the 5th of June 2014, the ECB decided to support bank lending to the euro area non-financial sector through a first series of Targeted Longer-Term Refinancing Operations (TLTROs). This policy measure is implemented through eight auctions, one each quarter from September 2014 to June 2016, and participation is open to institutions that are eligible for the Eurosystem open market operations. In July 2014 and February 2015 the ECB updated the rules on borrowing limits, maturities and early repayment options. A second series of four operations starting in June 2016 has been announced on the 10th of March 2016.

The ECB has been actively involved in supporting the financial system since the onset of the global financial crisis in September 2008. In October 2008, the ECB switched to a fixed-rate full-allotment mode for its refinancing operations, where the central bank sets an interest rate and banks can borrow an unlimited amount at that given rate. In this way the ECB provided a certain source of funding to banks, especially valuable in crisis time when other funding sources are impaired. The ECB also increased its support to the banking sector with Longer-Term Refinancing Operations (LTROs), complementing the weekly liquidity-providing transactions, that have usually a maturity of one to three months, with a one-year operation in July 2009 and two three-years operations in December 2011 and February 2012. This longer-term liquidity allows banks to relax the roll-over risk coming from the mismatch between assets and liabilities, thus favoring longer-term investment. The popularity of the two three-years LTROs is evident from banks' participation and take-up: these operations provided more than 1 trillion euros liquidity to euro area banks, with Spanish and Italian institutions among the main beneficiaries (Carpinelli and Crosignani, 2017). Banks used the provided liquidity for rolling over previous debt, issuing new loans to firms and household and buying sovereign bonds.

The TLTROs come within the framework of increasing support by the ECB, but with some novelties about both goals and rules. While previous operations were designed to support the banking sector, TLTROs explicitly target lending to the real economy. For this reason, this policy represents an ideal experiment to understand the full transmission mechanism from the central bank to firms and households, via the financial sector. Both the goals and the rules are implicitly designed to reduce the incentives to banks to use the liquidity for buying sovereign debt, as happened in previous operations (e.g. LTROs), and to roll over existing debt.[4]

Figure 2-1 shows the time-line of the first series of TLTROs. Participation to the operations was possible both on an individual basis and as a "TLTRO group" of banks, not necessarily all part of the same banking group. The individual institution

[4]It is worth noting that the TLTROs overlap with the end dates of the previous LTROs, maturing on January 29, 2015 and February 26, 2015, and therefore part of the funds were anyway used to roll over the expiring debts of LTROs. For this reason in our estimation strategy we account for expiring debt.

and the "lead institution" in the group should be an eligible Eurosystem counterpart. The eligibility criteria, valuation, haircuts and rules on the use of assets for collateral are the same of the other standard refinancing operations (ECB, 2014). The interest rate on the TLTROs will be fixed over the life of each operation at the rate on the Eurosystem Main Refinancing Operations prevailing at the time of take-up; an additional fixed spread of 10 basis points has been added for the first two TLTROs.

The main differences of TLTROs' rules relative to previous operations are on borrowing limits. The borrowing limits rules are different for the first two operations at the end of September and December 2014 and the last six, from March 2015 to June 2016. Define q_k^b the quantity borrowed by bank b (single or "TLTRO group") in operation k. The initial borrowing limit for the first two operations is computed using the following formula:

$$q_b^1 + q_b^2 \leq 0.07 \times EL_b^{April2014} \equiv Rule_b. \tag{2.1}$$

Bank b borrowing in the first two TLTROs cannot exceeds 7% of its outstanding amount of eligible loans on 30 April 2014 ($EL_b^{April2014}$). The eligible loans include lending to domestic non-financial corporations and households in the euro area, and exclude loans securitised or otherwise transferred without derecognition from the balance sheet.[5] Moreover, they exclude loans to household for house purchases to emphasize even more the willingness of the ECB to channel new liquidity into productive investment. In Section 2.4 we describe how we use the rules regarding the borrowing limit for the first two TLTROs in our identification strategy, while in Appendix B.2 we describe additional rules of the scheme for the last six operations and repayments.

[5] The definitions are detailed in ECB (2014).

2.2.2 The Italian Banking System

The supply of bank credit is particularly important in Italy as firms are heavily dependent on intermediated credit, relative for example to U.S. firms (Langfield and Pagano, 2016). Italian banks have traditional business models, based on loans to the real economy and close relationship with their customers, through a developed network of branches. Guiso et al. (2004) report that "The president of the Italian Association of Bankers (ABI) declared in a conference that the banker's rule-of-thumb is to never lend to a client located more than three miles from his office" and they show how distance continue to segment local markets. Between 2008 and 2013 the number of branches decreased by 7% from $34,100$ to $31,700$, mostly as a results of large groups reorganizations. Despite this reduction in the network, the number of banks' employees working in local branches is stable at 65% and a survey of senior executives of the main Italian banks reveal that business originations through branches will continue to play a leading role together with online banking (PwC, 2010). In our analysis we consider a province as the relevant market for banks lending to firms. Provinces are geographical entities very similar to U.S. counties and they are used by the Italian antitrust authority as proxies for the local markets for deposits (Bofondi and Gobbi, 2006; Felici and Pagnini, 2008; Crawford et al., 2018). Figure 2-2 shows the geographical distribution of the quartiles of the Herfindahl index (HI) across provinces calculated on the outstanding amounts of the term loans in the first quarter of 2014. It shows that, even if competition is slightly stronger in the north-east, generally there is a lot of variability among geographically neighboring provinces.[6]

Italian banks' funding has experienced significant changes during the European sovereign crisis. With respect to short-term funding, retail deposits remained a sta-

[6] The main exception here is Sardinia, that being a relatively distant island from the mainland suffers from isolation.

ble source for Italian banks, while short-term wholesale funding was affected by a widespread flight-to-quality from peripheral to core countries. Long-term unsecured wholesale funding became increasingly harder to obtain for Italian banks, which restored to secured long-term funding via covered bonds. The rating of the debt issued have deteriorated, mostly as a results of the increase in non-performing loans, due to a fall by 9% of GDP and 25% of industrial production. These losses impacted negatively on Italian banks' capital and together with the deleveraging needed to improve capital ratio, severely reduce the capacity to provide loans to the real economy. In this context, central bank liquidity become increasingly more important as a source of funding for banks. The reliance of Italian banks on ECB funding, measures as a percentage of assets, grew from less than 1% at the end of 2010 to more than 6% at the end of 2012 (Van Rixtel and Gasperini, 2013). The new TLTROs by the ECB strengthen this trend, by providing additional long-term liquidity to banks in the euro area, with the explicit goal of promoting loan to firms. In the first two TLTROs, the banks of the euro area borrowed collectively 212 billion euros, with Italian institutions in the first place borrowing 57 billion euros. The transmission of TLTROs could have therefore important implications for lending to the Italian economy. The local and bank-centered Italian loan market and the importance of the ECB TLTROs for the liquidity of Italian banks' make our environment particularly suitable to investigate the transmission mechanism of monetary policy to the real economy.

2.3 Data

In this work we construct a unique dataset at the bank-firm-time level, combining four different sources of data.[7] The main one is the Italian Credit register, which

[7]We use the term bank to indicate both standalone banks and banking groups henceforth. For banks belonging to a banking group we aggregate the data at the banking group level, which is

collects individual data on borrowers with exposure above 30 thousand euros from all the intermediaries operating in Italy. From this source we extract information at a monthly frequency about the interest rates of term loans charged on bank debt for each borrower. Each observation is a bank-firm pair and we observe a unique identifier for both the lending and the borrowing institution. We collapse the data at the level of firm-banking group relationship using the mapping from the Supervisory register of the Bank of Italy, where the legal structure of all the Italian banking groups is publicly available.

We complement this data with additional information from both the bank and the borrower side. On the one hand, we collect quarterly data on the geographical distribution of branches and the structure of its balance sheet for each bank from the confidential Supervisory reports and the Supervisory register of the Bank of Italy. On the other hand, we exploit the borrower identifier to add information on the geographical location, the credit quality and the size of the firm, matching our dataset with the Company Accounts Data Service (CADS) managed by Cerved, one of the most comprehensive sources of information about balance sheets of Italian firms, also used by banks for credit decision. A last piece of information includes confidential data about participation and the amounts lent from the central bank to the Italian banks after each TLTRO bid.

The final dataset is a quarterly balanced panel, in a time span between the start of 2014 and the second quarter of 2015. Table 2.1 shows the summary statistics of the variables of the dataset. Panel A shows the main dependent variable of the analysis is the overall interest rate (r_{bft}), including the accessory expenses, on the stock of term loans, charged by bank b to firm f at time t, shown in panel A of the table. The first and the last percentile of the distribution of the interest rates have been winsorized, to minimize the impact of outliers in the sample. The charged

the relevant entity for borrowing from the ECB.

interest rate has been equal on average to about 4% considering the whole time series and the whole distribution is included between about 0.5% and 12%. For this kind of loans the impact of the expenditures on the overall rate is not particularly strong. We also show the statistics on the interest rate on the flow of new term loans of each period, used in a robustness check, which are not substantially different from those on the stocks.

Panel B shows the Herfindahl Index of the local term loans markets. The first one is calculated using quantities of credit for each province in the first quarter of 2014.[8] The credit market in Italy is relatively concentrated, with an average value of the index of 0.17 and a range of values included between 0.09 and 0.36. In section 2.5.3 we assume in an extension of our empirical model that markets are segmented according to the credit quality of the borrower, summarized in nine ordinal categories by an index of credit riskiness taken from CADS and calculated from the available balance sheet data. We construct for this exercise separate HI assuming that the market of credit for firms of average and high credit quality (classes 1-6 of the rating index) is different from the one for firms of low quality (classes 7-9).[9] The statistics for the HI of the two segmented markets are very similar both among them and to those of the HI by province. We also show summary statistics for the total number of pawnshops that opened during the Italian Renaissance across Italian province that we compute aggregating the city level data from Pascali (2016). The average number of pawnshop by province is about one and it ranges from zero to eight.

Panel C shows the variables regarding the first two TLTROs; 78 banks in our sample participated at either the first or the second TLTRO and the average borrowed amount was about 670 million euros. Several of those banks used anyway either part or all the borrowed liquidity to rollover already existing debts with the

[8] We used the structure of 103 Italian provinces existing until 2005 to get a homogeneous classification of the provinces from the different datasets.

[9] We also segmented the credit market in three categories instead of two, but the final results were the same as those presented here.

Eurosystem; for this reason we calculated a corrected amount of the exposition to central bank coming from the first two TLTROs, netting out the debts towards the Eurosystem expiring in the same quarter. 43 banks had a positive net amount after this correction and the average net borrowed amount was of about 550 million euros; the distribution is skewed to the left and the range of values is included between 5 and about 5500 million euros. The borrowing limit for the first two TLTROs, calculated for the whole sample of 104 banks was on average of about 550 million euros too, but is more skewed to the left. From the comparison of the raw amount borrowed from the 78 banks participating to the TLTROs with their borrowing limit we find that more than 90% of those banks borrowed more than 95% of their limit.

In panel D we report the main structural characteristics of the banks in the first quarter of 2014: they had on average 30 billion euros of assets, almost half of which are loans and about 20% are government bonds. The riskiness of the credit portfolio of the banks and capital adequacy are respectively measured by the ratio between bad loans and overall loans, equal on average to about 9%, and by the capital ratio, based on the Basel rules, equal on average to about 15%.

Last, in panel E we report some statistics regarding firm characteristics, taken from the balance sheets in CADS for the year preceding the policy (2013) and used in the analysis of heterogeneous effects in Section 2.5.3. We show the distribution of firm assets, equal on average to 4 million euros, and the percentages of firms whose credit quality is either high/average (about three quarters of the sample) or low. We compare the statistics where the statistical unit is the firm with those where the statistical unit is the firm-bank relationship (which is the relevant statistical unit in our final dataset); the statistics are substantially similar in both cases, taking into account that on average bigger firms have more credit relationships and therefore their weight is bigger when the statistical unit is the relationship.

In Table 2.2 we compare the characteristics of the banks borrowing a positive additional amount of resources from the TLTROs and of their customer firms (treated group) with the other banks and firms (control group). Panel A shows the existing differences in the endogenous variables in the first three quarters of 2014, between relationships of firms with a treated bank and the other relationships. We do not find appreciable differences in the statistics. In panels B and C we check the borrowing limit and the structural characteristics for treated and control banks. We find that on average the former are bigger than the latter and have therefore a bigger borrowing limit, but they are substantially similar when checking for the other characteristics. In panel D we contrast the statistics weighted by the number of firm-bank relationships of the firms borrowing respectively from a treated or a control bank; also in this case we do not find evidence of relevant differences in the two samples.

2.4 Identification Strategy

First, to study the effect of unconventional monetary policy on the cost of credit, ideally one would randomly assign liquidity to identical banks lending to the same firm. Any decrease in the lending rate from the bank receiving the liquidity will come from the treatment and not from other banks characteristics (the two banks are identical) or firms characteristics (they are lending to the same firm). Second, to study the effect of bank competition on the pass-through of unconventional monetary policy, ideally one would like that the bank receiving the random liquidity injection operates in two identical markets, which differ only on the level of bank competition. Any differential decrease in the lending rate from the bank receiving the liquidity in the market with high bank competition will come from the differences in bank competition and not from other banks characteristics (it is the same bank) or other markets characteristics. Our empirical strategy proceeds in three steps to address the key identification challenges: simultaneous causality, selection into treatment and omitted variables.

Simultaneous causality. TLTROs were designed and implemented by the policymaker as a reaction to macroeconomic conditions to explicitly promote lending to the real economy. Therefore, macroeconomic shocks correlated to the policy may induce unobservable loan demand shifts that are contemporaneous to the ECB interventions, leading to simultaneity and omitted variables bias. An upward bias in the evaluation of the effects of the policy would result if safer firms demand from banks borrowing from TLTROs; while a downward bias would emerge if riskier firms increase their loan demand by more. To control for changes in lending opportunities we include in our specification interacted firm-time fixed effects. In this way, we capture firm-specific time-varying shocks to loan demand and we exploit only the variation within each firm-time pair across banks for identification.

We address possible concerns about differences at bank level controlling for time-invariant unobserved heterogeneity with bank fixed effects. In this way we capture, among other things, constant differences across banks in lending strategies and funding costs and we exploit only variation within bank over time. Moreover, we include time-varying bank controls (bank capital, non-performing loans, government bonds), that can have an effect on both banks' funding costs and borrowing decisions and are exogenous with respect to the rate decisions regarding a single transaction.

We estimate a difference-in-differences model on a balanced panel of firm-bank relationships.[10] We include in our equation time varying coefficients to capture the dynamics of the transmission mechanism and we cluster the standard errors both

[10]The use of the difference-in-differences methodology on a balanced panel implies that our conclusions only regards the credit relationships already existing before the start of the policy since the beginning of the pre-treatment period in the dataset (first quarter of 2014) and whose existence continued until the second quarter of 2015.

by firm and by bank-time. Hence, the resulting OLS empirical specification is:

$$Y_{bfmt} = \sum_{\tau} \alpha_\tau \mathbb{I}_{\tau=t} \times TLTRO_{b\tau} + \gamma_{ft} + \gamma_b + \theta X_{bt} + \varepsilon_{bfmt}, \quad (2.2)$$

where Y_{bfmt} is the loan rate from bank b to firm f in market m and period t; $TLTRO_{bt}$ is the treatment variable; γ_{ft} are firm-time fixed effects; γ_b are bank fixed effects and X_{bt} are time varying banks controls.

Selection into treatment. Even controlling for endogenous timing of TLTROs, participation is on a voluntary basis, within the rules set by the ECB and described in Section 2.2. This may add additional selection bias, due to non-random treatment assignment: the evaluation of the policy may be biased upward if banks with higher return to lending or lower funding costs *choose* to borrow more, or biased downward if banks with unobservable funding problems or lower marginal propensity to lend exploit more the ECB facilities. We explicitly address this self-selection problem, exploiting the institutional setting of the policy: we instrument *actual* borrowing for the first two TLTROs with the *maximum* borrowing limit rule described in equation (2.1) in Section 2.2. Our first stage regression of *actual* participation ($TLTRO_{bt}$) on the exogenous regressors and the excluded instrument is:

$$TLTRO_{bt} = \phi Rule_b \times Post_t + \gamma_{ft} + \gamma_b + \theta X_{bt} + \epsilon_{bfmt}, \quad (2.3)$$

where $TLTRO_{bt}$ is the actual treatment variable; $Rule_b$ is the allocation rule for bank b from equation (2.1) and $Post_t$ is a dummy equal to one after the implementation of the TLTROs. The borrowing limit has been set by the ECB in its announcement in June 2014 and it is based on an exogenous parameter, which is common across banks, and pre-determined banks' balance sheet characteristics.[11]

[11] We find a correlation of -0.007 between the loan-level interest rate in the pre-treatment period and the borrowing limit, suggesting that the borrowing limit is essentially uncorrelated with the

The identifying assumption is that the borrowing limit established by the ECB for the first two TLTROs is a valid instrument for bank access to central bank liquidity controlling for unobservable time-varying demand heterogeneity (firm-time fixed effects), unobserved bank heterogeneity (bank fixed effects) and time-varying bank characteristics. The resulting IV empirical specification is:

$$Y_{bfmt} = \sum_{\tau} \alpha_\tau \mathbb{I}_{\tau=t} \times \widehat{TLTRO}_{b\tau} + \gamma_{ft} + \gamma_b + \theta X_{bt} + \varepsilon_{bfmt}, \tag{2.4}$$

where $\widehat{TLTRO}_{bt}$ is the predicted participation and all other variables are as in equation (2.2).

Omitted variables. In the second part of the paper we study the role of the local banking system for the pass-through of TLTROs. To identify the effect of competition among lenders on the pass-through of unconventional monetary policy, we exploit variation in the competitive structure at the local geographical level. We measure competition with the HI for corporate loans in the province where a firm headquarter is located (HI_m), as Figure 2-2 shows. We augment equation (2.4) with time varying coefficients on the interaction between the treatment and the HI, to capture the dynamic effect of market power on the transmission mechanism:

$$Y_{bfmt} = \sum_{\tau} \alpha_\tau \mathbb{I}_{\tau=t} \times \widehat{TLTRO}_{b\tau} + \sum_{\tau} \beta_\tau \mathbb{I}_{\tau=t} \times \widehat{TLTRO}_{b\tau} \times HI_m + \gamma_{ft} + \gamma_b + \theta X_{bt} + \varepsilon_{bfmt}. \tag{2.5}$$

Variation in the HI can be correlated with other factors affecting the pass-through of unconventional monetary policy.[12] To account for endogeneity in market power we also instrument the HI using exogenous variation in the presence of pawnshops

dynamics of the cost of credit before the treatment.

[12]For example Beraja et al. (2017) show how the time-varying regional distribution of housing equity influences the aggregate consequences of monetary policy through its effects on mortgage refinancing.

across Italian cities during the Renaissance. Pascali (2016) shows that variation in the presence of Jewish communities and pawnshops during the Italian Renaissance is correlated with the variation in financial development across Italian cities today. We exploit the same historical variation to instrument for the level of competition in the banking sector today. Figure 2-2 shows the distribution of HI today across Italian provinces, while Figure 2-3 shows the number of pawnshops during the Renaissance in the currently established provinces. From a graphical inspection of the two maps we see that provinces with a high number of pawnshops during the Renaissance tend to have a less concentrated banking sector today. The correlation coefficient is -0.27 and we formally test the relevance of our instrument with the first stage regression:

$$TLTRO_{bt} \times HI_m = \phi Rule_b \times Post_t \times Pawnshop_m + \gamma_{ft} + \gamma_b + \theta X_{bt} + \epsilon_{bfmt}, \quad (2.6)$$

where $Pawnshop_m$ is the number of pawnshops across Italian provinces during the Renaissance. To capture jointly the causal effects of unconventional monetary policy and of competition on the transmission mechanism, we estimate the following IV empirical specification:

$$Y_{bfmt} = \sum_{\tau} \alpha_\tau \mathbb{I}_{\tau=t} \times \widehat{TLTRO}_{b\tau} + \sum_{\tau} \beta_\tau \mathbb{I}_{\tau=t} \times TLTR\widehat{O_{b\tau} \times} HI_m + \gamma_{ft} + \gamma_b + \theta X_{bt} + \varepsilon_{bfmt}, \quad (2.7)$$

where $TLTR\widehat{O_{b\tau} \times} HI_m$ is the predicted interaction between the policy and the HI from the first stage regression of the actual interaction on the exogenous variables and the excluded instruments (the allocation rule and the presence of pawnshops during the Renaissance). The interaction term $TLTR\widehat{O_{bt} \times} HI_m$ captures the causal effect of competition on the pass-through of unconventional monetary policy.

2.5 Results

In this section we describe our results. In Section 2.5.1 we show our first set of results on the effect of targeted monetary policy on the cost of credit. In Section 2.5.2 we discuss our second set of results on the role of bank competition for the transmission of targeted monetary policy. In Section 2.5.3 we study how the transmission mechanism varies with firms' and banks' characteristics, namely credit-risk and size.

2.5.1 The Effect of Targeted Monetary Policy

The first empirical result of interest is the identification of the causal effect of targeted monetary policy on the dynamics of the overall cost of credit. We estimate both one specification where the TLTRO variable is a dummy equal to one after the start of the policy if the institution participates in one of the first two operations and another specification where we use the log of the actual additional borrowed amount measuring the intensity of treatment.

Table 2.3 presents our results for the OLS model. Column (1) shows the results for the full sample in which we control for bank, firm and time fixed effects separately. Treated banks decrease interest rates relative to control banks, but the effects are not significant. In column (2) we estimate the OLS model on the sample of firms with multiple banking relationships and control for demand with interacted firm-time fixed effects. The effects are stronger and marginally significant. Banks borrowing from the ECB through TLTROs decrease lending rate relative to banks not borrowing by approximately 3 basis points on average. Finally in column (3) we add time-varying banks' control. The results are stronger and marginally more significant. In the last three columns of Table 2.3 we estimate the same model with the actual amount borrowers from the ECB, rather than the binary participation dummy. The results are similar to the ones with the binary treatment.

Table 2.4 presents our results for the IV model.[13] Column (1) shows the results for the full sample in which we control for bank, firm and time fixed effects separately, and we instrument the binary TLTROs participation with the ECB allocation rule. When we instrument the actual amount borrowed in the first two TLTROs in column (1) of Table 2.4, we find that treated banks decrease interest rates relative to control banks. Most notably, we find a statistically significant negative coefficients in the first and second quarter of 2015, therefore just after the implementation of the second round of the policy.

In column (2) of Table 2.4 we estimate the benchmark case with interacted firm-time fixed effects, to capture differences in firms credit demand. Treated banks decrease rate to the same firm on average by about 23 basis point relative to control banks in the first and second quarter of 2015. Finally, in column (3) we control for time varying bank factors that can affect differentially the pricing within firm-time across banks. The results are still significant and the magnitude is reduced to about 20 basis points. A comparison of columns (3) from Tables 2.3 and 2.4 shows that our IV estimates are stronger than the OLS estimates, suggesting that unobservable heterogeneity is likely to bias our estimates downward. For example banks choosing to borrow from the ECB may have been the ones planning to lower corporate rates for other reasons (e.g. business strategy), that can be correlated with the choice to borrow from the ECB in the first place.

Overall, our results on price suggest an outward shift after the second TLTRO in the supply of loan by banks exploiting the liquidity injection by the ECB. In the next section we further corroborate this hypothesis and explore if the competitive

[13]In Appendix C.1 we show the first stage regression for the benchmark case with interacted firm-time fixed effects. *Predicted* TLTROs participation has a significant positive effect on *actual* TLTROs participation. The overall Kleibergen-Paap F-statistics for the first stages, approximately 42 and 56 for dummy and continuous treatments respectively, are well above the 10% Stock and Yogo (2002) weak identification test critical values of about 16.

environment has an effect on the pass-through of unconventional monetary policy.

2.5.2 The Effect of Competition on the Transmission Mechanism

Our second set of results shows how bank competition affects the transmission mechanism of TLTROs to the cost of credit. Table 2.5 presents the results. Also in this section, we focus on firms with multiple lending relationship, to isolate a credit supply shock, and control for differences across banks with both banks' fixed effects and time-varying controls. The effect of the instrumented TLTROs treatment broadly confirm the results from Table 2.4: banks exploiting the ECB liquidity injections decrease loan rates for firms more than banks not participating to TLTROs.

The coefficients of interest capture the interaction between TLTROs treatment and bank competition, measured by the local HI. Our estimates in column (1) of Table 2.5 imply that high concentration reduce the pass-through of unconventional monetary policy to firms through the cost of credit. In markets with an average level of concentration treated banks pass on the lower rates to borrowers immediately after the treatment. In markets with higher level of concentration treated banks do not lower rates immediately after the policy change, but start after two quarters. This effect may be due to second round effects following the reactions of other competitors in the market.

We find that competition plays a significant role for the pass-through of ECB liquidity on the cost of credit. The magnitude of the result is also significant: a firm in a province with a standard deviation higher level of concentration experiences a 14 basis points lower decline in the cost of credit. Higher concentration reduces the transmission mechanism of unconventional monetary policy to firms by approximately 32% relative to the theoretical case of perfect competition.[14] Our estimates

[14]We compute the effect using the estimates from column (1) of Table 2.5 and taking the average

of the effect of competition on lending rates are slightly larger than the ones from recent works on the pass-through of monetary policy to mortgage and deposits rates (Scharfstein and Sunderam, 2014; Drechsler et al., 2017). There are many possible reasons for this difference. First, relationship lending, information frictions and market power may play a more important role for corporate lending than for mortgage lending and bank deposits, in which products are more standardized. Second, the type of policy we are looking at. Both Scharfstein and Sunderam (2014) and Drechsler et al. (2017) focus on the transmission of conventional monetary policy, while we look at targeted monetary policy operations. Third, our identification strategy differs in how we control for banks' lending opportunities.

In column (2) of Table 2.5 we show the estimates of equation (2.7), thus instrumenting for both participation to TLTROs and local competition with the number of pawnshop in the same province during the Italian Renaissance.[15] Column (2) of Table 2.5 shows that our results on the competition channel are robust to confounding factors at the market level. Higher concentration in the local banking market, coming from exogenous historical variation, significantly reduces the pass-through of central bank liquidity to lending rates to firms, confirming our baseline result. Finally in columns (3) and (4) of Table 2.5 we report the estimates using a continuous treatment variable and the results are robust.

In Appendix C.1 we show several robustness checks. First, we replicate the analysis using the raw amounts borrowed by banks in the TLTROs instead of the additional amount net of the rolled over already existing debts towards the Eurosystem. The results are qualitatively similar to the previous ones. Second, we reply the

of the effect of a standard deviation increase in concentration in each period.

[15]In Appendix C.1 we show the first stage estimate for our IV strategy, when we instrument both the TLTROs treatment and the interaction term TLTROs $\times$ HI. Our instruments are significant and have the expected sign. The overall Kleibergen-Paap F-statistics for the first stages for both dummy and continuous treatments and both endogenous variables are well above the 10% Stock and Yogo (2002) weak identification test critical values of about 7.

analysis for rates constructed with interest expenditures only, excluding accessory expenses from the calculation. As expected, the results are unaffected. Third, we show the results considering the interest rate on the flows of new loans of the period instead of the one on the overall stock. On one hand flows allow to better capture the dynamics of the new credit loans period by period, on the other hand they are less suitable than stocks to construct a representative balanced panel because the firm would need to borrow a new amount of credit in each period to be included in the sample. When considering the direct effect only, the results are stronger than for stocks and it is already statistically significant at the end of 2014, even if weaker than in the following quarters. The larger magnitude and significance can be explained by the fact that we are now only focusing on the new credit contracts agreed in each period and not on the overall stock of loans already agreed. When including the interaction with competition, the results are qualitatively similar to those for stocks, even if not strongly significant as the results of Table 2.5 because of the loss of precision in the estimates due to the smaller number of observations.

2.5.3 Heterogeneous Effects Across Firms and Banks

In this section we study whether there are heterogeneous effects in the pass-through of unconventional monetary policy and the impact of the competitive environment due to differences in some relevant banks' and firms' characteristics. In particular, we focus on riskiness and size, which the previous literature identified as important determinants of access to credit (Jiménez et al., 2014; Agarwal et al., 2018). In both cases we take ex-ante measures of credit risk and size, to deal with possible endogeneity concerns.

Table 2.6 shows the estimates of model (2.4) in the different subgroups.[16] Columns

[16]In Appendix C.1 we report the estimates for the same specification using the continuous TLTROs measure as treatment variable. Results are confirmed.

(1) and (2) focus on firms' credit risk. We assume that credit markets are segmented by credit rating of the firm and calculated a different HI separately for each group of firms. We split the full sample into two subgroups: firms with good or average credit rating (classes 1-6) and those with a bad one (7-9).[17] We find that the reduction in the cost of credit is driven by loans to safer firms, while we do not find significant reduction in the cost of credit for riskier firms. Moreover, competition affects the pass-through of unconventional monetary policy to safer firms, but plays no role for riskier firms. This result corroborates the hypothesis that banks using the ECB facility to compete for the safest borrowers, as proxied by their ex-ante riskiness, while there is less space for competition in riskier lending.

Columns (3) and (4) of Table 2.6 look at differences in the pass-through between large and small firms. Here we split the sample taking firms above and below the median of the distribution of assets in the pre-treatment year (2013). We find that both groups benefit from the reduction in the cost of credit following the first two TLTROs, but the effect is stronger and only significant for smaller firms. Banks taking the ECB facility lowered the cost of credit to small firms by about 60 basis point, while the decrease is about 30 basis points smaller and not significant for large firms. Competition affects the pass-through of policy to the cost of credit for small firms, while it plays no significant role for large firms. This result is consistent with the idea that small firms benefit more from competition between lenders, because they have less alternatives than large firms in raising funding (Berger and Udell, 1995; Beck et al., 2004).

Finally, in columns (5) and (6) of Table 2.6 we study heterogeneity on the supply side and compare the largest five banks in Italy with other medium and co-operative banks. Treated large banks decrease their lending rate relative to control banks, while we do not find significant differences when the treated bank is of smaller size.

[17] We also considered a sample split in three categories (1-3) (4-6) (7-9) and the results were very similar to the split in two groups presented here.

Competition affects how large is the banks' pass-through to lending rates of the ECB liquidity. We find a positive significant interaction between the policy and the HI. Large banks decrease lending rate as a response to the lower funding cost in markets where they face competition from other banks, while they increase profit margins in markets where they have market power.

2.6 Conclusions

In this paper we empirically study the transmission mechanism of unconventional monetary policy to lending to firms and how it is affected by banks' market power. We exploit a rule set by the ECB on banks' borrowing limit as an instrument to identify an exogenous expansion in banks' funding availability, together with rich transaction-level dataset on term loans bank-firm lending relationship and exogenous historical variation in competitiveness of local lending market.

We show three main new findings. First, banks participating to the first two TLTROs decrease on average loan rates to the same firm by approximately 20 basis points relative to banks not participating to the ECB liquidity injection. Second, competition in the banking sector plays a significant role for the pass-through of TLTROs on the cost of credit: a one standard deviation increase in concentration reduces the decline in the cost by about 14 basis points, thus lowering the effect of unconventional monetary policy by approximately 32% relative to a perfect competition benchmark. Third, our effects are driven by large banks passing-through the ECB liquidity injection via lower loan rates to smaller and ex-ante safer firms, especially in more competitive markets.

Our results have important implications for both the implementation of monetary policy and the design of regulation to promote competitiveness in lending markets. Our analysis suggests that targeted monetary policy could be an effective tool for channeling banks funding into productive investment such as corporate lending, potentially avoiding unintended consequences emphasized in recent studies (Acharya and Steffen, 2015; Crosignani et al., 2017). However, variation in banking competition changes the effects of monetary policy, potentially amplifying pre-existing differences in credit access and local economic conditions. We leave a more thorough analysis of optimal regulation and the effects for the real economy to future work, but our results suggest that it is important for policy makers to consider the interactions between monetary and competition policies, especially following the recent changes in the competitive landscape due to consolidations, branch closures and the rise of shadow banks (Buchak et al., 2017; Stackhouse, 2018).

2.7 Main Figures and Tables

Figure 2-1: **TLTRO timeline**

The figure shows a timeline of the ECB TLTROs. On the 5th of June 2014, the ECB decided the first series of Targeted Longer-Term Refinancing Operations (TLTROs). The policy measure is implemented through eight auctions, one at the end of each quarter from the end of September 2014 to the end of June 2016. Banks borrowing in the first two TLTROs cannot exceeds 7% of the outstanding amount of eligible loans on 30 April 2014. All TLTROs will mature in September 2018, but banks have the option to repay any part of the amounts they were allotted in a TLTRO after 24 months at a biannual frequency. The ECB imposes a mandatory early repayment in September 2016, if some lending requirements are not satisfied. A second series of four operations starting in June 2016 has been announced on the 10th of March 2016.

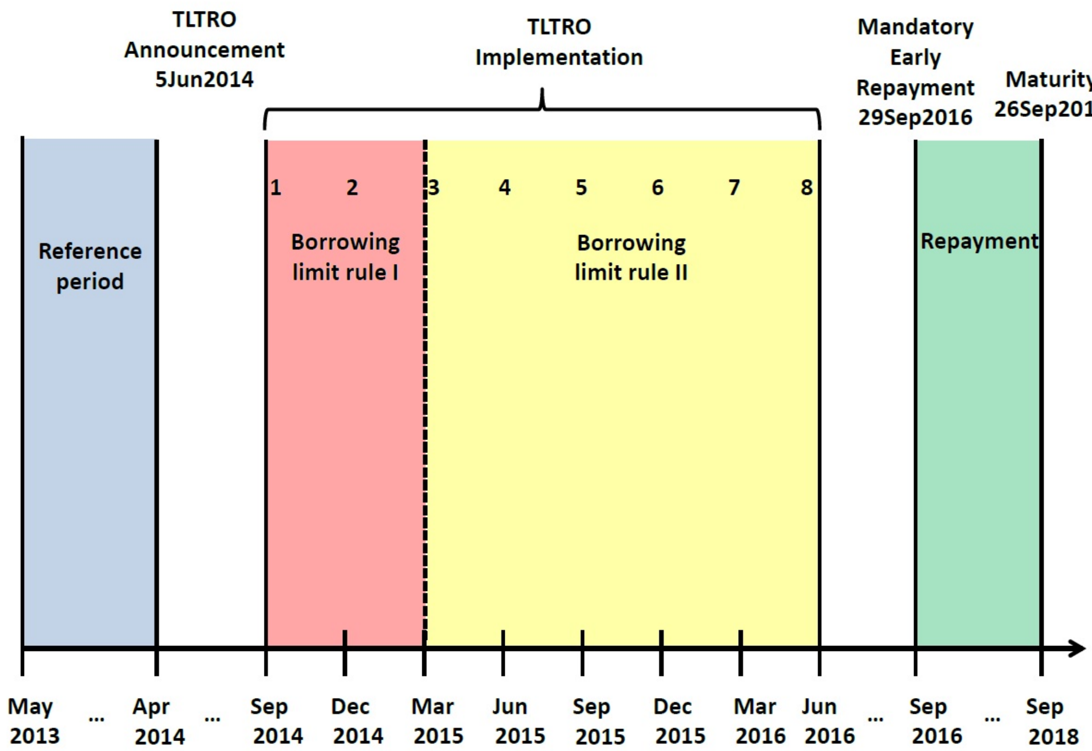


Figure 2-2: **Geographical distribution of Herfindahl Index**

The figure shows the geographical distribution of the quartiles of the Herfindahl index in the term loan sector. The index is calculated using quantities of credit for each province in the first quarter of 2014. We used the structure of 103 Italian provinces existing until 2005 to get a homogeneous classification of the provinces from the different datasets. The credit market in Italy is relatively concentrated, with an average value of the index of 0.17 and a range of values included between 0.09 and 0.36 (see Table 2.1).

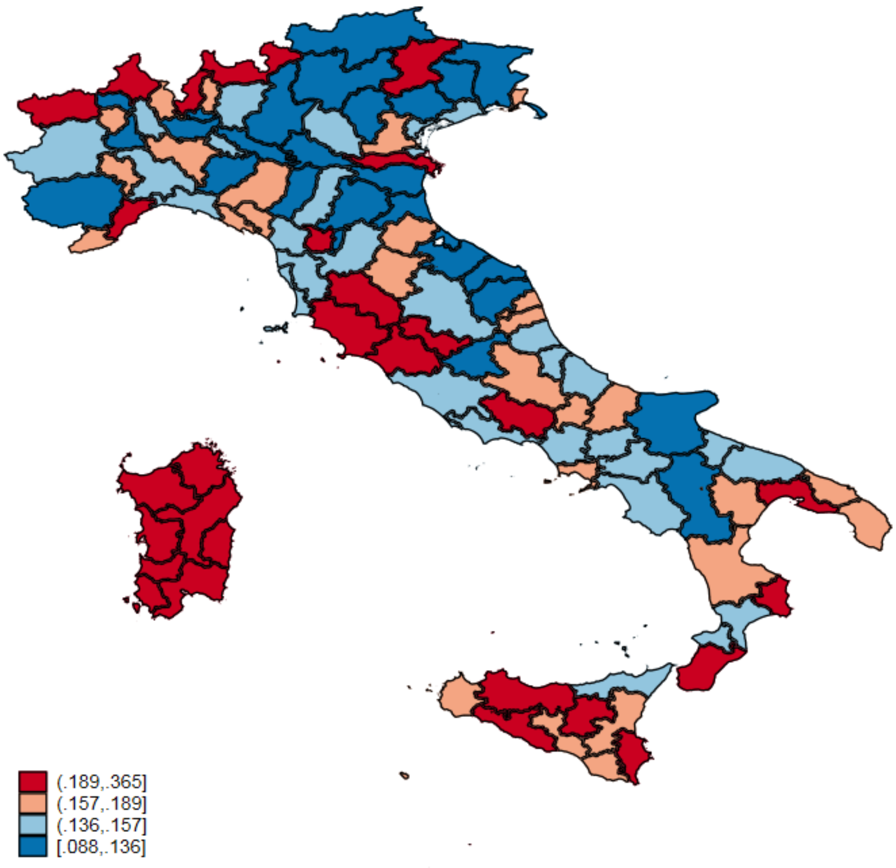


Figure 2-3: **Geographical distribution of pawnshops**

The figure shows the geographical distribution of the number of pawnshop during the Renaissance. The index is calculated aggregating the number of pawnshops by cities using the structure of 103 Italian provinces existing until 2005. The number of pawnshops comes from Pascali (2016).

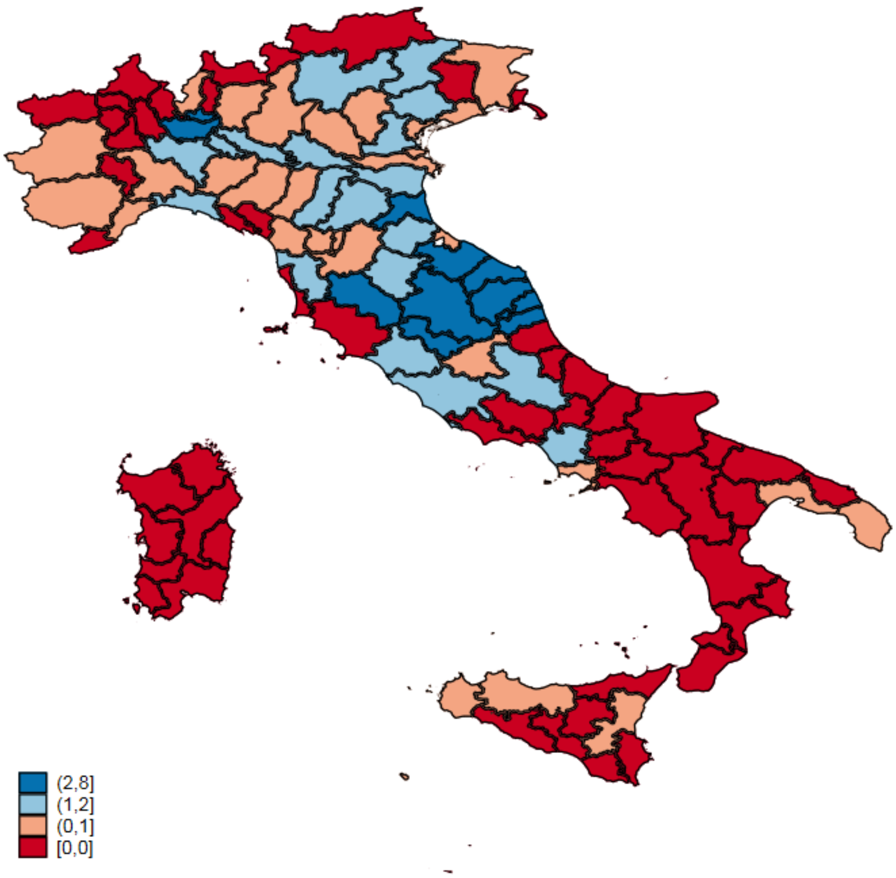


Table 2.1: **Descriptive statistics**

The table shows the summary statistics for the main variables in our analysis. Panel A shows the overall interest rate, with and without accessory expenses, on the stock of term loans and including expenditure for the flows of new loans. In Panel B, Herfindahl index at province level is calculated using quantities of credit for each province; the one at province and rating level is constructed segmenting markets by province, separately for firms of average and high credit quality (classes 1-6 of the rating index) and firms of low quality (classes 7-9). Pawnshops is the total number of pawnshops in each province using data from Pascali (2016). In Panel C amount borrowed is the total amount borrowed in the first two TLTROs; additional amount borrowed is the corrected amount of the exposition to central bank coming from the first two TLTROs, netting out the debts towards the Eurosystem expiring in the same quarter; maximum allowance is the borrowing limit computed from expression (2.1). In panel D we report the main structural characteristics of the banks in the first quarter of 2014: total assets and ratio of government bonds, total loans, bad loans and capital. In Panel E we report the distribution of firm assets and compare the statistics where the statistical unit is the firm with those where the statistical unit is the firm-bank relationship (which is the one we use in our final dataset); the statistics are substantially similar in both cases, taking into account that on average bigger firms have more credit relationships and therefore their weight is bigger when the statistical unit is the relationship.

	Obs	Mean	Std. Dev.	Min	Median	Max
PANEL A: TRANSACTION LEVEL VARIABLES (1ST QUARTER 2014-2ND QUARTER 2015)						
Interest rate incl. expenditures (%)	671951	4.06	1.96	0.49	3.85	12.10
Interest rate w/out expenditures (%)	671951	4.05	1.95	0.49	3.85	11.83
Interest rate incl. expenditures (flows; %)	58098	4.85	2.30	0.50	4.56	14.31
PANEL B: PROVINCE LEVEL VARIABLES (1ST QUARTER 2014 FOR HI)						
Province level HI on credit amount	103	0.17	0.06	0.09	0.16	0.36
Province - Rating 1-6 HI	103	0.17	0.06	0.08	0.16	0.36
Province - Rating 7-9 HI	103	0.18	0.08	0.09	0.16	0.48
Pawnshops (number)	103	1.02	0.50	0.00	0.0	8.00
PANEL C: I-II TLTRO VARIABLES (BANK LEVEL)						
Amount borrowed (million euros)	78	670.0	1843	5	85.72	12500
Additional amount borrowed (million euros)	43	542.7	1167	5	123	5495
Maximum allowance (million euros)	104	560.3	1635	16.11	83.49	12500
PANEL D: OTHER BANK LEVEL VARIABLES (1ST QUARTER 2014)						
Assets (billion euros)	104	30.19	101.27	0.46	2.97	777.91
Loans over assets ratio (%)	104	54.07	11.64	8.21	55.75	74.86
Bad loans over loans ratio (%)	104	9.33	5.44	0.09	8.75	27.57
Government bonds over assets ratio (%)	104	18.26	8.86	1.09	18.25	43.30
Capital ratio (%)	104	15.48	9.24	0.25	13.86	94.89
PANEL E: FIRM LEVEL VARIABLES (2013)						
Assets (million euros; by firm)	73174	3.95	30.08	1	0.59	2548.20
Assets (million euros; by relationship)	113246	7.24	40.66	1	0.95	2548.20
		Percentage distribution				
Classes:		1-6			7-9	
Credit rating (by firm)		73%			27%	
Credit rating (by relationship)		74%			26%	

Table 2.2: **Descriptive statistics for treated and controls**
The table shows the summary statistics for the main variables in our analysis in the group of treated and control banks. Panel A shows the main the overall interest rate, with and without accessory expenses, on the stock of term loans and including expenditure for the flows of new loans. In Panel B maximum allowance is the borrowing limit computed from expression (2.1). In panel C we report the main structural characteristics of the banks in the first quarter of 2014: total assets and ratio of government bonds, total loans, bad loans and capital. In Panel D we report the distribution of firm assets and the percentages of firms whose credit quality is either high/average (about three quarters of the sample) or low, using as statistical unit the firm-bank relationship (which is the relevant statistical unit in our final dataset).

	Treated			Controls		
	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
PANEL A: TRANSACTION LEVEL VARIABLES (1ST-3RD QUARTER 2014)						
Interest rate incl. expenditures (%)	220776	4.23	2.04	115046	4.14	1.84
Interest rate w/out expenditures (%)	220776	4.22	2.03	115046	4.12	1.82
Interest rate incl. expenditures (flows; %)	21243	5.21	2.27	7806	4.74	2.16
PANEL B: I-II TLTRO VARIABLES (BANK LEVEL)						
Max allowance (million euros)	43	841.7	2238	61	359	979.1
PANEL C: OTHER BANK LEVEL VARIABLES (1ST QUARTER 2014)						
Assets (billion euros)	43	47.87	145.61	61	17.72	48.81
Loans over assets ratio (%)	43	53.20	10.25	61	54.68	12.58
Bad loans over loans ratio (%)	43	7.85	2.65	61	10.38	6.57
Government bonds over assets ratio (%)	43	17.93	7.79	61	18.50	9.60
Capital ratio (%)	43	16.75	12.68	61	14.58	5.64
PANEL D: FIRM LEVEL VARIABLES (2013)						
Assets (million euros)	74372	6.75	38.14	38874	8.17	45.04

	Percentage distribution			
	Treated		Controls	
Classes:	1-6	7-9	1-6	7-9
Credit rating	75%	25%	72%	28%

Table 2.3: **Targeted monetary policy - OLS estimates**

The table reports the estimated parameters and their standard errors from the OLS estimation of equation (2.2). Column (1) reports the estimates with the full balanced dataset. Columns (2) and (3) report estimates with the balanced panel of relationships for firms with more than one lender. The dependent variable is the interest rate including expenditure on the stock of loan from bank b to firm f in quarter t. Binary treatment is a dummy equal to one if the bank borrows from the TLTROs. Continuous treatment is a continuous variable equal to the logarithm of the actual additional amount the bank borrows from the TLTROs. Bank-time controls include bank capital, non-performing loans, government bonds. All standard errors are double clustered by firm and bank-quarter. *,**, *** indicates significance at the 0.10, 0.05 and 0.01 levels, respectively.

	Binary treatment			Continuous treatment		
	All	Within		All	Within	
	(1)	(2)	(3)	(4)	(5)	(6)
TLTROs (bt) $\times$						
2014 - Q3	-0.034	-0.025	-0.032	-0.0019	-0.0014	-0.0017
	(0.041)	(0.028)	(0.028)	(0.002)	(0.0015)	(0.0014)
2014 - Q4	0.025	0.011	-0.013	0.001	0.00047	-0.00061
	(0.035)	(0.022)	(0.023)	(0.0017)	(0.0011)	(0.0011)
2015 - Q1	-0.011	-0.024	-0.047*	-0.0011	-0.0015	-0.0026**
	(0.039)	(0.024)	(0.025)	(0.0018)	(0.0012)	(0.0012)
2015 - Q2	-0.019	-0.051**	-0.065**	-0.0014	-0.0027**	-0.0033***
	(0.047)	(0.024)	(0.025)	(0.0023)	(0.0012)	(0.0013)
Observations	654,948	354,600	354,060	654,948	354,600	354,060
Adjusted R^2	0.71	0.36	0.36	0.71	0.36	0.36
Fixed effects						
Firm (f)	Yes	No	No	Yes	No	No
Time (t)	Yes	No	No	Yes	No	No
Bank (b)	Yes	Yes	Yes	Yes	Yes	Yes
Firm-time (ft)	No	Yes	Yes	No	Yes	Yes
Controls (bt)	No	No	Yes	No	No	Yes

Table 2.4: **Targeted monetary policy - IV estimates**

The table reports the estimated parameters and their standard errors from the IV estimation of equation (2.4). Column (1) reports the estimates with the full balanced dataset. Columns (2) and (3) report estimates with the balanced panel of relationships for firms with more than one lender. The dependent variable is the interest rate including expenditure on the stock of loan from bank b to firm f in quarter t. Binary treatment is a dummy equal to one if the bank borrows from the TLTROs. Continuous treatment is a continuous variable equal to the logarithm of the actual additional amount the bank borrows from the TLTROs. Both the binary and the continuous treatment are instrumented. Bank-time controls include bank capital, non-performing loans, government bonds. All standard errors are double clustered by firm and bank-quarter. *,**, *** indicates significance at the 0.10, 0.05 and 0.01 levels, respectively.

	Binary treatment			Continuous treatment		
	All	Within		All	Within	
	(1)	(2)	(3)	(4)	(5)	(6)
TLTROs (bt) ×						
2014 - Q3	-0.18	-0.12	-0.12	-0.0067	-0.0043	-0.0044
	(0.14)	(0.097)	(0.082)	(0.005)	(0.0035)	(0.003)
2014 - Q4	-0.049	0.039	0.076	-0.0018	0.0014	0.0026
	(0.12)	(0.083)	(0.069)	(0.004)	(0.0028)	(0.0023)
2015 - Q1	-0.39**	-0.23**	-0.20***	-0.014**	-0.0085**	-0.0073***
	(0.18)	(0.098)	(0.076)	(0.0057)	(0.0033)	(0.0026)
2015 - Q2	-0.36*	-0.24*	-0.19*	-0.013*	-0.0087**	-0.0071*
	(0.21)	(0.13)	(0.11)	(0.0071)	(0.0044)	(0.0041)
Observations	654,948	354,600	354,060	654,948	354,600	354,060
Adjusted R^2	0.71	0.36	0.36	0.71	0.36	0.36
Fixed effects						
Firm (f)	Yes	No	No	Yes	No	No
Time (t)	Yes	No	No	Yes	No	No
Bank (b)	Yes	Yes	Yes	Yes	Yes	Yes
Firm-time (ft)	No	Yes	Yes	No	Yes	Yes
Controls (bt)	No	No	Yes	No	No	Yes

Table 2.5: **Targeted monetary policy and competition**

The table reports the estimated parameters and their standard errors from the IV estimation of equations (2.5) and (2.7). All columns report estimates with the balanced panel of relationships for firms with more than one lender. The dependent variable is the interest rate including expenditure on the stock of loan from bank b to firm f in quarter t. Binary treatment is a dummy equal to one if the bank borrows from the TLTROs. Continuous treatment is a continuous variable equal to the logarithm of the actual additional amount the bank borrows from the TLTROs. Bank-time controls include bank capital, non-performing loans, government bonds. All standard errors are double clustered by firm and bank-quarter. *,**, *** indicates significance at the 0.10, 0.05 and 0.01 levels, respectively.

	Binary treatment		Continuous treatment	
	(IV-OLS) (1)	(IV-IV) (2)	(IV-OLS) (3)	(IV-IV) (4)
TLTROs (bt) $\times$				
2014 - Q3	-0.48**	-1.60**	-0.018**	-0.061**
	(0.23)	(0.69)	(0.0088)	(0.025)
2014 - Q4	-0.44*	-1.38**	-0.016*	-0.054**
	(0.25)	(0.69)	(0.009)	(0.025)
2015 - Q1	-0.38	-2.08***	-0.014*	-0.077***
	(0.24)	(0.8)	(0.0086)	(0.028)
2015 - Q2	-0.42*	-1.71**	-0.016*	-0.063**
	(0.24)	(0.76)	(0.0086)	(0.027)
TLTROs (bt) $\times$ HI (m) $\times$				
2014 - Q3	2.61*	10.8**	0.097*	0.41**
	(1.56)	(4.87)	(0.058)	(0.18)
2014 - Q4	3.72*	10.4**	0.13**	0.40**
	(1.91)	(4.97)	(0.065)	(0.18)
2015 - Q1	1.29	13.6**	0.052	0.50**
	(1.81)	(5.68)	(0.064)	(0.20)
2015 - Q2	1.66	10.9**	0.065	0.40**
	(2.02)	(5.46)	(0.071)	(0.19)
Observations	354,060	354,060	354,060	354,060
Adjusted R^2	0.36	0.35	0.36	0.35
Fixed effects				
Firm-time (ft)	Yes	Yes	Yes	Yes
Bank (b)	Yes	Yes	Yes	Yes
Controls (bt)	Yes	Yes	Yes	Yes

Table 2.6: **Targeted monetary policy and competition - Heterogeneity**
The table reports the estimated parameters and their standard errors from the IV estimation of equation (2.5) in different subsets of the data. All columns report estimates with the balanced panel of relationships for firms with more than one lender. The dependent variable is the interest rate including expenditure on the stock of loan from bank b to firm f in quarter t. TLTROs is a dummy equal to one if the bank borrows from the TLTROs. High risk firms are firms with a bad credit score (7-9), while low risk are firms with a good or average credit rating (classes 1-6). Small firms are firms below the median of the distribution of assets in the pre-treatment year (2013). Large banks are the top 5 banks in Italy. Bank-time controls include bank capital, non-performing loans, government bonds. All standard errors are double clustered by firm and bank-quarter. *,**, *** indicates significance at the 0.10, 0.05 and 0.01 levels, respectively.

	Firm risk		Firm size		Bank size	
	High	Low	Small	Large	Large	Small
	(1)	(2)	(3)	(4)	(5)	(6)
TLTROs (bt) $\times$						
2014 - Q3	-0.59	-0.34**	-0.65**	-0.37	-0.43**	0.46
	(0.48)	(0.19)	(0.33)	(0.27)	(0.21)	(0.80)
2014 - Q4	-0.25	-0.28	-0.58	-0.32	-0.55***	1.30
	(0.54)	(0.19)	(0.39)	(0.27)	(0.19)	(1.02)
2015 - Q1	-0.58	-0.20	-0.53	-0.30	-0.55***	1.18
	(0.50)	(0.18)	(0.37)	(0.26)	(0.17)	(1.34)
2015 - Q2	-0.18	-0.43**	-0.78**	-0.22	-0.36	0.05
	(0.47)	(0.18)	(0.36)	(0.28)	(0.23)	(1.40)
TLTROs (bt) $\times$ HI (m) $\times$						
2014 - Q3	4.35	1.36	3.29	2.18	1.90	-3.56
	(3.77)	(1.22)	(2.37)	(1.87)	(1.22)	(6.85)
2014 - Q4	2.84	2.36**	4.95*	2.76	3.71***	-9.61
	(3.89)	(1.35)	(2.90)	(2.00)	(1.26)	(9.85)
2015 - Q1	3.04	-0.03	1.72	1.11	3.20***	9.81
	(3.47)	(1.27)	(2.62)	(2.07)	(1.12)	(12.30)
2015 - Q2	0.65	1.43	3.61	0.60	2.64*	1.14
	(3.16)	(1.32)	(2.60)	(2.43)	(1.33)	(11.90)
Observations	81,930	272,130	154,458	199,602	135,936	106,680
Adjusted R^2	0.30	0.36	0.31	0.34	0.41	0.34
Fixed effects						
Firm-time (ft)	Yes	Yes	Yes	Yes	Yes	Yes
Bank (b)	Yes	Yes	Yes	Yes	Yes	Yes
Controls (bt)	Yes	Yes	Yes	Yes	Yes	Yes

Chapter 3

Down Payment and Mortgage Rates: Evidence from Equity Loans

3.1 Introduction

Down payments are a ubiquitous feature of mortgage contracts (Stein, 1995). Interest rates are higher on lower down payment mortgages to reflect higher risk (Bester, 1985; Adams et al., 2009).[1] Low down payments can increase risk through two channels. First, low down payments attract riskier borrowers (Campbell and Cocco, 2003, 2015; Corbae and Quintin, 2015). Second, a lower down payment also means less protection for the lender against falls in the value of the housing collateral and a higher expected loss in case of borrower default (Admati and Hellwig, 2014). Disentangling these two channels is fundamental to understand whether lenders are concerned about the quality of the pool of borrowers or about house price risk—

[1] Across countries, house buyers with a larger down payment get better mortgage rates (Al-Bahrani and Su, 2015; Andersen et al., 2015; Benetton et al., 2017; Basten and Koch, 2015).

both important channels that contributed to the global financial crisis (Mian and Sufi, 2009).

In this paper we study the causal effect of down payment on interest rate through asymmetric information. In other words, we isolate how lenders price the risk signal from down payment size. We exploit the institutional features of a UK affordable housing scheme that offers households equity loans to top up their down payment. The equity loans generate variation in down payment for mortgages with the same collateral and the same loan-to-value ratio (LTV). In standard mortgages, a 20 percentage points lower down payment increases the interest rate at origination by about 200 basis points, but this combines the effect of a higher default probability and a higher LTV. Using our experiment, we find that only 22 basis points (c. 10%) can be attributed to unobservable borrower quality signaled by the down payment. We provide supporting evidence that, ex-post, borrowers with 5% down payment are twice as likely to miss mortgage payments than those with 25% down payment. This result is important for the innovative mortgage products that we study. Equity loans can make house purchases more affordable, in particular for households with limited down payment, and may dampen the adverse macroeconomic effects of house price volatility (Mian and Sufi, 2015; Greenwald et al., 2017). The benefits of equity loans would however be muted if lenders charged substantially higher mortgage rates when households contribute only a small portion of the home equity.

We design an identification strategy that exploits variation in down payment for the same collateral and LTV, leveraging on unique contractual features of the UK Help to Buy - Equity Loan (EL) scheme. The scheme was introduced in 2013 and offers households a 20% equity loan—a contribution to the down payment to purchase a property—in exchange for a 20% share of any future capital gains resulting from a sale of the property. The borrower contributes a 5% down payment. The mechanics of the contract is better explained with an example, that we graphically show in Figure 3-1. Consider two mortgages both with a 75% loan-to-value ratio: a "standard" mortgage where the borrower pays a 25% deposit; and a EL where the borrower pays only a 5% deposit and the remaining 20% is provided by the scheme. The LTV on the two mortgages is the same but the down payment from the borrower is different, and we test whether this difference affects pricing.

We build a novel dataset which contains about 92,000 mortgages originated between April 2013 and June 2016 and combines information on the EL scheme (from the Homes and Communities Agency), mortgage origination and performance (Financial Conduct Authority) and house prices (Land Registry). We create two groups of borrowers with different down payments but same LTV and we test whether the group with the lower down payment pays a higher mortgage rate, controlling for observable borrower and product characteristics. These characteristics capture the *hard* information used in mortgage pricing and available to both the lender and the econometrician. *Soft* information (observable to the lender, but not to the econometrician) is unlikely to matter given the centralized pricing strategies in the mortgage market—the UK mortgage market is a "supermarket", with standardised products priced on a limited number of variables (Best et al., 2015; Benetton, 2017).

We find a 16 basis points premium on EL mortgages when we compare the interest rates on EL mortgages and "standard" 75% loan-to-value mortgages. As expected, we find a large difference in terms of the size of the down payment (in monetary terms), while differences in terms of house prices and borrower characteristics, such as age and income, are more muted. Compared to standard borrowers, EL borrowers purchase, on average, houses that are £21,000 (8%) cheaper but their down payment is £51,000 (80%) smaller. The EL premium increases to 22 basis points when we compare EL and standard mortgages issued by the same lender, in the same period, with the same product characteristics (eg. fixed vs variable mortgage rate). These are the main characteristics on which mortgages are priced in the UK market. The premium is robust to additional regional and borrower controls that are not explicitly priced but could vary between EL and standard mortgages. Only when we control for the down payment the EL premium disappears.

To corroborate our story based on higher unobservable risk we test whether EL borrowers with a low down payment also have a higher delinquency rate than borrowers with standard mortgages and similar loan-to-value ratios. We find that delinquency rates are higher for EL mortgages compared to standard 75% loan-to-value mortgages. Finally, we assess competing explanations for the difference in mortgage rates between the two groups. We test whether there is less bank competition in the supply of EL mortgages or whether properties bought with EL have a higher depreciation risk (in which case the same LTV might result in different loss given default), but these explanations are not supported by the data.

Related literature Our paper contributes to two related streams of literature. First, we contribute to the household finance literature that looks at mortgage products (see among others Campbell and Cocco, 2003; Guiso et al., 2013; Campbell and Cocco, 2015). The 2008 crisis has revamped the debate about optimal mortgage design (Cocco, 2013; Campbell, 2013; Miles, 2015), and several recent papers have suggested and analyzed alternative mortgage products, such as shared appreciation mortgages (Shiller, 2007; Greenwald et al., 2017); option adjustable rate mortgages (Piskorski and Tchistyi, 2010); fixed rate mortgages with underwater refinancing (Campbell, 2013); and convertible fixed rate mortgages (Eberly and Krishnamurthy, 2014). We build on this literature and study a new government scheme designed to promote affordability in the UK mortgage market by providing an equity loan to the borrower. We look at the supply side and study how lenders react to the scheme by adjusting their pricing strategy, thus affecting the benefits of alternative mortgage products.

Second, our work contributes to the literature that tests empirically whether lenders use collateral as a screening device (Adams et al., 2009). Despite the importance of the mortgage market, this paper is, to our knowledge, the first to look at how down payment is used as a screening mechanism in this context. Most of the literature uses collateral data to evaluate corporate or small-medium enterprise lending—see Berger et al. (2011) for a survey. For households, Adams et al. (2009) analyse the relationship between down payment and borrower quality in the market for subprime car loans; while Agarwal et al. (2016) study home equity release products and find that less creditworthy borrowers choose contracts with less collateral. Our identification approach exploits contractual features of mortgages to estimate the effect of information asymmetries on pricing, along the lines of recent papers by Ambrose et al. (2016) and Hansman (2017). Similarly to these paper we look at the effect of down payment on contract choice and default, but we also consider how this is reflected on pricing with an innovative research design.

The rest of the paper is organized as follows. Section 3.2 describes the setting and the data. Section 3.3 presents our identification strategy and shows the main result. Section 3.4 provides additional evidence on mortgage performances and addresses alternative explanations for our findings. Section 3.5 concludes.

3.2 Setting and data

EL is a UK shared home equity scheme that allows households to buy new properties with a lower down payment. In this section we highlight the importance of down payment in the UK mortgage market and explain how the EL scheme works. We also show that, in the data, a lower down payment is associated with higher mortgage rates and more frequent delinquencies.

3.2.1 The UK mortgage market

In international context, the UK mortgage and housing markets are characterized by high household indebtedness, medium levels of home ownership, and adjustable rate contracts with short initial fixed-rate periods (Campbell, 2013; Jordà et al., 2016).

Mortgage originations Since April 2005 UK mortgage lenders have been required to report all their mortgage originations to the Financial Conduct Authority (the Financial Services Authority until 2013). The submissions include detailed information on loan, borrower and property characteristics. This information is collected in the FCA's Product Sales Data (PSD), on which we base our analysis.[2]

In the UK mortgage leverage—as measured by the LTV ratio—is driven by the size of the down payment rather than the value of the house. Figure 3-2 uses the full set of PSD originations to show the distribution of house values and down payments by LTV. The average house price is relatively flat (about £200,000) up to 75% LTV and then decreases gradually. The average down payment instead falls steadily with LTV.

Moreover, UK lenders set an interest rate schedule that increases with the LTV. Mortgages are priced on a limited number of variables, typically LTV, borrower type (first-time buyer, home mover, remortgager) and rate type (length of fixed period). Other indicators of borrower quality, such as loan-to-income and credit rating are used to approve or reject the application, but do not affect mortgage rates.[3] To demonstrate the importance of LTV for UK mortgage rates, we follow Best et al. (2015) and regress the interest rate at originations on a set of product and time

[2]The PSD includes remortgages and excludes buy-to-let mortgages. Some of the variables contained in the PSD are: borrower type (first-time buyer, home mover, remortgagor), age, income, loan value, loan-to-income ratio (LTI), maturity, product type (e.g. fixed, floating), property value, location (full six-digit postcode).

[3]Moreover, rates are not dependent on the location of the property.

dummies and LTV bins. Figure 3-3 shows the results. The conditional interest rate increases with discrete jumps at the relevant LTV thresholds. The jumps in the interest rate are largest for LTVs above 85 and 90.

Mortgage performance data Since summer 2015 UK mortgage lenders have been required by the FCA to provide a loan-level snapshot of their current mortgage holdings. These mortgage performance data are part of the PSD and include a number of loan characteristics, such as date of origination, original and current loan balance, remaining mortgage term, and whether the mortgage has ever been delinquent.[4] We define delinquent borrowers (or borrowers in arrears, in UK terminology) as those that missed payments for a total amount exceeding the value of three regular monthly payments.

We use the mortgage performance data in Section 3.4 where we evaluate the repayment performance of EL borrowers against other purchasers of equivalent, non-EL mortgages. We employ the snapshot of owner-occupied mortgages as of December 31, 2016 and single out loans that have been in arrears at least once since origination.

In general, mortgages with higher leverage (and hence lower down payment) are more likely to be delinquent. Figure 3-4 shows that the proportion of delinquent borrowers increases more than proportionally with LTV. This fact holds both unconditionally (Figure 3-4a) and when we control for a rich set of borrower and loan characteristics (Figure 3-4b).

3.2.2 The Help To Buy - Equity Loan scheme

The UK government started the EL scheme in April 2013, with the objective of supporting "credit-worthy but liquidity constrained" households and increase the

[4]These variables do not perfectly overlap with the ones in the origination data, but the two datasets can be combined by matching on the postcode and date of birth of the borrower.

supply of new housing.[5] The government originally planned to phase out the scheme in 2016, but it has now extended it until 2021. The scheme is available in England and Wales. A similar, but separate, scheme is available in Scotland.

While there had been other schemes to support home ownership prior to EL, these were on a smaller scale. For example, its immediate predecessor, FirstBuy, had a budget of £250 million. The UK government initially set a maximum budget for EL of £3.7 billion. In October 2017 it pledged a further £10 billion and promised to continue to scheme until 2021.

The EL scheme provides an equity loan of up to 20% of the value of the house. In exchange, the scheme receives interest and participates in any capital gains or losses resulting from the sale of the property. To be eligible, the borrower has to provide a minimum 5% down payment. The bank or building society provides a mortgage for the remaining balance (up to 75%).[6] In case of default, the EL scheme holds a "second charge" on the property. The proceeds from a sale of the property go first to the bank or building society that provided the mortgage.

Eligibility is not subject to income restrictions and there are no checks on whether the borrower could provide a larger down payment. However, borrowers must meet affordability requirements to ensure that they will be able to repay the mortgage.[7]

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[5]First-time buyers and new builds were particularly affected by the housing downturn of 2007-08. The supply of high LTV mortgage in the UK fell sharply following the crisis of 2007-08, as mortgage lenders sought to reduce credit risk. First-time buyers experienced an increase in the average down payment (15% pre-crisis to over 25% in 2010) and a fall in mortgage lending (which halved between 2007 and 2008). Younger households were affected most. In 1991, 67% of the 25 to 34 age group were homeowners. By 2014, this had declined to 36% (Office for National Statistics, 2016). The sharp fall in house prices also affected house construction, which fell from over 200,000 per annum in 2007 to less than 150,000 in 2010 . Demand was constrained by limited mortgage availability for new properties, in particular at high LTVs.

[6]The description of the EL scheme is based on National Audit Office (2014), Gov.uk (2016a) and Gov.uk (2016b).

[7]These include, for instance, a 4.5 loan-to-income (LTI) limit based only on the mortgage. The affordability measures do not include the equity loan. One possible reason for the low EL premium that we measure on mortgage rates could be that lenders take reassurance from the additional checks that the Government carries out on borrowers. However, given that there is no additional requirement on borrowers compared to other mortgages, and the LTI constraints are in fact eased

The scheme is available to both first-time buyers and home movers, but not for second homes or buy-to-let investment. The property must have a purchase price of £600,000 or less. The borrower has to pay to the scheme only a £1 fee for the first five years. After that, the annual interest fee is 1.75%, increasing each year with the Retail Price Index (RPI). Payments of this fee do not amortize the equity loan capital. The borrower can make principal repayments at any time. The minimum repayment is 10% and is calculated on the basis of the market valuation of the house.[8] The borrower must repay the full value of the loan when the property is sold or after a maximum of 25 years.

The scheme is administered by the Department for Communities and Local Government (DCLG) and the Homes and Communities Agency (HCA) through a network of local agents, who process the applications. EL operates under slightly different criteria in Wales and the Greater London area. In Wales, the maximum property price is £300,000.[9] In London, the EL limit was increased from 20% to 40% in February 2016.[10] We exclude Wales and London (after January 2016) from our analysis.

EL originations and performance data We obtained from the HCA the complete database of all EL loans for the first 39 months of the scheme, from April 2013 to June 2016. The dataset includes 91,759 loans with information on full postcode, size of the mortgage, purchase price, lender name, and expected completion date.

Appendix Table C.1 shows descriptive statistics for the EL dataset. The total value of these equity loans is £4.17 billion, whereas the total value of properties sold under the scheme is £20.82 billion. According to the England and Wales Land

by the equity loan, this effect is likely to be small or nonexistent.

[8]For example, if the value of the property has increased from £200,000 to £220,000 the minimum repayment is £22,000.

[9]See Welsh Government (2016).

[10]See HM Government (2016).

Registry there were 286,593 sales of new properties in England between April 2013 and June 2016, implying that one third of the new build market was financed by EL. Since new builds correspond to approximately 10 percent of all housing transactions, EL financed 3 percent of all housing sales in England.

We match the EL dataset to the PSD to identify mortgage originations that are associated with an EL.[11] We then restrict our analysis to two groups of borrowers with the same collateral but different down payment. The first group is composed of EL borrowers that contribute with a 5%-10% down payment (with the vast majority putting down the minimum 5%—see Appendix Figure C-1), while the scheme finances an additional 20% of the purchase price. The second group is composed of borrowers that contributed a 25%-30% down payment with a standard 70-75% LTV mortgage. For simplicity, from now on we refer to the first group as EL borrowers and second group as "standard" borrowers.[12]

Table 3.1 shows descriptive statistics for EL and standard borrowers, while Figure 3-5 shows the different distributions of house purchase prices, incomes, mortgage sizes, and down payments. By construction, the size of the down payment constitutes the main difference between the EL and standard borrowers. EL allows borrowers to purchase similar (but slightly cheaper) houses with similar (but slightly smaller) mortgages. Table 3.1 also shows that EL borrowers are younger and have lower incomes, are more likely to be first time buyers, and are less likely to buy a property in London.

As an anticipation of the main result of this paper, we show in Table 3.1 that the average interest for the EL group is 11 basis points (4%) higher than for standard borrowers. Moreover, EL borrowers are more likely to become delinquent: the delinquency rate for EL borrowers is 0.29%, almost double the rate for the standard

[11]Data cleaning and matching are described in Appendix Table C.2.

[12]These groups are neither the universe of EL borrowers (a few EL borrowers contribute a down payment higher than 5%) nor that of "standard" mortgages (we exclude mortgages with other LTVs).

borrowers (0.15%).[13]

As with the universe of UK mortgages, in our subsample of interest we observe a correlation between down payment, mortgage rates, and delinquencies. In this sample we can exclude that the correlation between down payment and mortgage rates is caused by different losses in the event of default, which are set equal for all loans, suggesting that the EL premium is driven by the higher default risk of low down payment borrowers. In the next section, we develop an identification strategy to test whether the correlation between down payment and mortgage rates is robust to controlling for observable borrower and loan characteristics.

3.3 Down payment and mortgage rates

Theories of collateral as a screening mechanism predict that lower collateral—in the case of mortgages, down payment— should be associated both with higher interest rate and higher risk (Bester, 1985). In this section we measure the effect of collateral on mortgage rates, while in section 3.4 we focus on mortgage delinquencies.

3.3.1 Hypothesis

The mortgage rate r needs to compensate for the risk the borrower will not repay in full, which depends on the probability of non-repayment p and on the loss in case of non-repayment l. The mortgage rates also need to compensate operational costs c and a mark-up m:[14]

$$r = p(X, d) \cdot l(\Delta h, d) + c + m, \tag{3.1}$$

[13]Given the recent introduction of the EL scheme (2013), the number of loans in arrears is limited. In our sample, 110 EL borrowers are in arrears, compared to 24 standard borrowers.

[14]The components l, c and m are all expressed as a proportion of the loan. We do not assess whether lenders are pricing risk correctly.

where the probability of non-repayment p is a function of observable X and non-observable χ risk characteristics: $p = p(X, \chi)$. If the down payment d is a signal of non-observable risk ($d = d(\chi)$), then: $p = p(X, d)$.

The down payment however affects the interest rate in another way, too. In case of default, the lender can repossess the property. The lender incurs a loss if the current value the property is below the value of the outstanding loan, which can happen if the fall in house value Δh is larger than the original down payment d.

Equation (3.1) highlights our channel of interest - the effect of down payment (d) on mortgage rate (r) through the probability of non-repayment (p) - and the main confounding factors that we need to control for. All else equal, we expect lower d to be associated with (a) higher mortgage rates r and (b) higher risk p.

3.3.2 Research design

Our goal is to establish a causal link from down payment to interest rate, *only* through default risk. This objective requires us to observe the interest rates for two identical mortgages by the same lender, for the same property, taken by two borrowers who differ only in the size of the down payment. This is unlikely in most mortgage markets because, even conditioning on all observable borrower and mortgage characteristics, a lower down payment affects interest rates through both p and l in equation (3.1).

To isolate empirically the effect of d through unobservable risk χ we proceed as follows. First, we keep l constant by comparing the two groups of mortgages, EL and standard (as defined in the previous section), with the same collateral but different down payment and adding regional fixed effects to control for house price volatility Δh. Second, to remove variation in operational costs c and mark-up m we add interacted product-time fixed effects, which also remove differences in risk across products and time. Third, we control for observable risk X by adding exogenous borrower characteristics. At this point, we attribute any remaining EL premium after introducing these controls to the lower down payment provided by EL borrowers. As a last step, we check this by introducing the down payment d in the regression and verifying that the EL premium disappears.

We estimate the following empirical model:

$$r_{ijkt} = \alpha EL_i + \beta_{jt} + \gamma_k + \delta X_i + \eta Z_i + \epsilon_{ijt} \tag{3.2}$$

where r_{ijkt} is the interest rate paid at origination by borrower i for product j to purchase a property in region k in month t; EL_i is a dummy variable equal to one if the mortgage is under the government scheme; β_{jt} are interacted product-time fixed effects;[15] γ_k are geographic fixed effects; X_i are exogenous borrower characteristics and Z_i are additional borrower controls—house prices and down payment.

Our coefficient of interest is α which captures the EL interest rate premium. Our hypothesis is that that α falls to zero only when we add the down payment as a control, but remains positive otherwise.

3.3.3 Results

Table 3.2 presents our main result on mortgage rates. We test different explanations for the interest rate differential shown in section 3.3.2 by gradually introducing the controls in equation (3.2).

Column (1) in Table 3.2 shows the regression of the loan-level interest rate on the EL dummy. As shown in the descriptive stats in Section 3.2.2, lenders on average set an interest rate that is 11 basis points higher for EL mortgages than for mortgages within the same LTV band.

In column (2) we add the interacted product-time fixed effects (β_{jt}) to control

[15] A product in our setting is the combination of a lender, an interest rate type (e.g. fixed or variable) and a borrower type (first time buyer, home mover).

non-parametrically for differences in product characteristics. We exploit only the variation in interest rate within product-month-LTV, effectively comparing the interest rate on mortgages offered by the same lender, in the same month, to the same borrower type (first-time buyer vs. home mover) at the same conditions (e.g. fixed rate for two years). We find that the EL premium increases to 22 basis points.

In column (3) we include geographic fixed effects γ_k. The EL premium may be driven by local factors if borrowers with EL mortgages tend to buy houses in locations with higher house price volatility or macroeconomic risk. However, when adding geographic fixed effects, we find that the coefficient on the EL dummy decreases by only 1 basis point.

In column (4) we control for exogenous borrower characteristics (X_i). We include age and income of the borrower, employment status (employee or self-employed) and type of mortgage application (joint- or single-income application). Even if mortgage pricing in the UK is not borrower specific, selection into certain types of products can affect the pricing strategy of lenders (see section 3.2). If low-income borrowers systematically choose EL mortgages, the higher interest rate associated to EL will capture the effect of lower income. The EL premium stays stable at about 22 basis points.

In our data we are unable to observe all the information that lenders have on borrower risk characteristics. For example, we do not have data on credit scores. As explained in Section 3.2.1, this additional information is not used directly to price UK mortgages, but may affect pricing indirectly through average borrower risk. However, we note that adding observable borrower characteristics to the regression has a small effect on the EL premium, suggesting that product fixed effects are able to absorb a substantial amount of variation in borrower risk characteristics.

Finally, we control for additional borrower variables (Z_i) to test our main mechanism. In column (5) we add the house value to compare mortgages for houses with similar prices, in the spirit of Figure 3-1. The EL premium remains around 22 basis points. Income becomes insignificant when we add house value, due to the high correlation between the two variables. In column (6) we control for loan size instead of house price. Given that we restrict the estimation sample to loans with the same LTV, controlling for house value or loan size yields the same result.

In column (7) we add down payment to the regression in order to test explicitly whether differences in down payment explain the interest rate difference between EL and standard borrowers with similar LTV, mortgage product, and houses. The price difference between EL and standard borrowers decreases by 10 basis points. Finally in column (8) we allow the down payment to enter nonlinearly in the model, making the whole EL premium insignificant.

To summarize, the size of the down payment provides information on borrowers over and above their risk characteristics and housing choices. We find that lenders price EL mortgages about 22 basis point higher than equivalent standard mortgages. This premium is explained by the lower down payment. In our restricted sample, the down payment contributed by EL borrowers is 20 percentage points lower than that contributed by standard borrowers (5% and 25% respectively)—a difference of about £50,000.

Heterogeneity Table 3.3 shows the results on heterogeneity in EL mortgage rates across borrowers and lenders. In the first two columns we compare first-time buyers and home movers. The EL premium is larger for home movers by about 10 basis points. This finding may seem counterintuitive given that first-time buyers have no credit history in the mortgage market. However, the inability to make a large down payment seems to carry a particularly bad signal for home movers, who may have had the possibility to build home equity with their previous house.

In the remaining columns of Table 3.3, we study heterogeneity across lenders.

Previous studies have shown that pricing of risk can vary with lender characteristics, such as size and funding structure (He et al., 2012; Jiménez et al., 2014; Dagher and Kazimov, 2015). In columns (3) and (4) of Table 3.3, we look at lender size. We compare the top four lenders in our sample with the smaller lenders and building societies. The EL premium for the lenders accounting for the vast majority of originations is close to the baseline of 20 basis points, as expected. The other lenders charge EL mortgages more, at almost 35 basis points. This difference can be attributed to both demand and supply factors. Borrowers taking EL from smaller lenders may be relatively riskier than the standard borrowers. Alternatively, smaller lenders may be more cautious in pricing unobservable risk.

For the largest lenders we collect additional information on their capital buffers and funding costs. In columns (5) and (6) of Table 3.3 we study heterogeneity based on capital buffers, defined as the difference between a bank's capital resources and the minimum regulatory capital requirement (both measured as a percentage of total assets). We find that the EL premium is almost 30 basis points for lender with a low buffer and around 12 basis points for lenders with a larger buffer. Better capitalized lenders pass on the scheme to borrowers at lower prices. Moreover, this result seems to suggest that lenders with lower capital do not extend cheap credit to riskier borrowers, in contrast with recent evidence in other settings (Jiménez et al., 2014).

Columns (7) and (8) of Table 3.3 compare lenders with different funding costs, which we proxy lenders' credit default swaps. We find that for lenders with high funding costs the EL premium reaches 34 basis points, while lenders with low funding costs price it at about 16 basis points. Lenders with lower funding costs pass on the scheme to borrowers at lower prices.

3.4 Down payment and risk

In the previous section we showed that lenders price EL mortgages higher than equivalent standard mortgages and the difference is due to unobservable factors related to the size of the down payment. In this section, we provide evidence that EL mortgages are ex-post riskier, consistent with our main finding of an EL premium in mortgage rates. We also address alternative mechanisms that could explain the premium.

3.4.1 Ex-post performance

In equation (3.1), the down payment affects the mortgage rate because it signals unobservable borrower characteristics that increase the probability of default. But to extract the signal, the lender must observe that, all else equal, lower down payment borrowers are ex-post riskier. In Section 3.2.2 we have shown that, unconditionally, EL borrowers are twice as likely to become delinquent than standard borrowers. In this section we show that this relation holds after controlling for observable borrower and loan characteristics.

To measure the effect of down payment on ex-post performance controlling for confounding factors, we estimate a model similar to (3.1) but with the probability of delinquency as dependent variable. This takes the form of the following probit model:

$$Delinquent_{ilt} = \beta EL_i + \gamma_l + \gamma_t + \alpha Z_i + \delta X_i + \epsilon_{ilt}. \tag{3.3}$$

where $Delinquent_{ilt}$ is a dummy equal to one if borrower i borrowing from lender l in year t has been delinquent at any point before the end of 2016. Our coefficient of interest is β which captures the additional risk associated with EL mortgages; with this variable we aim to isolate *only* the effect of the unobservable risk on delinquencies that the borrower signals via a lower down payment. To control for other factors affecting the probability of delinquency we include a full set of year of origination and lender fixed effects, borrower and property level controls. We also estimate (3.3) with the interest rate at originations (r_{ijt}) among the controls, although the results of this specification have to be taken with caution, given the endogenous nature of mortgage rates.

Table 3.4 presents the results. Column 1 replicates the unconditional marginal effect of EL on the delinquency rate (0.13 percentage points). In column 2-4 we add similar controls to those in the price regression in Table 3.2. We incrementally add year and region fixed effects (column 2), borrower characteristics and house value (column 3) and lender fixed effects (column 4). Due to the limited number of observed delinquencies, we use separate lender and year fixed effects rather than the full set of product-by-month fixed effects. We find that the effect of EL on the delinquency rate remains around 0.10 percentage points, and is still significant at the 10% level, despite the small number of delinquencies in the sample.

In the last column of Table 3.4 we show the results including the mortgage interest rate in the regression. This specification checks that the different delinquency probabilities between EL and standard borrowers are not simply due to the fact that EL borrowers pay higher rates (as shown in the previous section) and therefore have a harder time servicing their mortgage. However, mortgage rates are themselves an endogenous outcome variable, which hinders the interpretation of the conditional effects estimated by the regression: EL borrowers are charged more precisely because of their higher delinquency probability. With this caveat in mind, column 5 shows that EL borrowers are still 0.07 percentage points more likely to become delinquent than standard borrowers, but the difference is now statistically insignificant.

What unobservable risk characteristics does the down payment signal? Our finding of a higher delinquency rate for EL borrowers could be due to either lower borrower quality at origination or stronger incentives to default due to higher leverage.

Under the first interpretation, borrowers that are illiquid today are also likely to be illiquid tomorrow, and unable to pay in case of income shock (Adams et al., 2009). This intuition can be formalized in models where households save for precautionary reasons. In Campbell and Cocco (2003) and Campbell and Cocco (2015) impatient mortgage borrowers with a higher discount rate accumulate a smaller buffer stock on liquid financial assets and are more likely to miss mortgage payments.

Under the second interpretation, EL borrowers are more leveraged and hence more likely to fall into negative equity than the control group. For example, a fall in property value from £100,000 to £90,000 would be sufficient to push into negative equity an EL borrower with a £5,000 deposit at origination, but not a standard 75-percent LTV mortgage with £25,000 home equity at origination. This higher leverage increases the probability of negative equity and hence the opportunities for strategic default (for a recent example see Hansman, 2017).

It is worth pointing out, however, that the incentive to strategically default are not as high for EL borrowers as for other homeowners that put a 5% down payment. Figure 3-6 shows how the home equity position of borrowers varies depending on house prices and type of mortgages, assuming an initial house value of 100. For simplicity, we assume an interest only mortgage, where payments cover only the interest and none of the principal is repaid until sale. The initial home equity of EL owners is the same as that of 95%-LTV borrowers, but its sensitivity to house price movements is lower. Because of the cushion provided by the government scheme, the EL household will reap lower gains for any increase in house value, but will also suffer lower losses for any house price decline. It takes a fall in house prices of more than 6.25% for a EL borrower to be in negative equity.[16]

Two additional considerations point towards a bigger role for borrower qual-

[16] In the simplified case of an interest-only mortgage, EL borrower home equity is $E_t = 0.8HP_t - Q_t = 0.8HP_t - 0.75HP_0$, where HP_t and Q_t are, respectively, the house price and the outstanding mortgage balance at the end of the period, while HP_0 is the purchase price of the house.

ity as opposed to strategic defaults. First, between 2013 and 2016 average house prices grew across all regions in England. All 370 local authorities experienced an increase in house prices except for Redcar and Cleveland (in North East England) and Allerdale (in North West England).[17] Therefore arrears in our sample are not driven by negative equity.

Second, the UK framework for treating mortgages in default is full recourse. UK mortgage borrowers can be pursued for up to six years for any remaining mortgage obligation (Lambrecht et al., 2003; Aron and Muellbauer, 2016). They remain liable for their debt even after the property has been repossessed by the lender, if the sale value of the property does not cover the value of the debt. Lambrecht et al. (2003) find that UK lenders' foreclosure decisions depend more on cash flow shocks (income, interest rates) than on leverage.[18] Evidence for the US indicates that full recourse significantly reduces, but does not completely eliminate, incentives for strategic default (Ghent and Kudlyak, 2011).

We conclude with a back-of-the-envelope calculation of the effect of down payment on mortgage rates. Borrowers for EL mortgages put the same down payment (5%) as borrowers with standard 95%-LTV mortgages. However, standard 95%-LTV mortgages entail a significantly different loss given default for lenders. Figure 3-3 shows that in the UK the average difference in mortgage rates between 75 and 95%-LTV mortgages is around 200 basis points. In this paper we show that borrowers who put only a 5% down payment pay, *ceteris paribus*, a mortgage rate premium of 20 basis points relative to borrowers who put a 25% down payment. We can therefore conclude that probability of default explains approximately 10% of the differential between 5% and 25% down payment mortgages, with the bulk of the

[17]We checked local house price trends using the house price indices available at `https://www.gov.uk/government/statistical-data-sets/uk-house-price-index-data-downloads-march-2017`.

[18]This is confirmed by regulatory surveys in which strategic default does not seem to be a concern for lenders operating in the UK market.

differential (90%) explained by differences in loss given default.

3.4.2 Alternative explanations

The analysis in section 3.4.1 is consistent with an interpretation of the EL premium in terms of default risk, driven by ex-ante selection. But our results could also be consistent with alternative mechanisms. First, the EL premium could also reflect higher repayment risk. Second, the premium could be compensating lenders for higher depreciation risk for EL properties. Third, the EL premium could reflect a markup due to lower competition in the EL segment, compared to standard mortgages, within the new build market. We explore each explanation in turn, but find limited evidence in their support.

Lenders are exposed to the risk that the borrower terminates the contract early to refinance at a lower rate (Campbell and Cocco, 2003). The borrowers in our sample have an incentive to refinance at the end of the fixed-rate period (typically two or five years) after which the mortgage rate reverts to a higher "standard variable rate" (Miles, 2004). The original lender receives lower cash flows, compared to the standard variable rate, if it offers a new fixed-rate contract, but loses all future cash flows if the borrower switches to another provider or sells the property. The descriptive statistics in Table 3.1 however indicate that, unconditionally, EL borrowers are *less* likely than standard borrowers to refinance or sell the house.[19]. We test this result by substituting refinancing and sale as the dependent variables in probit regressions similar to Equation 3.3. The results in Table 3.5 indicate that differences between the two groups in the probability of resale or refinance with the same bank are either not significant. The difference is statistically significant but economically marginal in the case of refinance with another bank (EL borrowers are slightly less risky).

[19]We consider all refinancing ans sales activity between origination and the end of 2016.

New houses usually sell at a premium compared to other properties of comparable characteristics.[20] For our identification strategy, this premium is only problematic to the extent that it affects EL properties more than other equivalent new builds. This differential impact could be due to: (1) lower price elasticity of EL buyers, (2) less maintenance effort by EL buyers (possibly because of the risk sharing component of the EL contract as in Shiller and Weiss, 2000), or (3) developers using EL as an alternative to the variety of incentives that have been on offer to other buyers, which might include discounts to list price, or higher specifications of homes or features.[21]

To check that our results are not driven by depreciation risk, we identify which properties in the treatment and control group were resold within the sample period. We match the PSD mortgage flow dataset with the England and Wales Land Registry and find 485 cases of sales (186 in the control group and 299 in the treatment group). We compute the appreciation of properties as the (log) ratio between the transaction price at sale and the purchase price. Table 3.6 shows that, unconditionally, EL properties have lower appreciation rates, by approximately four percentage points. However, once we control for purchase year, or for purchase year and sale year, the difference becomes insignificant. Additional controls for region fixed effects drive the difference close to zero.

Lower competition in the EL market compared to standard mortgages on new builds could lead to a higher markup for EL mortgages. For example, the administrative burden associated with offering EL mortgages could inhibit entry by some lenders, especially smaller banks. Mortgages lenders interviewed as part of DCLG (2016)'s evaluation of the EL scheme indicate that mortgage lending for the new build market is more concentrated than for the overall property market. The main barrier to entry are the fixed costs required to establish a relationship with devel-

[20] "[H]ouses are a bit like new cars, which lose value immediately upon being driven off the lot." (Coulson et al., 2016)

[21] EL mortgages could be issued in areas with higher house price volatility, and this would also induce higher depreciation. However, our geographic fixed effects address this problem.

opers' sales offices. However, what matters for our analysis is whether entry in the EL segment is more difficult than for standard mortgages in new build. According to DCLG (2016) the EL scheme helped smaller lenders establish these relationships with developers and increased their appetite to enter the new build market.[22]

We test for differences in concentration between the supply of EL and standard mortgages. In our dataset, we find that supply is more concentrated for EL mortgages: the Herfindahl-Hirschman concentration index (HHI) is .26 compared to .20 for standard mortgages. Higher concentration does not lead to lower competition if consumers are able to switch across providers. Most EL borrowers are first-time buyers and have not developed brand loyalty from previous experiences in the mortgage market. Lenders could have built brand loyalty through other financial products, in particular current accounts. However, only about 20%-30% of UK mortgages are sold by the the same bank that the borrower has a current account with.[23]

We also examine concentration at the full (six-digit) postcode level,[24] which we use as a proxy for concentration within individual new developments. Developers can enter agreements to steer mortgage demand for their new built properties towards specific lenders.[25] If the EL scheme strengthens vertical relations between developer and lender, this should result in higher concentration at postcode level. In fact, as Figure 3-7 shows, we find that concentration is *lower* in postcodes with EL scheme participation.

Price discrimination between EL and standard mortgages could also lead to price differences. This explanation requires that EL have a higher willingness to pay for mortgages. However, when addressing depreciation risk, we showed that EL borrowers do not pay more than other borrowers for the same property. For this alternative mechanism to be true, we would need EL borrowers to be willing to pay

[22]Lenders do not need to register with DCLG or HCA to provide EL mortgages.
[23]Oliver Wyman (2012), Competition and Markets Authority (2014)
[24]In the UK, a full postcode corresponds on average to 10-15 properties.
[25]See Stroebel (2016) on vertical relations between developers and lenders.

relatively more for the mortgage, but not for the house, which we consider unlikely.

3.5 Conclusion

In this paper we study the causal effect of down payment on interest rate through asymmetric information. Using a UK affordable housing scheme that offers households equity loans to top up their down payment, we find that 22 basis points can be attributed to unobservable borrower quality signaled by the down payment. We provide supporting evidence that, ex-post, EL borrowers with 5% down payment and a 20% EL top-up are twice as likely to miss mortgage payments than non-EL borrowers with 25% down payment (on similar mortgage products).

The effect of asymmetric information that we uncover can be driven by adverse selection and moral hazard. The menu of available mortgage contracts provides incentives to choose a larger down payment, because of the lower associated interest rate. Low down payments may attract borrowers that are less able or willing to save. Borrowers that are illiquid today are likely to be illiquid tomorrow and have limited savings to absorb future shocks (Campbell and Cocco, 2003, 2015).[26] An alternative explanation of higher expected defaults for low down payment borrowers is based on ex-post moral hazard (Adams et al., 2009; Guiso et al., 2013; Campbell and Cocco, 2015). A low down payment increases the probability of negative equity, which gives borrowers an incentive to default and walk away from their losses. We do not disentangle these potential explanations, but the institutional features of the scheme and of the UK mortgage market suggest that adverse selection is the

[26]Mortgage borrowers, in particular first-time buyers, have very little financial assets left after purchasing the property (as the "wealthy hand-to-mouth" in Kaplan and Violante, 2014 and Cloyne and Surico, 2017).
This explanation is consistent with an interpretation of a higher down payment as a signal of family wealth. According to this view, a borrower with a high down payment could have parents or other family members who are willing and able to help financially.

predominant channel.

Our paper has implications for both housing and macroprudential policies. Equity loans may become increasingly common if growing house prices threaten the affordability of homeownership (Miles, 2015). On top of their potential to improve affordability, these type of contracts have been suggested to improve risk sharing between borrowers and lenders (Mian and Sufi, 2015; Greenwald et al., 2017). Our results indicate that affordable housing policies that promote ownership by offering equity loans (and other policies that seek to supplement the down payment) are likely to attract riskier borrowers. The more lenders are concerned about adverse selection, the more expensive the mortgages associated with equity loans become, potentially lowering the benefits of these products for house buyers. For the mortgage products that we study, our results suggest that lenders see the size of the down payment as a signal for unobservable risk, but its relative importance is limited, as it accounts for only 10% of the difference in mortgage rates between loans with 5% and 25% down payment.

Under the Help To Buy EL scheme, house purchases require financing from mortgage lenders, households and the government. This paper focuses on the supply of mortgages. In future research we plan to study the scheme from the borrower's perspective to understand what drives the choice to participate in the scheme. Another possible avenue of research would assess the scheme from the perspective of the government, and its stated objectives to address barriers to homeownership and encourage developers to build more new homes (National Audit Office, 2014).

3.6 Main Figures and Tables

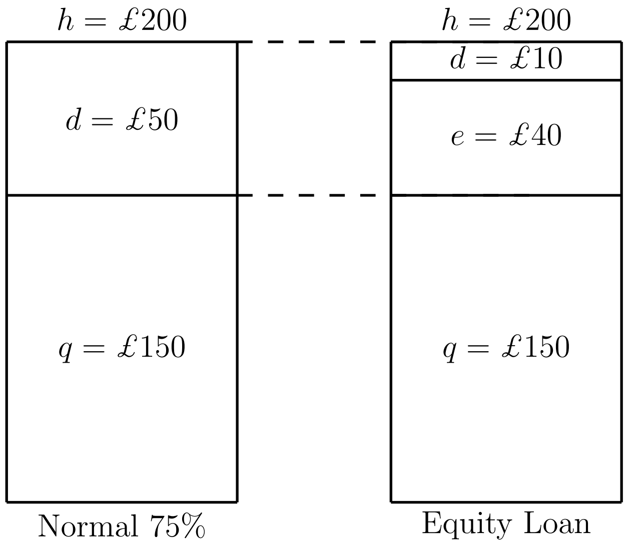


Figure 3-1: **Standard mortgage vs. Help To Buy Equity Loan (EL) mortgage: Borrower's balance sheet**
The figure show the liability side of two borrowers that buy a house (h) worth £200K and borrow (q) £150K from a bank. The left-hand side household makes a £50K down payment (d) and uses a standard mortgage. The right-hand side household makes a £5K down payment and borrows £40K from the government through the EL scheme (e).

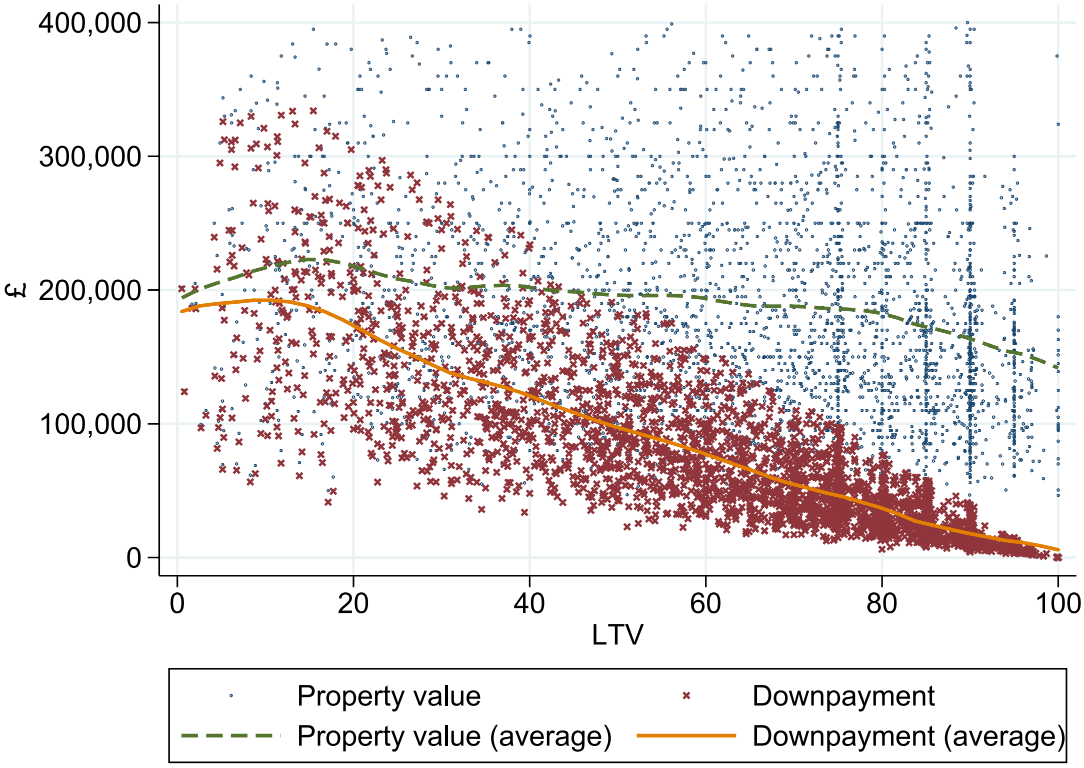


Figure 3-2: **Evidence on the relation between loan-to-value ratio (LTV) and down payment**
The figure shows the distribution of down payment and house prices at different LTVs. Data are taken from the UK Financial Conduct Authority's Product Sales Data (PSD), which contains information on all owner occupied mortgages issued in the UK since 2005 (including remortgages). To facilitate visualization we restrict the scatter plot to a random 0.025% sample of the data (3750 mortgages) and exclude properties with price above £400K (corresponding to the 90th percentile of the distribution of house prices in the PSD).

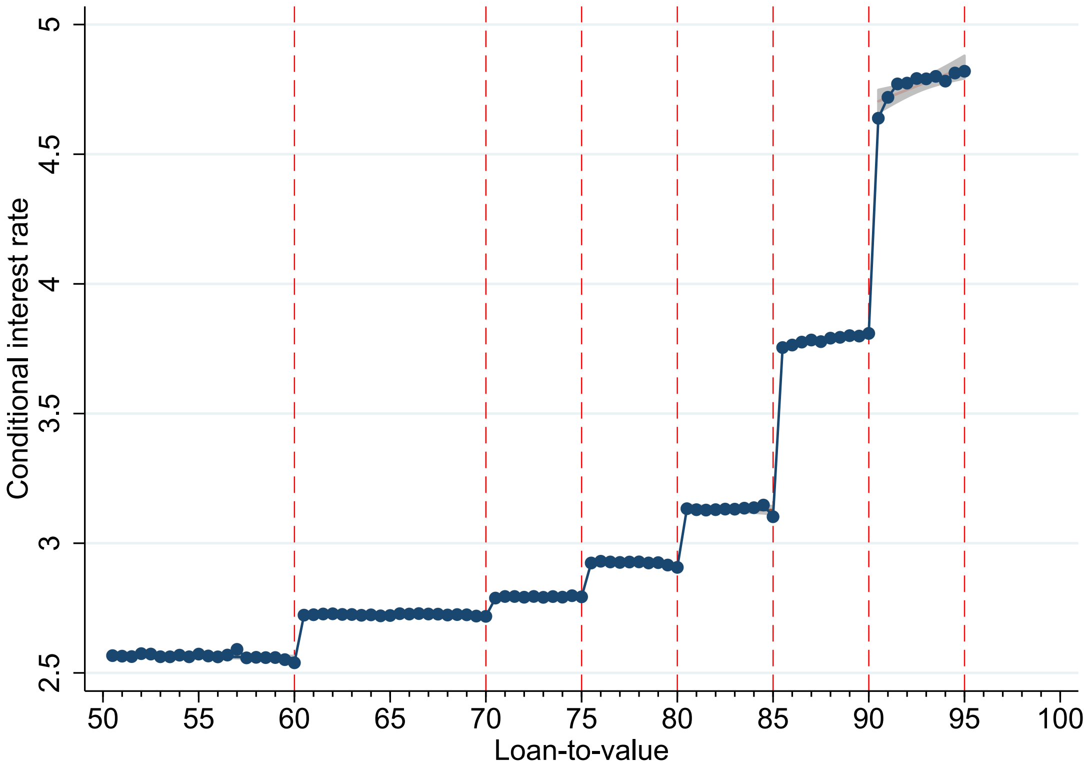
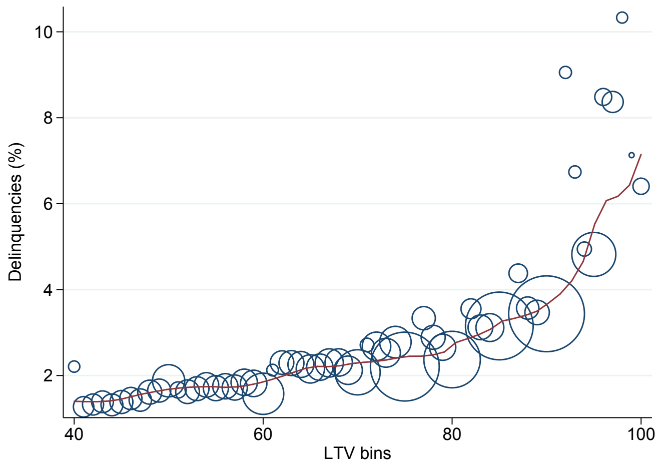
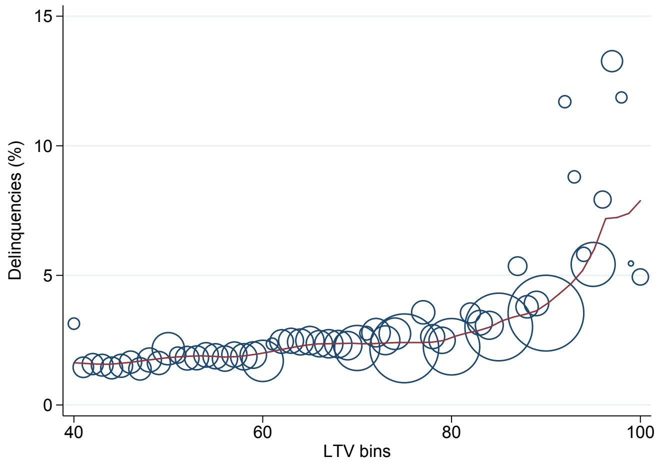


Figure 3-3: **Evidence on the relation between down payment and mortgage interest rate**

The figure shows the conditional interest rate (r_i) as a function of the loan-to-value (LTV) bin from the following specification: $r_i = \sum_{k=60}^{95} LTVbin_k + control_i$. The sample is made of the universe of mortgage originations since 2015 from the FCA's Product Sales Data. Control variables include the characteristics of the mortgage—whether it is a first-time buyer or a home-mover mortgage, or a remortgage; whether the interest rate is fixed or variable; the name of the lender; the term of the mortgage.

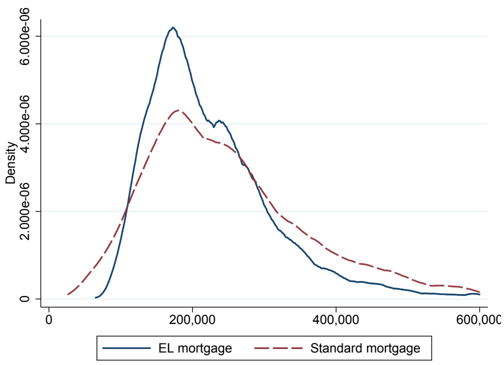


(a) Unconditional correlation

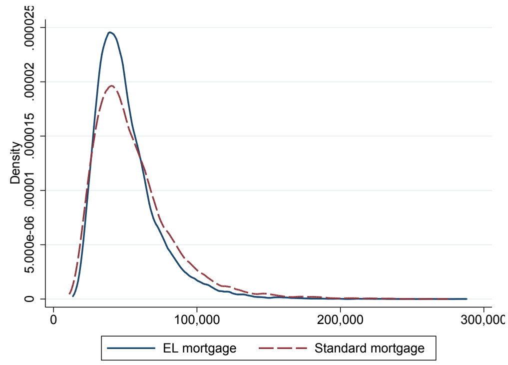


(b) Residual correlation

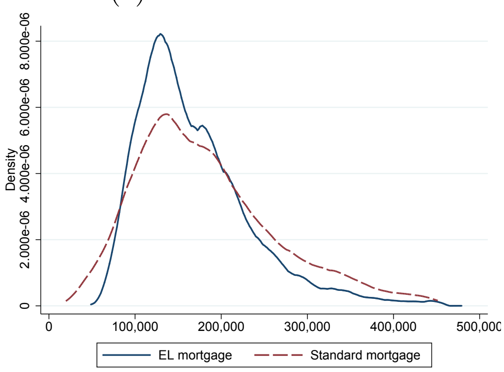
Figure 3-4: **Evidence on the relation between down payment and default**
The figure shows the correlation between the initial loan-to-value ratio (LTV) and the fraction of delinquent mortgages. Panel (a) shows the unconditional correlation. In Panel (b) we control for mortgage characteristics: whether it is a first-time buyer or a home-mover mortgage, or a re-mortgage; whether the interest rate is fixed or variable; the name of the lender; the term of the mortgage. We use mortgage performance data by the UK Financial Conduct Authority. Delinquencies are defined as missing payments for a total amount exceeding the value of three regular monthly payments.



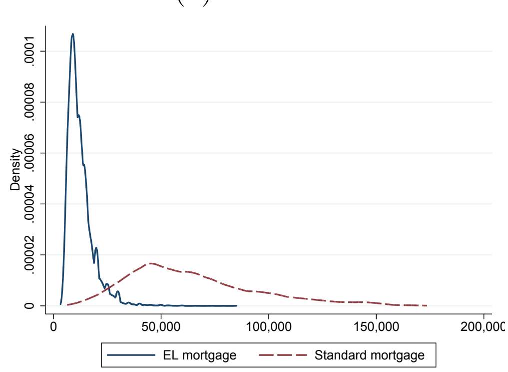
(a) Purchase price



(b) Income



(c) Mortgage



(d) Down payment

Figure 3-5: **Distribution of key variables**

The charts show the distribution of the purchase price, income, loan value, and down payment for the the group of EL mortgages and the group of standard 70-75% LTV mortgages. All mortgages are on new build properties and were issued in England between 2013 and 2016.

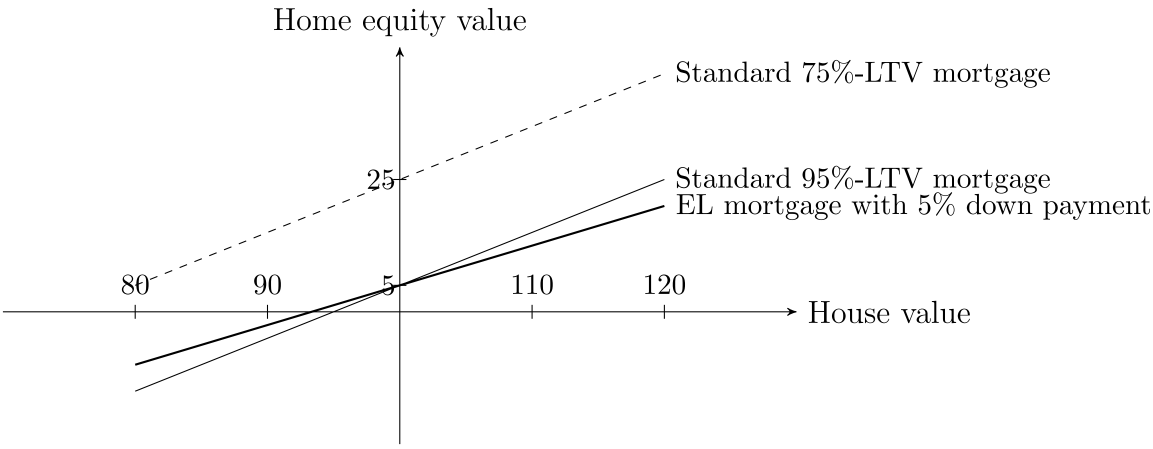


Figure 3-6: **Home equity values under different mortgages**
The horizontal axis in the diagram represents the value of the property, whose purchase price is normalised to 100. The vertical axis represents the equity invested by the homebuyer, which equals the down payment at the moment the house is purchased. The three diagonal lines represent the final home equity values for homebuyers using three different types of mortgages, as a function of how the house value evolves. The owner is in negative equity when the mortgage line is below the horizontal axis. The diagram shows that an EL mortgage with 5% down payment is less likely to be in negative equity than a standard 95%-LTV mortgage.

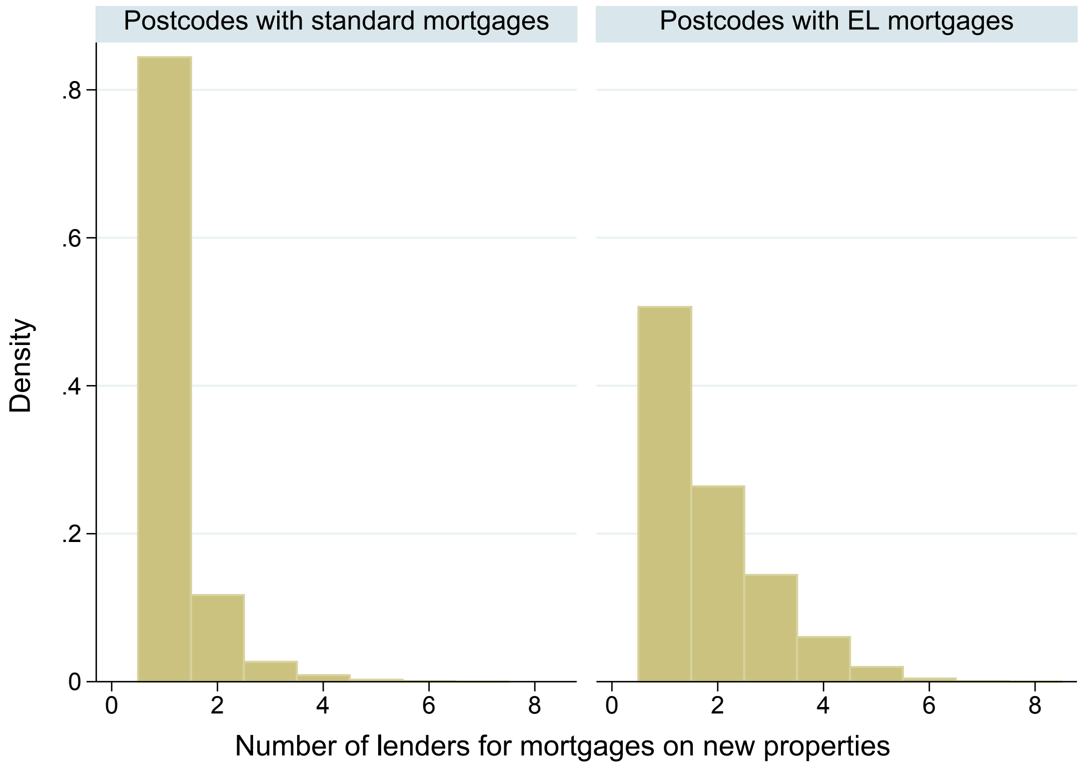


Figure 3-7: **Competition between lenders within postcodes**

The two histograms show the number of lenders that have issued a mortgage in any of the full 6-digit postcodes that form our estimation sample. The left-hand side chart includes all the postcodes where at least one standard 70-75% mortage on a new property was issued. The right-hand side chart includes all the postcodes where at least one EL mortgage was issued. The sample refers to the 2013-2016 period.

Table 3.1: **Descriptive statistics**

The table compares two groups of mortgages on new properties with 70-75% LTV issued in 2013-2016. The first group includes mortgages associated with an equity loan, while the second group only include standard mortgages. The first row of the table simply reports the size of the two groups of observations. The remaining rows show the mean value of the relevant variables for each group as well as their standard deviation. The last column of the table shows the mean difference between the two groups; ***: $p < 0.001$, **: $p < 0.01$, *: $p < 0.05$. Down payment, delinquencies, and the interest rate are highlighted in bold. LTI stands for loan to income ratio; MTI stands for mortgage payment to income ratio.

	70-75% LTV				
	Equity Loans		**Standard mortgages**		
	Mean	SD	Mean	SD	Diff
Obs	37,744		10,036		
Downpayment	12,393	5,980	64,107	29,834	-51,714***
Interest	2.72	0.60	2.61	0.59	0.11***
Delinquencies	0.003	0.057	0.002	0.046	0.001**
Sold	0.008	0.089	0.019	0.135	-0.011***
Refinanced (same bank)	0.000	0.010	0.003	0.052	-0.003***
Refinanced (other bank)	0.001	0.037	0.016	0.125	-0.015***
Purchase price	224,718	88,006	246,017	111,511	-21,300***
Loan value	167,956	65,690	181,911	82,209	-13,955***
HTB equity loan	44,759	17,590	0	0	44,759***
Gross income	51,007	22,411	55,471	28,231	-4,464***
Age borrower	31.45	6.89	34.49	8.32	-3.03***
Self employed	0.04	0.20	0.07	0.26	-0.03***
Joint income	0.36	0.48	0.34	0.47	0.02***
Single income	0.17	0.37	0.30	0.46	-0.13***
Fixed 2 years	0.57	0.49	0.52	0.50	0.05***
Fixed 3 years	0.06	0.23	0.04	0.20	0.01***
Fixed 5 years	0.35	0.48	0.25	0.43	0.09***
Fixed (unknown)	0.02	0.15	0.18	0.39	-0.16***
First-time buyer	0.76	0.42	0.52	0.50	0.25***
LTV	74.59	1.03	74.01	1.73	0.58***
Mortgage term	29.24	5.04	26.96	5.92	2.28***
Monthly payment	710.16	300.53	814.21	403.03	-104.05***
LTI	3.41	0.70	3.43	0.89	-0.01**
MTI	0.17	0.04	0.18	0.05	-0.01***
London	0.04	0.20	0.17	0.37	-0.12***
S and E England	0.40	0.49	0.41	0.49	-0.01**
Rest of England	0.55	0.50	0.42	0.49	0.13***
2013	0.02	0.13	0.18	0.38	-0.16***
2014	0.12	0.33	0.22	0.41	-0.09***
2015	0.57	0.49	0.42	0.49	0.16***
2016	0.29	0.45	0.19	0.39	0.10***

Table 3.2: **Main regression results, mortgage rates**
The table shows results from our main regression of mortgage rate at origination on loan characteristics, including an indicator variable for EL, our variable of interest. All standard errors are double clustered at the month-product level. The first column contains an estimate of the unconditional interest rate difference between EL mortgages and standard 70-75% mortgages. The remaining columns of the table show results from different specifications obtained by progressively adding controls to the regression. In the second column, product-time fixed effects capture the effect of the combination of type of borrower (first time buyer or home mover), lenght of fixed period (two, three, five years or unknown), lender and month. In the third column, Region corresponds to one of the nine English regions: Greater London, South East, South West, East of England, North West, Yorkshire and the Humber, East Midlands, West Midlands, North of England. In the fourth column, Joint and Single describe whether the income provided in the documentation of the mortgage comes from an individual or from a couple—the omitted category is made of mortgages where this detail is unknown. Columns (5)-(8) refer to regressions that include endogenous choice variables such as the value of the house, the size of the loan or the down payment. These variables are expressed in British pounds.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	interest	interest	interest	interest	interest	interest	interest	interest
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
EL	0.106	0.225***	0.215***	0.217***	0.215***	0.216***	0.098**	0.037
	(0.083)	(0.046)	(0.044)	(0.043)	(0.042)	(0.042)	(0.041)	(0.044)
Income(log)				-0.103***	-0.006	-0.008	-0.016	-0.014
				(0.016)	(0.011)	(0.011)	(0.011)	(0.011)
Age				-0.003	-0.000	-0.000	-0.002	-0.001
				(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age^2				0.000	-0.000	-0.000	0.000	0.000
				(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Self employed				-0.033***	-0.023**	-0.024**	-0.023**	-0.022**
				(0.010)	(0.010)	(0.010)	(0.010)	(0.009)
Joint				-0.067***	-0.071***	-0.072***	-0.058***	-0.062***
				(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
Single				-0.088***	-0.088***	-0.089***	-0.075***	-0.080***
				(0.004)	(0.004)	(0.004)	(0.005)	(0.004)
House value (.000)					-0.001***		-0.000*	-0.000
					(0.000)		(0.000)	(0.000)
Loan size (.000)						-0.001***		
						(0.000)		
Downpayment (.000)							-0.002***	-0.005***
							(0.001)	(0.001)
Downpayment^2 (.00,000,000)								0.002**
								(0.001)
Product-Time	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region	No	No	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.01	0.76	0.76	0.77	0.77	0.77	0.77	0.77
Observations	47,780	47,754	47,754	47,754	47,754	47,754	47,754	47,754

Table 3.3: **Mortgage rates and heterogeneity**

This table shows results from regressions with the same specification as column (4) in Table 3.2 for different subsamples of the data. All standard errors are double clustered at the month-product level. We examine heterogeneity along the following dimensions: first-time buyers (FTB) vs. home movers (HM) (columns 1-2), top 4 UK banks vs. other banks (columns 3-4), high vs. low capital buffers (columns 5-6), and high vs. low funding costs (columns 7-8). Lenders have high capital buffers when they exceed the median value in the sample. The same applies to lenders with high funding costs.

	Borrower		Size		Buffer		Funding cost	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	FTB	HM	Big 4	Others	High	Low	High	Low
EL	0.166***	0.284***	0.193***	0.359***	0.119**	0.295***	0.350***	0.167***
	(0.047)	(0.056)	(0.040)	(0.114)	(0.048)	(0.065)	(0.059)	(0.045)
Income(log)	-0.010	0.008	-0.001	-0.039**	-0.005	-0.001	0.031	-0.017*
	(0.008)	(0.020)	(0.012)	(0.018)	(0.012)	(0.016)	(0.021)	(0.009)
Age	-0.002	-0.009*	0.001	-0.010	0.002	-0.002	-0.001	-0.000
	(0.002)	(0.005)	(0.002)	(0.007)	(0.002)	(0.002)	(0.003)	(0.003)
Age^2	0.000	0.000	-0.000	0.000	-0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Self employed	-0.009	-0.040***	-0.013	-0.069**	-0.014	-0.019	-0.017	-0.021
	(0.012)	(0.011)	(0.009)	(0.028)	(0.011)	(0.013)	(0.012)	(0.014)
Joint	-0.070***	-0.080***	-0.071***	0.000	-0.066***	0.000	-0.069***	0.025
	(0.004)	(0.011)	(0.005)	(0.000)	(0.006)	(0.000)	(0.005)	(0.015)
Single	-0.093***	-0.084***	-0.087***	-0.038*	-0.085***	-0.011	-0.061***	0.000
	(0.004)	(0.016)	(0.004)	(0.020)	(0.005)	(0.012)	(0.004)	(.)
House value (.000)	-0.001***	-0.001***	-0.001***	-0.000*	-0.001***	-0.001***	-0.000***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Product-time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.80	0.70	0.77	0.73	0.78	0.76	0.83	0.72
Observations	34030	13724	41125	6629	20819	23205	14308	29716

Table 3.4: **Probability of being delinquent**
The table shows results from a probit regression of delinquencies (defined as missing payments for a total amount exceeding three regular months) on mortgage characteristics. The parentheses contain Huber-White robust standard errors. Results are displayed in terms of marginal effects computed at the mean value for all variables.

	Unconditional	Robustness			
	(1)	(2)	(3)	(4)	(5)
EL	0.0013*	0.0013*	0.0015**	0.0009*	0.0007
	(0.0007)	(0.0007)	(0.0007)	(0.0005)	(0.0005)
Income(log)			-0.0026**	-0.0007	-0.0007
			(0.0012)	(0.0007)	(0.0007)
Age			0.0000	-0.0001**	-0.0001**
			(0.0000)	(0.0000)	(0.0000)
Self employed			0.0030*	0.0012	0.0012
			(0.0017)	(0.0009)	(0.0009)
Joint			-0.0003	-0.0005	-0.0004
			(0.0006)	(0.0004)	(0.0005)
Single			0.0006	0.0002	0.0003
			(0.0007)	(0.0006)	(0.0006)
House value (.000)			0.0000	0.0000	0.0000
			(0.0000)	(0.0000)	(0.0000)
Interest (%)					0.0004
					(0.0003)
Year	No	Yes	Yes	Yes	Yes
Region	No	Yes	Yes	Yes	Yes
Lender	No	No	No	Yes	Yes
Pseudo R^2	.002	.022	.034	.076	.077
Observations	41,499	41,499	41,499	41,448	41,448

Table 3.5: **Probability of property sale and refinancing**

The three panels show results from probit regressions of different outcomes in the mortgage performance data, comparing EL mortgages with standard mortgages. The parentheses contain Huber-White robust standard errors. Results are displayed in terms of marginal effects computed at the mean value for all variables.

Panel A: Property sale

	(1)	(2)	(3)	(4)	(5)
EL	-0.0085***	-0.0003	-0.0006	-0.0003	-0.0005
	(0.0009)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Time	No	Yes	Yes	Yes	Yes
Region	No	Yes	Yes	Yes	Yes
Borrower characteristics	No	No	Yes	Yes	Yes
Lender	No	No	No	Yes	Yes
Pseudo R^2	.014	.129	.137	.139	.139
Observations	47,780	47,780	47,780	47,435	47,435

Panel B: Refinancing with same bank

	(1)	(2)	(3)	(4)	(5)
EL	-0.0008***	-0.0002**	-0.0001*	-0.0000	-0.0000
	(0.0002)	(0.0001)	(0.0001)	(0.0000)	(0.0000)
Time	No	Yes	Yes	Yes	Yes
Region	No	Yes	Yes	Yes	Yes
Borrower characteristics	No	No	Yes	Yes	Yes
Lender	No	No	No	Yes	Yes
Pseudo R^2	.121	.209	.271	.314	.315
Observations	47,780	23,460	23,460	21,679	21,679

Panel C: Refinancing with another bank

	(1)	(2)	(3)	(4)	(5)
EL	-0.0064***	-0.0013***	-0.0010***	-0.0023***	-0.0013***
	(0.0005)	(0.0003)	(0.0003)	(0.0006)	(0.0004)
Time	No	Yes	Yes	Yes	Yes
Region	No	Yes	Yes	Yes	Yes
Borrower characteristics	No	No	Yes	Yes	Yes
Lender	No	No	No	Yes	Yes
Pseudo R^2	.108	.242	.255	.256	.286
Observations	47,780	35,033	35,033	24,291	24,291

Table 3.6: **Property appreciation**

The table shows results from a robustness analysis of the 486 properties in the sample for which we can observe a subsequent sale. The coefficients in the table come from a regression of the log appreciation of properties in this restricted sample on the EL indicator variable and some fixed effects. The parentheses contain Huber-White robust standard errors. Column (1) shows the unconditional difference in appreciation between properties bought through the EL scheme and properties bought with a standard mortgage. Column (2) includes region fixed effects in the regression, column (3) adds purchase-year fixed effects (2013, 2014, 2015 or 2016), and column (4) includes sale-year fixed effects.

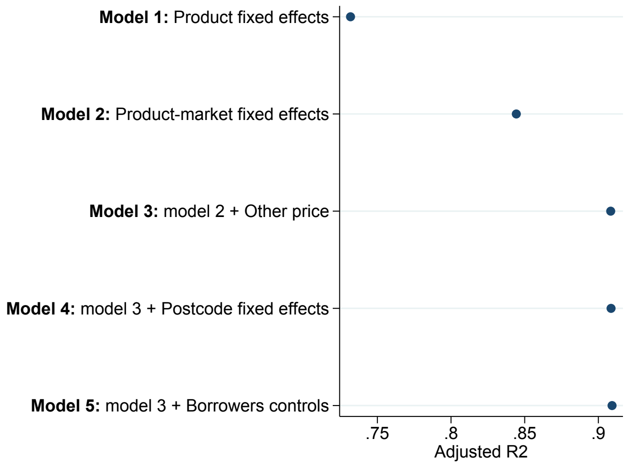
	(1)	(2)	(3)	(4)
	Δp	Δp	Δp	Δp
EL	-0.041***	-0.022**	0.003	-0.004
	(0.012)	(0.010)	(0.011)	(0.010)
Region	No	Yes	Yes	Yes
Purchase year	No	No	Yes	Yes
Sale year	No	No	No	Yes
R^2	0.03	0.35	0.38	0.42
Observations	485	485	485	485

Appendix A

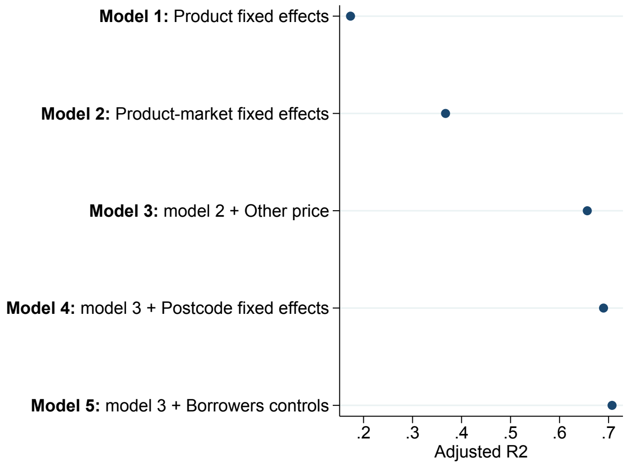
Appendix Chapter 1: Leverage Regulation and Market Structure: An Empirical Model of the UK Mortgage Market

A.1 Facts: Additional Material

Figure A-1: Pricing: mortgage supermarket



(a) Interest



(b) Fee

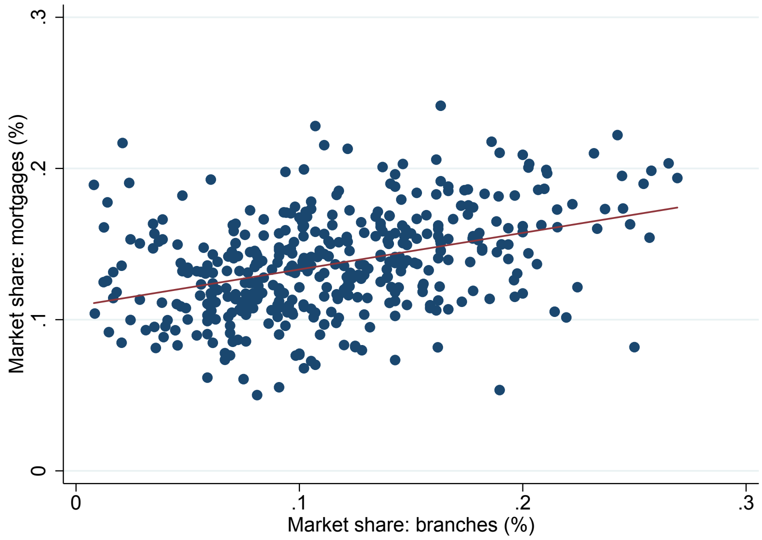
Notes: the chart reports the ajusted R^2 of regressions of borrower level interest rates and fees (r_{ijm} and f_{ijm}) on a set of dummy variables. Model (1) includes only dummy for the product, defined by the interaction of mortgage type, lender and loan-to-value band. Model (2) adds dummies for the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

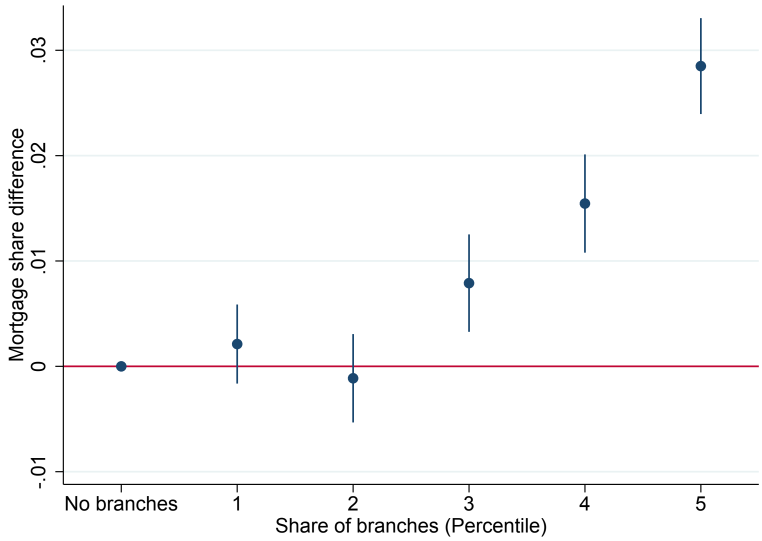
	FTB	HM	RMGT
Full sample	81.5	72.5	72.5
Type			
Fix 2 years	61.7	52.8	50.7
Fix 5 years	19.9	19.7	21.8
Max LTV			
50-60	4.2	9.4	17.8
60-70	5.0	9.9	17.2
70-75	5.8	9.3	13.3
75-80	7.7	9.8	10.8
80-85	15.8	14.2	8.9
85-90	29.8	16.6	4.4
90-95	13.3	3.2	
Lender			
Big six	69.9	58.5	55.6
Challenger	4.9	5.7	7.4
Building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



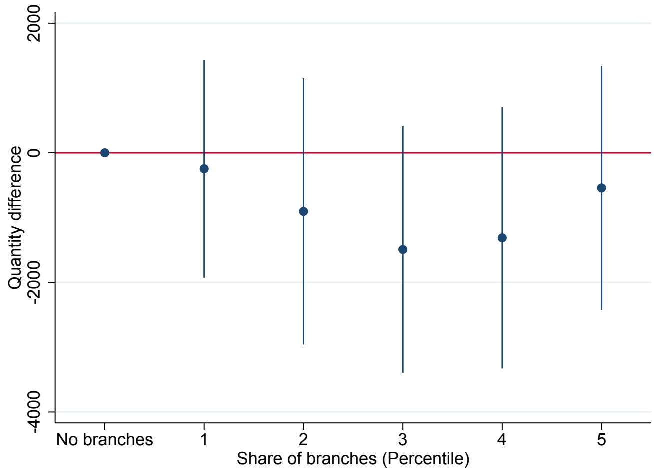
(a) Correlation



(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: $share_{la} = \gamma_l + \gamma_a + \sum_{k=1}^{5} \beta^k branch_{la}^k$, where γ_l and γ_a are lender and area (postcode) fixed effects and $branch_k$ are quintile of the branch share distribution. We normalize the constant to be the case of no branches in the postcode area.

Figure A-3: Branches and loan choice



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

A.2 Model: Additional Material

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

$$\epsilon^q_{ijm} = \frac{\partial q_{ijm}}{\partial r_{jm}} \frac{r_{jm}}{q_{ijm}} = \frac{\partial \ln(q_{ijm})}{\partial r_{jm}} r_{jm} = -\alpha r_{jm} \tag{A.1}$$

$$\begin{aligned}
\epsilon^d_{ijm} &= \frac{\partial s_{ijm}}{\partial r_{jm}} \frac{r_{jm}}{s_{ijm}} = -\mu \exp(-\alpha r_{jm} + \beta X_j + \xi_{jm} + \eta D_i + \zeta_i) s_{ijm}(1 - s_{ijm}) \times \frac{r_{jm}}{s_{ijm}} \\
&= -\alpha\mu \exp(-\alpha r_{jm} + \beta X_j + \xi_{jm} + \eta D_i + \zeta_i)(1 - s_{ijm}) r_{jm}
\end{aligned} \tag{A.2}$$

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

$$\epsilon^q_{jm} = \frac{1}{N_{jm}} \sum_{i=1}^{N_{jm}} \frac{\partial q_{ijm}}{\partial r_{jm}} \frac{r_{jm}}{q_{ijm}} \tag{A.3}$$

$$\epsilon^d_{jm} = \frac{1}{N_{jm}} \sum_{i=1}^{N_{jm}} \frac{\partial s_{ijm}}{\partial r_{jm}} \frac{r_{jm}}{s_{ijm}} \tag{A.4}$$

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

$$\begin{aligned}
PV(q, r, R, t, T) = q \sum_{k=1}^{t} &\left[\frac{r(1+r)^T}{(1+r)^T - 1} - \frac{c(1+c)^T}{(1+c)^T - 1} \right] + \\
\gamma b \sum_{k=t+1}^{T} &\left[\frac{R(1+R)^{T-t}}{(1+R)^{T-t} - 1} - \frac{c(1+c)^{T-t}}{(1+c)^{T-t} - 1} \right],
\end{aligned} \tag{A.5}$$

where $R > r$ is the reset rate, t is the length of the initial period and b the remaining balance at the end of the initial period. I also allow for the possibility that borrowers default like in the model from Section 1.3.2, assuming that lenders setting interest rate do not forecast the probability of default in each period, but consider an average proability of default, as in Crawford et al. (2015). The net return becomes:

$$
\begin{aligned}
PV(q,r,R,t,T) \approx q\left[t(r-c)+\gamma(T-t)(R-c)\right] - dq\left[tr+\gamma(T-t)R\right] = \\
q\left[tr+\gamma(T-t)R\right](1-d) - q\left[tc+\gamma(T-t)c\right]. \qquad \text{(A.6)}
\end{aligned}
$$

Given the demand system and the present value of the net revenue from interest payment A.6, the problem of the lender becomes:

$$
\begin{aligned}
\max_r \Pi_{lm}(r_{jm}) = & \sum_{j\in J_{lm}} \Pi_{jm}(r_{jm}) = \\
& \sum_{j\in J_{lm}} \sum_{i\in I_t} s_{ijm}(r_{jm}, r_{-jm}) \times PV(r_{jm}) = \\
& \sum_{j\in J_{lm}} \sum_{i\in I_m} s_{ijm}(r_{jm}, r_{-jm}) \times q_{ijm}(r_{jm}) \times \\
& \underbrace{\left[(t_j r_{jm} + \gamma_j(T_j-t_j)R_j)(1-d_{ijm}) - (t_j + \gamma_j(T_j-t_j))c_{jm}\right]}_{\chi_{jm}=\text{Effective mark-up}}. \qquad \text{(A.7)}
\end{aligned}
$$

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):

$$
\begin{aligned}
\frac{\partial \Pi_j}{\partial r_j} = & S_j Q_j (1-D_j) t_j + \\
& S_j \frac{\partial Q_j}{\partial r_j}\left[(t_j r_j + \gamma_j(T_j-t_j)R_j)(1-D_j) - (t_j c_j + \gamma_j(T_j-t_j)c_j)\right] + \\
& \sum_{k\in J_l} \frac{\partial S_k}{\partial r_j} PV_k - S_j Q_j \frac{\partial D_j}{\partial r_j}(t_j r_j + \gamma_j(T_j-t_j)R_j) = 0, \qquad \text{(A.8)}
\end{aligned}
$$

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

$$
\begin{aligned}
r_j^* = & \overbrace{\frac{c_j(t_j + \gamma_j(T_j - t_j))}{t_j\left((1-D_j) - \frac{\frac{\partial D_j}{\partial r_j}}{\frac{\partial S_j}{\partial r_j}\frac{1}{S_j} + \frac{\partial Q_j}{\partial r_j}\frac{1}{Q_j}}\right)}}^{\text{Effective marginal cost}} + - \overbrace{\frac{1}{\frac{\partial S_j}{\partial r_j}\frac{1}{S_j} + \frac{\partial Q_j}{\partial r_j}\frac{1}{Q_j} - \frac{\partial D_j}{\partial r_j}\frac{1}{1-D_j}}}^{\text{Full mark-up}} \\
& - \underbrace{\gamma_j \frac{R_j(T_j - t_j)}{t_j}}_{\text{“Add-on” effect}} - \underbrace{\sum_{k \neq j \in J_l} \frac{\frac{\partial S_k}{\partial r_j} PV_k}{t_j\left(\frac{\partial S_j}{\partial r_j} Q_j(1-D_j) + S_j \frac{\partial Q_j}{\partial r}(1-D_j) - S_j Q_j \frac{\partial D_j}{\partial r_j}\right)}}_{\text{Other products}}.
\end{aligned} \tag{A.9}
$$

Note that if there is no default risk ($\frac{\partial D_j}{\partial r_j} = 0$ and $D_j = 0$), all borrowers remortgage at the end of initial period ($\gamma_j = 0$) and demand one unit of loan ($Q_j = 1$), and all lenders offer only one product then equation (A.9) collapses to the standard mark-up pricing formula: $r_j^* = c_j - \frac{S_j}{\frac{\partial S_j}{\partial r_j}}$. Compare to the optimal price from Section 1.3.2 the marginal cost is higher to account for the fraction that does not refinance the loan, but the add-on effects lower the optimal rate, as the lenders are getting the revenues from the reset rate.

Consumer surplus. Finally I report the formula that I use in the calculation of several variables and indexed in the counterfactual simulations of section 1.6. I calculate expected consumer surplus following Small and Rosen (1981). To convert the utility measure into money terms I face a complication due to the fact that income enters non-linearly. Herriges and Kling (1999) discuss alternative options to allow for non-linear income effects. I adopt the representative consumer approach and compute welfare within each group type, thus allowing for observable heterogeneous effects for different income and age groups and regions. The expected compensating variation $E[cv]$ for a change in interest rate, all else equal, is given implicitly by:

$$E\left[\max_{j\in J^0} U(y, r_j^0, X_j, \epsilon_j)\right] = E\left[\max_{j\in J^0} U(y, r_j^1 - cv, X_j, \epsilon_j)\right] \tag{A.10}$$

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

$$E\left[\max_{j\in J^0} U(y, r_j^0, X_j, \epsilon_j)\right] = E\left[\max_{j\in J^1} U(y, r_j^1 - cv, X_j, \epsilon_j)\right] \tag{A.11}$$

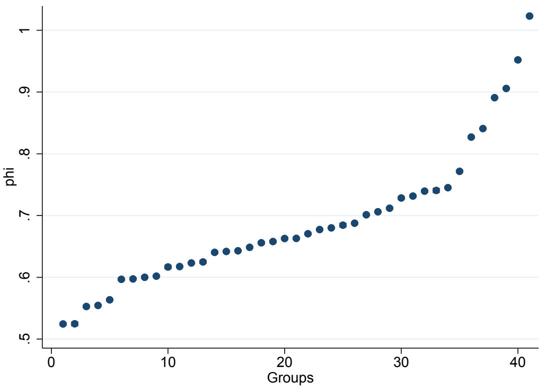
Where J^1 is the new choice set. The change in consumer surplus is then given by:

$$\Delta E[CS] = \frac{1}{\lambda}\left[\ln(\sum_{j=1}^{J^1} \exp(V_j^1)) - \ln(\sum_{j=1}^{J^0} \exp(V_j^0))\right] \tag{A.12}$$

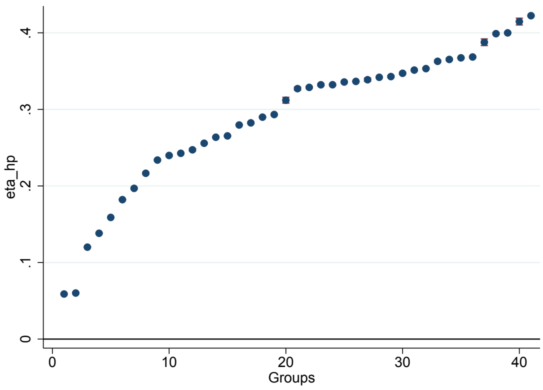
With $\lambda = \frac{-\alpha\mu\exp(-\alpha r_j)}{q}$.

A.3 Fit: Additional Material

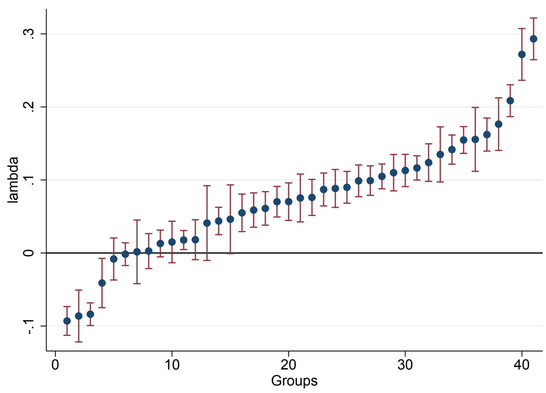
Figure A-4: Demand parameters: first stage



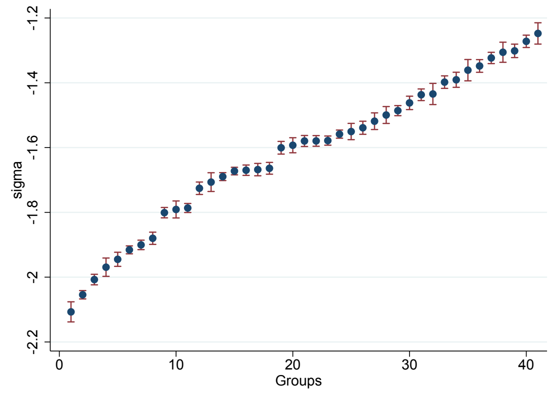
(a) Income (log)



(b) House prices (log)



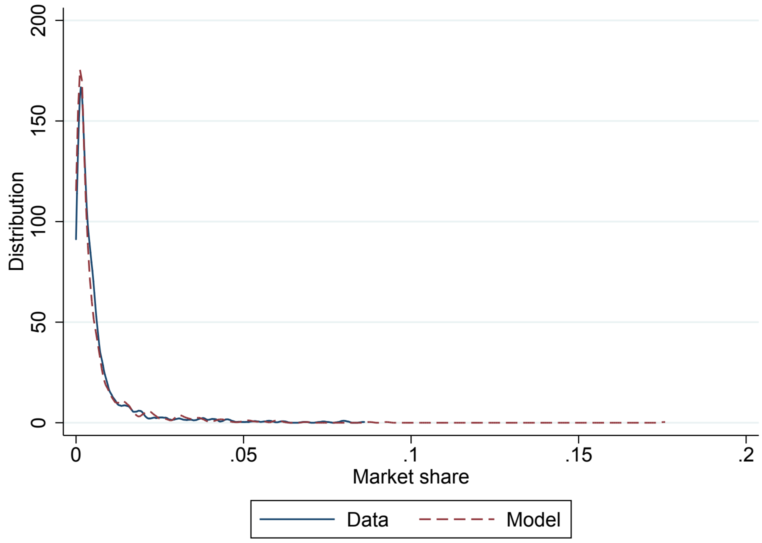
(c) Branches (log)



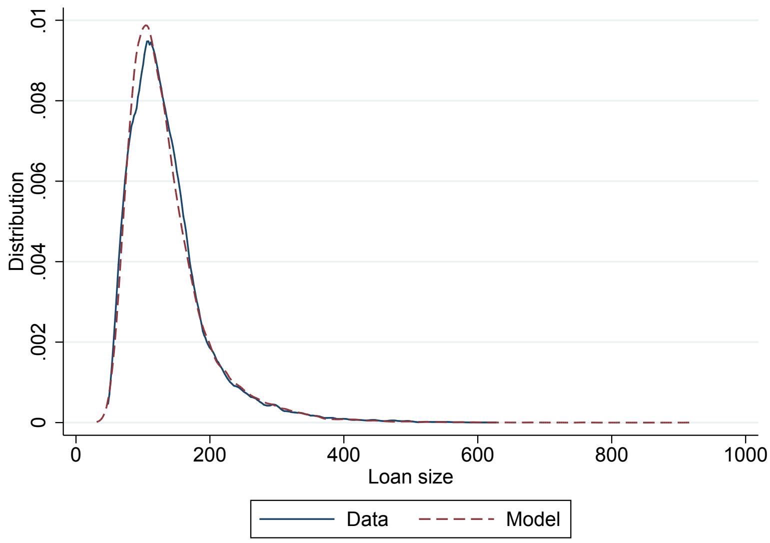
(d) Heterogeneity

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 A-5: Model fit: product and loan demand



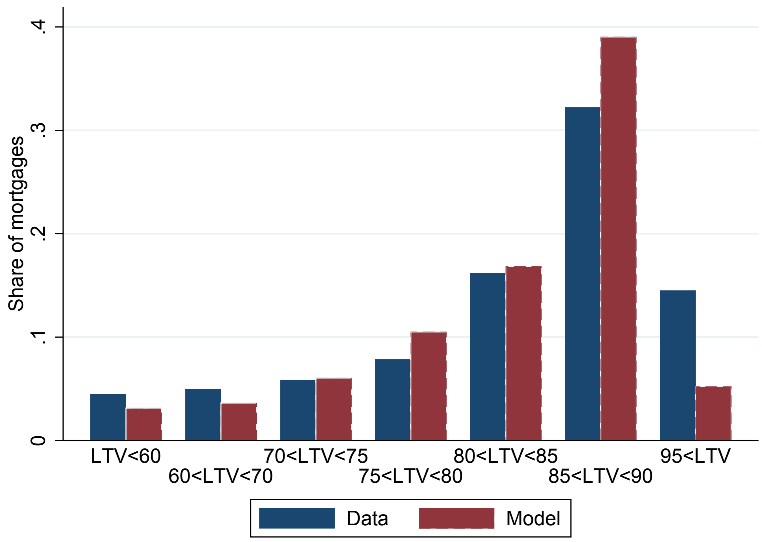
(a) Product share



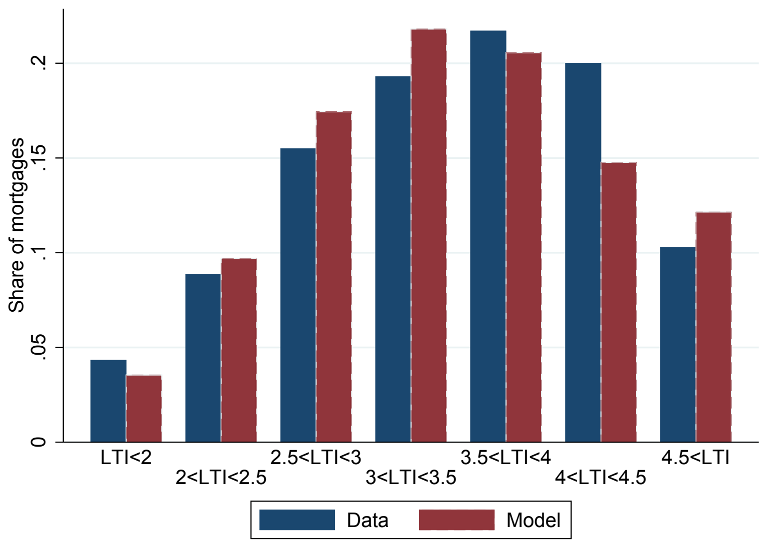
(b) Loan demand

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 A-6: Model fit: LTV and LTI



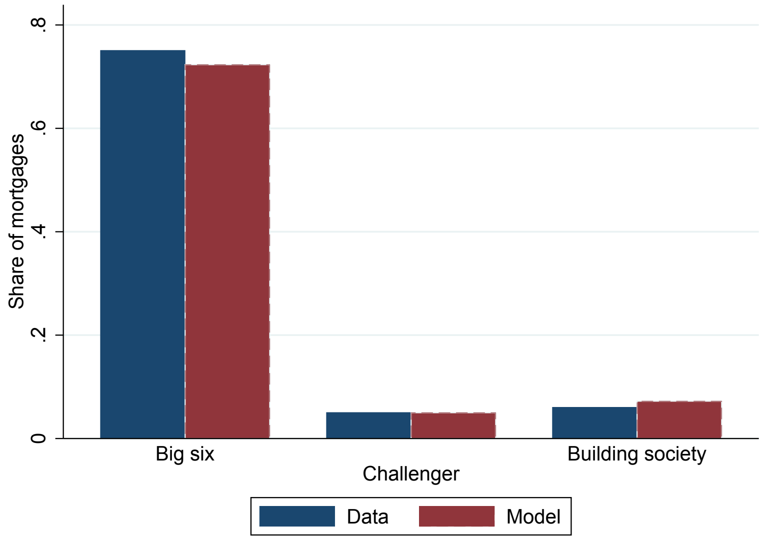
(a) Loan-To-Value



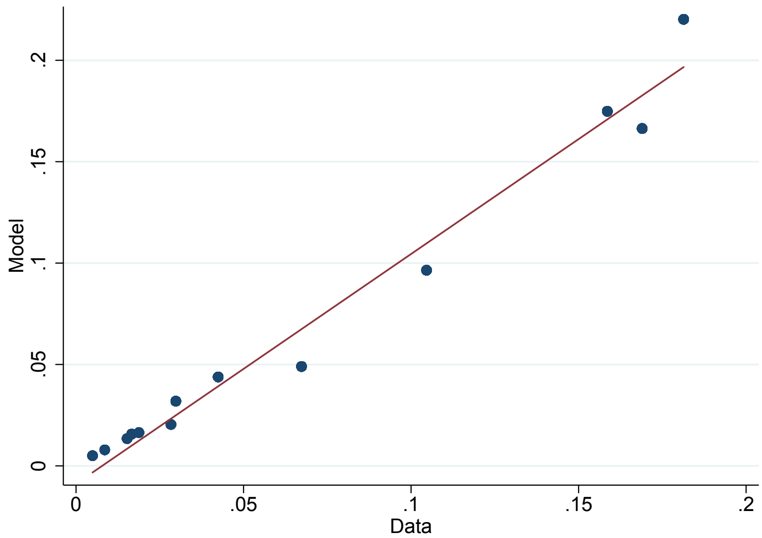
(b) Loan-To-Income

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 A-5 and sum across maximum LTI. We use a random subsample of 10% of the whole population.

Figure A-7: 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 A.2: 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 1.4.2. 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 A.2. 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.

Table A.3: 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 **??**. 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 A.4: 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 ≤ 70	224	1.783	4.362	1.793	4.396
$70 <$ LTV ≤ 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 (1.8) without default risk ($D_j = 0$ and $\frac{\partial D_j}{\partial r_j}$). Effective marginal cost includes both the discrete-continuous choice and default risk, captured by average arrears at the product level and the average response of arrears to the interest rate estimated in section **??**. Without add-on is the case of equation (1.8) with every borrowers refinancing at the end of the initial period t ($\gamma_j = 0$), while with add-on is the case with a fraction $\gamma_j > 0$ paying the higher standard variable rate. The marginal costs are expressed in percentage points. We report the average elasticities for all products and by different product characteristics: lender type, maximum LTV and fix period.

A.4 Robustness

In this section I show several robustness checks. Figure A-8 shows the structural parameters capturing the demand elasticity to the interest rate for the OLS model and two IV models. Panel b shows the case in which we use the risk-weights of the lender originating the mortgage as an instrument for the interest rate; Panel d shows the case in which we use the average risk-weights of other lenders as an instrument for the interest rate. Figure A-9 reports the same parameter for two additional exercises. In Panel a I estimate the model using the Annual Percentage Rate (APR) as the price variable, thus also including information on the fees. In Panel b I estimate jointly the second step demand parameters and the supply parameters with simulated method of moments. I construct the moments using the structural demand error term in each group of borrowers from (1.15) and the structural supply error term from (1.17). The two set of moments are related by the markup and given by:

$$\begin{aligned} E\left[\xi^g_{jm}(\alpha^g, \beta^g)\right| z_{jm}\right] = 0, \quad g = 1, ..., G \quad & \textit{Demand} \\ E\left[\kappa_{jm}(\alpha^1, ..., \alpha^G, \tau)\right| z_{jm}\right] = 0 \qquad\qquad & \textit{Supply,} \end{aligned} \tag{A.13}$$

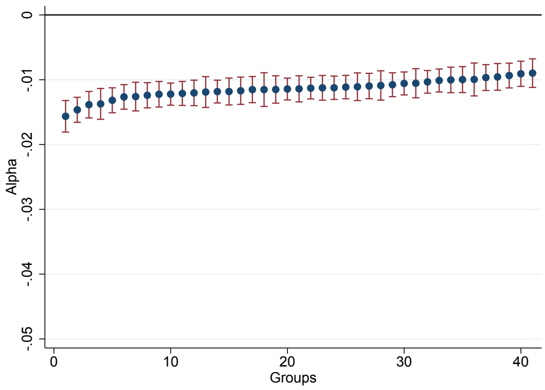
in the population, and:

$$m(\alpha, \beta, \tau) = \begin{bmatrix} \sum_m^M \sum_{j \in J_m} \left[\hat{\delta}^g_{jm} - (-\alpha^g r_{jm} + \beta^g X_j)\right] z_{jm} = 0, \quad g = 1, ..., G \\ \sum_m^M \sum_{j \in J_m} \left[r_{jm} - (\tau_X X_j + \tau_c c_{jm} + \tau_R \underline{\mathrm{K}}_{lt} \rho_j + \tau_t) + \frac{\sum_{i \in I} s_{ij} q_{ij}}{\sum_{i \in I}(s_{ij}\frac{\partial q_{ij}}{\partial r_j} + \frac{\partial s_{ij}}{\partial r_j} q_{ij})})\right] z_{jm} = 0 \end{bmatrix} \tag{A.14}$$

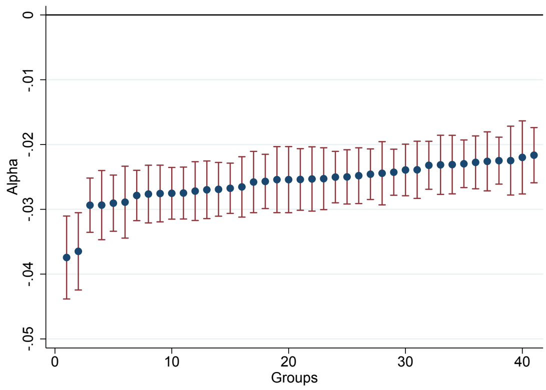
in the sample. The method of simulated moments estimator is given by:

$$(\hat{\alpha}, \hat{\beta}, \hat{\tau}) = \arg\max \left[\sum_{g=1}^{G} m(\beta^g, \alpha^g)' W^{-1} m(\beta^g, \alpha^g) + m(\tau, \alpha)' W^{-1} m(\tau, \alpha) \right]. \quad \text{(A.15)}$$

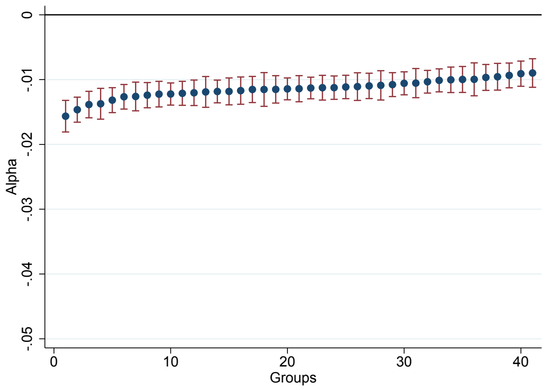
Figure A-8: Demand parameters: second stage - robustness



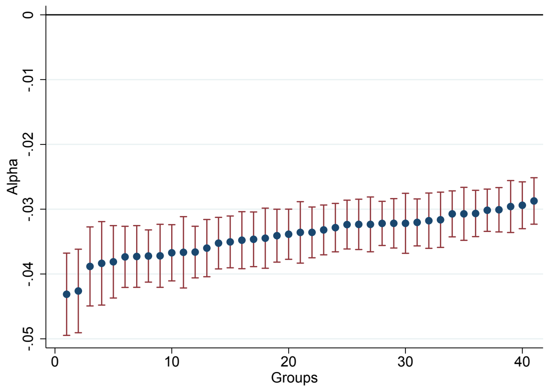
(a) OLS



(b) IV: Risk weights



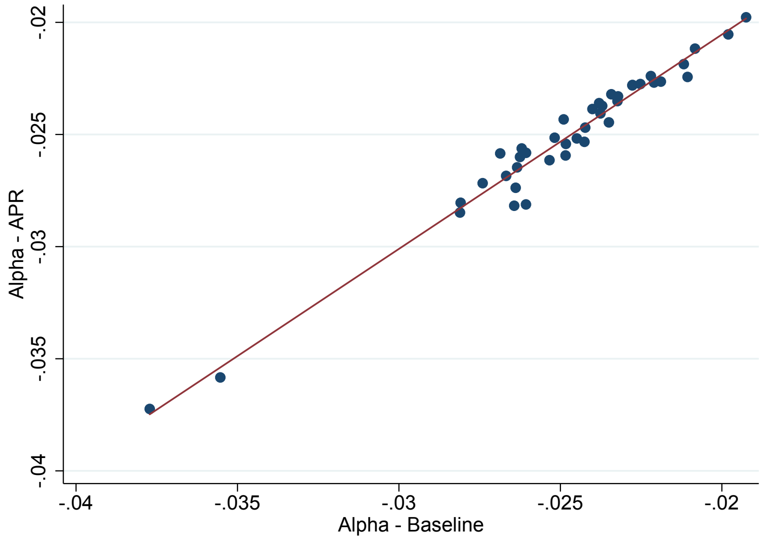
(c) OLS



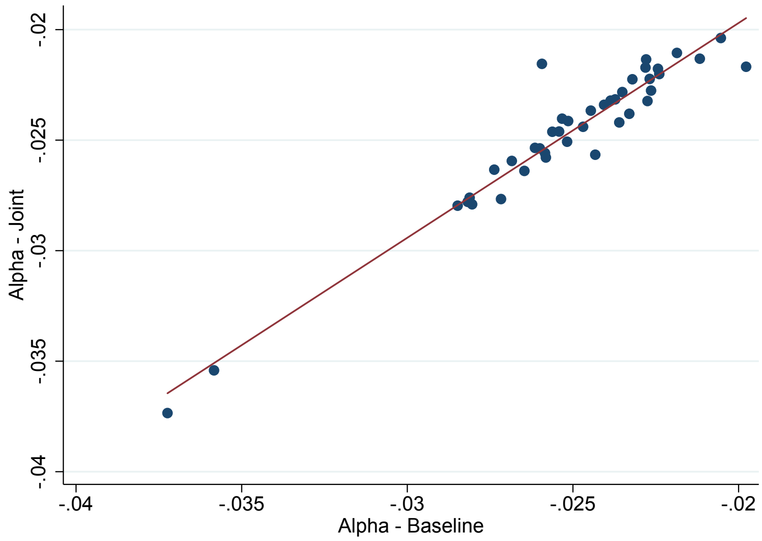
(d) IV: Risk weights (others)

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 1.4.1 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 A-9: 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 .

A.5 Counterfactuals: Additional Material

A.5.1 Reduced-Form Evidence

In this section I provide reduced-form evidence about the effects of the leverage regulations, that I study in my counterfactual exercises. I look at the effects of risk weights on mortgage rates and of loan-to-income limits on mortgage originations.

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

$$r_{jm} = \beta RW_{jm} + X_j + \gamma_m + \epsilon_{jm} \tag{A.16}$$

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 A.7 shows the results. I find that a one-percentage-point higher risk weight leads to an approximately 1.5 basis point higher interest rate. In column (2) I show the specification with the full set of fixed effects, to control for time invariant differences across lenders and for time varying common factors that affect pricing, and in column (3) I add a full set of interacted market-lender fixed effects. The results are similar across these specifications. In the remaining columns I run model (A.16) separately for the different borrower types. I find a strong and significant effect of risk-adjusted capital requirements for first-time buyers. A one-percentage-point higher risk weight translates into a 3.4 basis points higher mortgage rate. The effect is lower, but significant for home movers, and not different from zero for remortgagers.

Leverage limits. I provide reduced-form evidence about the effects of regulat-

Table A.5: Risk weights and pricing

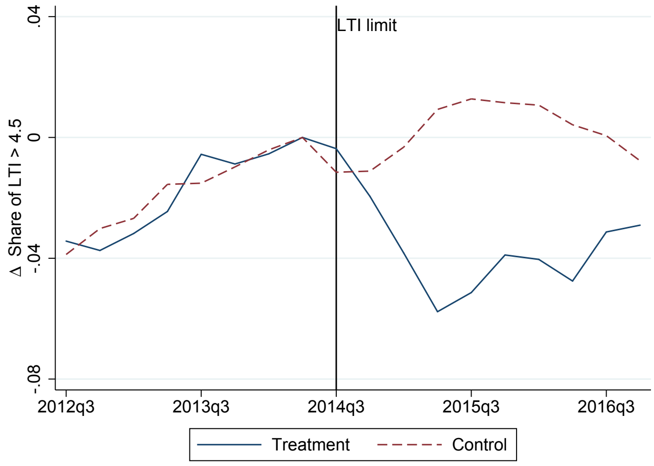
	Whole sample			Borrower type		
	(1)	(2)	(3)	(FTB)	(HM)	(RMGT)
Risk weights (%)	0.014***	0.014***	0.016***	0.034***	0.011*	0.005
	(0.003)	(0.004)	(0.004)	(0.006)	(0.005)	(0.005)
Fix 5		0.731***	0.733***	0.692***	0.731***	0.739***
		(0.047)	(0.047)	(0.061)	(0.063)	(0.049)
Min down (%)		-0.043***	-0.042***	-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 (A.16). 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.

ing household leverage, exploiting variation from a recommendation by the Financial Policy Committee (FPC) in June 2014 that limited mortgage originations with a loan-to-income (LTI) above 4.5 to 15 percent of the total number of new mortgage loans (Bank of England, 2014).[1] I divide lenders into two groups based on their fraction of mortgages with a loan-to-income above 4.5 before the date of the recommendation, and I define as treated the lenders with a fraction above the median. Figure A-10 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

[1]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."

Figure A-10: Loan-to-income limit and originations



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

group reduce more new high loan-to-income mortgages relative to the control group.[2]

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

$$Share_{lm} = \beta_1 Treatment_l + \beta_2 Post_m + \beta_{12} Treatment_l \times Post_m + \epsilon_{lm} \qquad (A.17)$$

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 A.6 shows the results. In column (1) I show the baseline difference-in-

[2]In Appendix A.5 I explore further the effect of the FPC recommendation on high loan-to-income originations.

difference model and I find that treated lenders reduce their fraction of high LTI mortgages by almost four percent more relative to control lenders. In column (2) I add a full set of time and lender fixed effects. The result is still significant and the magnitude is unaffected. Finally, in the remaining columns of table A.6 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 A.6: 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 (A.17). 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.

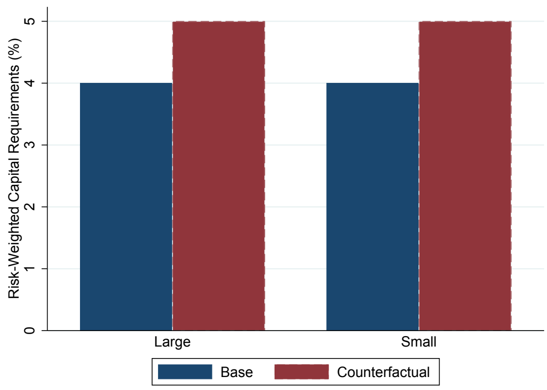
A.5.2 Extra Charts and Tables

Table A.7: Common increase in capital requirements

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

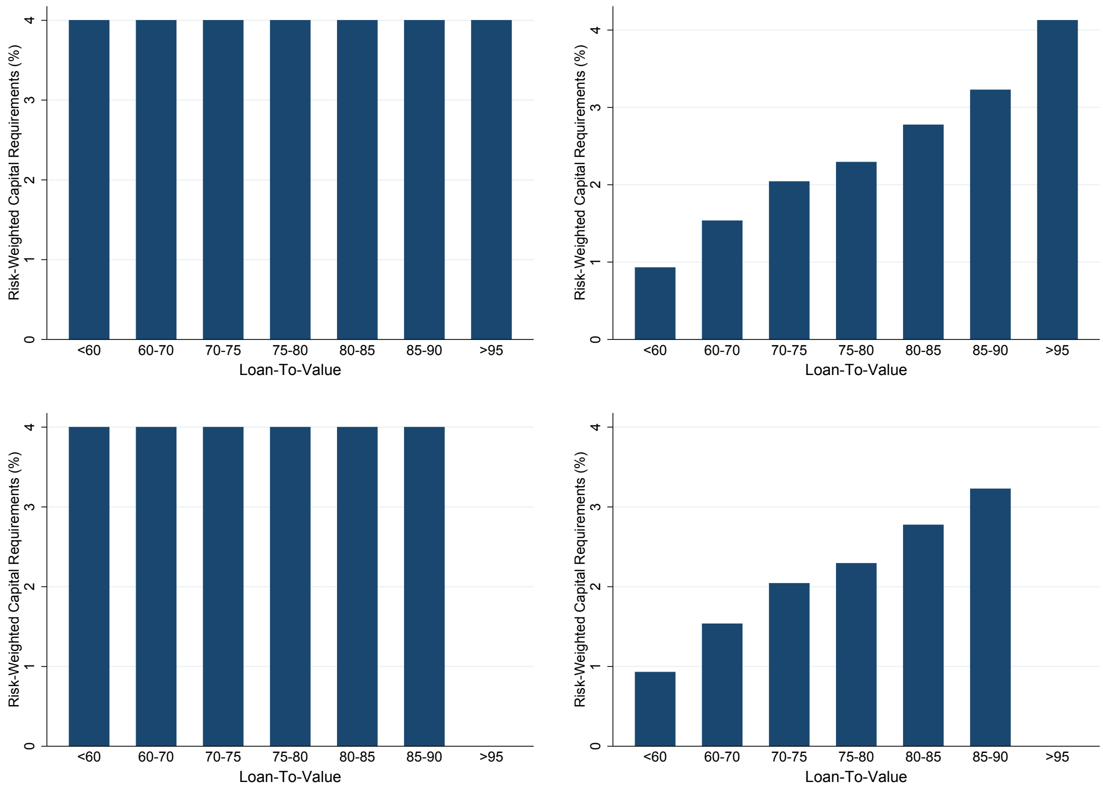
Notes: The table shows the results from the counterfactual simulation in which I increase the capital requirements by 10 percentage points for all lenders in a random subsample of first-time buyers. Cost is the marginal cost in percentage points; price is the interest rate in percentage points; demand is the total number of borrowers; quantity is the average loan amount; monthly payment is the monthly payment from the mortgage; PTI is the monthly payment divided by the gross income of the borrower; consumer surplus is the log sum of the indirect utility of a representative consumer (see appendix A.2); lender profits is the average profit across lenders in thousand £; default is the average number of defaults in percentage points; buffer is the difference between the equity and the predicted loss. Value is the actual value in the benchmark and counterfactuals; Δ is the absolute change of the value in the counterfactual relative to the benchmark; $\Delta\%$ is the percentage change of the value in the counterfactual relative to the benchmark.

Figure A-11: 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 A-12: 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 the risk-weighted capital requirements for different counterfactuals at different loan-to-value levels. Panel a shows at the top the case in which all banks have a capital requirement of 8 percent and a risk-weight of 50 percent, as in the Basel I regime; Panel b shows at the top the risk-weighted capital requirement in the current system, averaging across banks with both internal model and standardized approach. The bottom panels show the two cases after removing mortgages with a loan-to-value above 90 percent.

Appendix B

Appendix Chapter 2: Bank Competition and The Pass-through of Unconventional Monetary Policy

B.1 Additional Figures and Tables

Table B.1: **Targeted monetary policy - First stage**

The table reports the estimated parameters and their standard errors for the first stage of the IV model of equation (2.4). All columns report estimates with the balanced panel of relationships for firms with more than one lender. The dependent variables are the TLTROs binary and continuous treatments. Rule is the allocation rule for bank b from equation (2.1), Post is a dummy equal to one after the implementation of the TLTROs. Bank-quarter control includes bank capital, non-performing loans, government bonds. The Kleibergen-Paap F-statistic test for weak instruments with cluster-robust standard errors. The Kleibergen-Paap LM-statistic test for underidentification with cluster-robust standard errors. All standard errors are double clustered by firm and bank-quarter. *,**, *** indicates significance at the 0.10, 0.05 and 0.01 levels, respectively.

	Binary treatment	Continuous treatment
	(1)	(2)
TLTROs Rule (bt)	2.15***	0.080***
	(0.287)	(0.012)
Observations	354,060	354,060
Adjusted R^2	0.82	0.82
Fixed effects		
Firm-time (ft)	Yes	Yes
Bank (b)	Yes	Yes
Controls (bt)	Yes	Yes

Table B.2: **Targeted monetary policy and competition - First stage**

The table reports the estimated parameters and their standard errors for the first stage of the IV model of equation (2.7). All columns report estimates with the balanced panel of relationships for firms with more than one lender. The dependent variables in columns (1) and (3) are the TLTROs binary and continuous treatments, while in columns (2) and (4) the dependent variables are the interactions with the HI. Rule is the allocation rule for bank b from equation (2.1). Post is a dummy equal to one after the implementation of the TLTROs. Pawnshop is the number of pawnshops across Italian provinces during the Renaissance. Bank-time controls include bank capital, non-performing loans, government bonds. The Kleibergen-Paap F-statistic test for weak instruments with cluster-robust standard errors. The Kleibergen-Paap LM-statistic test for underidentification with cluster-robust standard errors. All standard errors are double clustered by firm and bank-quarter. *,**, *** indicates significance at the 0.10, 0.05 and 0.01 levels, respectively.

	Binary treatment		Continuous treatment	
	(1)	(2)	(3)	(4)
TLTROs Rule (bt)	1.825***	-0.548	0.073***	-0.001
	(0.278)	(0.058)	(0.011)	(0.003)
TLTROs Rule (bt) × HI (m)	2.428*	2.645***	0.051	0.091***
	(1.313)	(0.461)	(0.054)	(0.021)
Observations	354,060	354,060	354,060	354,060
Adjusted R^2	0.8231	0.8129	0.8186	0.8086
Fixed effects				
Firm-time (ft)	Yes	Yes	Yes	Yes
Bank (b)	Yes	Yes	Yes	Yes
Controls (bt)	Yes	Yes	Yes	Yes

Table B.3: **Targeted monetary policy and competition - Main - Robustness**
The table reports the estimated parameters and their standard errors from the IV estimation of equation (2.5) for different robustness exercises. All columns report estimates with the balanced panel of firms with more than one lender. The dependent variable is the interest rate on the loan from bank b to firm f in quarter t. Binary treatment is a dummy equal to one if the bank borrows from the TLTROs. Continuous treatment is a continuous variable equal to the logarithm of the actual additional amount the bank borrows from the TLTROs. Bank-time controls include bank capital, non-performing loans, government bonds. All standard errors are double clustered by firm and bank-quarter. *,**, *** indicates significance at the 0.10, 0.05 and 0.01 levels, respectively.

	No correction		No expenditure	
	Binary (1)	Continuous (2)	Binary (3)	Continuous (4)
TLTROs ×				
2014 - Q3	-0.92	-0.024*	-0.53**	-0.020**
	(0.56)	(0.014)	(0.23)	(0.0086)
2014 - Q4	-0.78	-0.021	-0.52**	-0.019**
	(0.54)	(0.014)	(0.25)	(0.0087)
2015 - Q1	-0.85*	-0.021*	-0.46**	-0.017**
	(0.51)	(0.013)	(0.23)	(0.0082)
2015 - Q2	-0.96*	-0.024*	-0.51**	-0.019**
	(0.54)	(0.013)	(0.23)	(0.0083)
TLTROs × HI ×				
2014 - Q3	4.91	0.13	3.01**	0.11**
	(3.57)	(0.091)	(1.53)	(0.056)
2014 - Q4	6.37	0.17*	4.22**	0.15**
	(3.95)	(0.099)	(1.91)	(0.063)
2015 - Q1	3.17	0.081	1.78	0.07
	(3.54)	(0.09)	(1.71)	(0.061)
2015 - Q2	3.84	0.099	2.26	0.087
	(3.92)	(0.099)	(1.88)	(0.067)
Firm-time f.e.	Yes	Yes	Yes	Yes
Bank f.e.	Yes	Yes	Yes	Yes
Bank-time controls	Yes	Yes	Yes	Yes
Observations	354,060	354,060	354,060	354,060
Adjusted R^2	0.36	0.36	0.36	0.36

Table B.4: **Targeted monetary policy and competition - New loans - Robustness**

The table reports the estimated parameters and their standard errors from the IV estimation of equations (2.4) and (2.5) for the flows of new loans. All columns report estimates with the balanced panel of firms with more than one lender. The dependent variable is the interest rate on the loan from bank b to firm f in quarter t. Binary treatment is a dummy equal to one if the bank borrows from the TLTROs. Continuous treatment is a continuous variable equal to the logarithm of the actual additional amount the bank borrows from the TLTROs. Bank-time controls include bank capital, non-performing loans, government bonds. All standard errors are double clustered by firm and bank-quarter. *,**, *** indicates significance at the 0.10, 0.05 and 0.01 levels, respectively.

	Direct effect only		Including interaction with competition	
	Binary (1)	Continuous (2)	Binary (3)	Continuous (4)
TLTROs ×				
2014 - Q3	-0.12	-0.004	-1.92	-0.054
	(0.15)	(0.004)	(1.78)	(0.034)
2014 - Q4	-0.34**	-0.014***	-1.77	-0.055*
	(0.15)	(0.003)	(1.38)	(0.028)
2015 - Q1	-0.73***	-0.025***	-2.42	-0.073*
	(0.15)	(0.004)	(1.64)	(0.032)
2015 - Q2	-0.91***	-0.031***	-2.31*	-0.071*
	(0.23)	(0.005)	(1.33)	(0.025)
TLTROs × HI ×				
2014 - Q3			8.17	-0.23
			(8.32)	(0.16)
2014 - Q4			6.51	-0.18
			(6.22)	(0.12)
2015 - Q1			7.71	0.22
			(7.15)	(0.14)
2015 - Q2			6.4	0.18*
			(5.56)	(0.11)
Firm-time f.e.	Yes	Yes	Yes	Yes
Bank f.e.	Yes	Yes	Yes	Yes
Bank-time controls	Yes	Yes	Yes	Yes
Observations	33,528	33,528	33,528	33,528
Adjusted R^2	0.68	0.69	0.68	0.69

Table B.5: **Targeted monetary policy and competition - Heterogeneity - Robustness**

The table reports the estimated parameters and their standard errors from the IV estimation of equation (2.5) in different subsets of the data. All columns report estimates with the balanced panel of relationship for firms with more than one lender. The dependent variable is the interest rate including expenditure on the stock of loan from bank b to firm f in quarter t. TLTROs is the logarithm of the actual additional amount the bank borrows from the TLTROs. High risk firms are firms with a bad credit score (7-9), while low risk are firms with a good or average credit rating (classes 1-6). Small firms are firms below the median of the distribution of assets in the pre-treatment year (2013). Large banks are the top 5 banks in Italy. Bank-quarter controls include bank capital, non-performing loans, government bonds. All standard errors are double clustered by firm and bank-quarter. *,**, *** indicates significance at the 0.10, 0.05 and 0.01 levels, respectively.

	Firm risk		Firm size		Bank size	
	High	Low	Small	Large	Large	Small
	(1)	(2)	(3)	(4)	(5)	(6)
TLTROs (bt) $\times$						
2014 - Q3	-0.018	-0.013*	-0.024**	-0.014	-0.018*	0.034
	(0.013)	(0.007)	(0.012)	(0.01)	(0.008)	(0.071)
2014 - Q4	-0.006	-0.011	-0.02	-0.012	-0.023***	0.094
	(0.015)	(0.007)	(0.013)	(0.01)	(0.008)	(0.12)
2015 - Q1	-0.02	-0.008	-0.02	-0.012	-0.023***	-0.09
	(0.014)	(0.006)	(0.013)	(0.009)	(0.007)	(0.16)
2015 - Q2	-0.006	-0.017**	-0.029**	-0.009	-0.014	-0.011
	(0.015)	(0.006)	(0.013)	(0.01)	(0.009)	(0.12)
TLTROs (bt) $\times$ HI (m) $\times$						
2014 - Q3	0.13	0.054	0.12	0.082	0.08	-0.28
	(0.099)	(0.047)	(0.083)	(0.07)	(0.05)	(0.62)
2014 - Q4	0.078	0.088*	0.17*	0.098	0.16***	-0.73
	(0.10)	(0.049)	(0.094)	(0.074)	(0.054)	(1.08)
2015 - Q1	0.097	0.001	0.067	0.045	0.14***	0.75
	(0.10)	(0.048)	(0.091)	(0.075)	(0.048)	(1.42)
2015 - Q2	0.024	0.058	0.13	0.026	0.11*	0.15
	(0.094)	(0.05)	(0.091)	(0.087)	(0.058)	(1.03)
Observations	81,930	272,130	154,458	199,602	135,936	106,680
Adjusted R^2	0.30	0.36	0.31	0.34	0.41	0.33
Fixed effects						
Firm-time (ft)	Yes	Yes	Yes	Yes	Yes	Yes
Bank (b)	Yes	Yes	Yes	Yes	Yes	Yes
Controls (bt)	Yes	Yes	Yes	Yes	Yes	Yes

B.2 Additional Features of TLTROs

In this appendix we briefly describe some additional features of the TLTROs.The borrowing limit on the third to eight TLTROs is differently computed from the first two operations. The ECB defines a benchmark BE_b^k for each bank b in each TLTRO k given by the formula:

$$\begin{aligned} BE_b^k &= 0 \qquad\quad\; for\ k = 3, ..., 8 \quad if\ \overline{NL} \geq 0 \\ BE_b^k &= \overline{NL} \times n_k \quad for\ k = 3, ..., 8 \quad if\ \overline{NL} < 0 \end{aligned} \tag{B.1}$$

where $\overline{NL} = \frac{(NL_b^{May2013} + ... + NL_b^{Apr2014})}{12}$ is the average eligible net lending of institution b from May 2013 to April 2014 and $n_k = 9$ for $k = 3$ and $n_k = 12$ for $k = 4, ..., 8$.[1] The additional borrowing limit is then computed as:

$$q_b^k \leq \ 3(CNL_b^k - BE_b^k) - \sum_{j=3}^{k-1} q_b^j \ for\ k = 3, ..., 8 \tag{B.2}$$

where $CNL_b^k = NL_b^{May2014} + ... + NL_b^{Month(k)-2}$ is the cumulative net lending in operations from May 2014 until two months before operations k takes place.

Finally, the ECB set also some special rules for the TLTROs on repayment. Even if all TLTROs will mature in September 2018, there are prepayment options and a mandatory repayment rule. On the one hand, intermediaries have the option to repay any part of the amounts they were allotted in a TLTRO after 24 months at a biannual frequency. On the other hand, the ECB imposes a mandatory early repayment (MR_b) in September 2016, if some lending requirements are not satisfied. The early repayment rule is applied according to the following formula:

[1] "Eligible net lending"means gross lending in the form of eligible loans net of repayments of outstanding amounts of eligible loans during a specific period. For details see again ECB (2014).

$$
\begin{aligned}
MR_b &= \textstyle\sum_{j=1}^{8} q_b^j & \text{if } BE_b^8 > CNL_b^8 \\
MR_b &= \textstyle\sum_{j=3}^{8} q_b^j - 3(CNL_b^8 - BE_b^8) & \text{if } BE_b^8 \leq CNL_b^8.
\end{aligned}
\tag{B.3}
$$

Thus the bank has to repay the whole borrowed amount through the TLTROs if the total eligible net lending in the period May 2014-April 2016 (CNL_b^8) is less than the benchmark for the last operation. Otherwise, the bank has to pay back in September 2016 the amount borrowed in the last six TLTROs in excess of the amount used for the calculation of the additional allowance for the last operations, that is thrice the cumulative net lending exceeding the benchmark.

Appendix C

Appendix Chapter 3: Down Payment and Mortgage Rates: Evidence from Equity Loans

C.1 Additional Figures and Tables

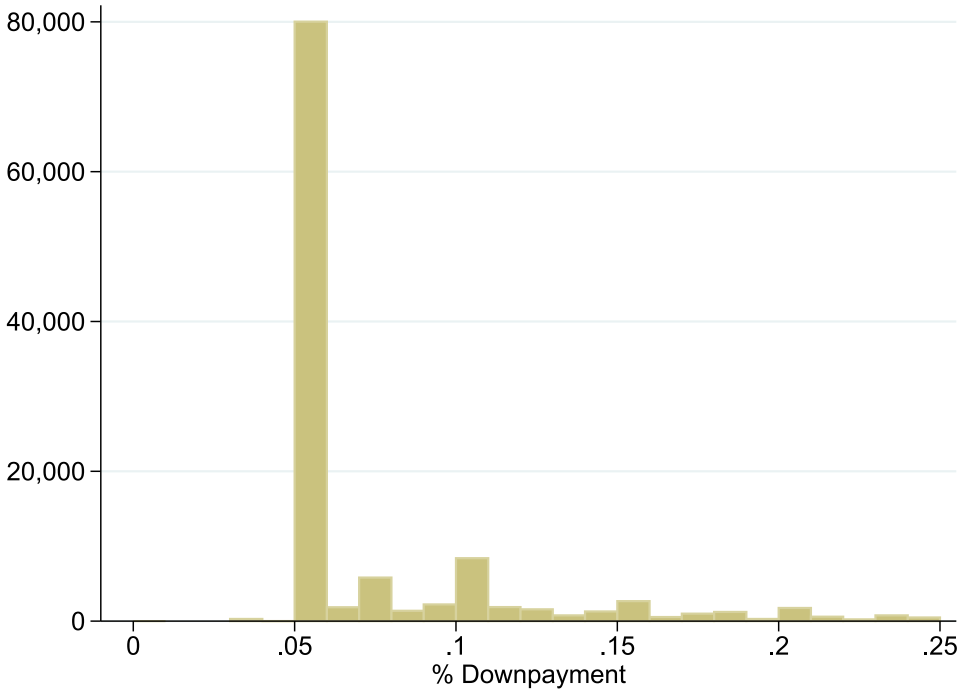


Figure C-1: **Down payments of EL borrowers**
The histogram shows data from the Help To Buy Equity Loan dataset from the UK Home and Communities Agency (HCA). All EL borrowers who joined the scheme since its inception, in April 2013, to June 2016.

Table C.1: **Descriptive statistics: EL data**
The table displays aggregate statistics for all Equity Loans issued between April 2013 and June 2016 in England. Values are in British pounds.

Number of loans	91,759
Average purchase price	226,887
Average equity loan	45,442
Total value purchased properties	20,818,909,184
Total value equity loans	4,169,738,752

Table C.2: **Matching the data and constructing the estimation dataset**
The table describes the sequential steps taken to construct the estimation sample. The dataset construction has three parts. In the first part, we open the universe of residential mortgage originations in the UK (the Product Sales Data from the Financial Conduct Authority) and we restrict the sample to the period and geographic area of interest, and we exclude mortgages for refinancing purposes (remortgages). In the second part, we match the data on Help To Buy Equity Loans (EL) from the Homes and Communities Agency into the mortgage originations data. In the third part, we restrict the data to the EL group and the standard mortgage group used in the main analysis of the paper; these include only mortgages on new build and with a loan-to-value (LTV) ratio between 70 and 75%. (In practice we set the LTV limit at 76 because in the UK mortgage fees are often rolled over into the principal, raising the measured LTV).

Sample	Observations
1) Preparing mortgage originations data	
Full Product Sales Data, 4/2005 - 3/2017	15,520,210
England only, 4/2013 - 3/2017	3,432,251
No remortgages	2,177,956
No duplicates in price, lender, date of birth, postcode, loan value	2,170,761
2) Matching EL data and mortgage originations data	
Joinby 1 (full postcode, price, lender)	66,617
Drop duplicates and implausible matches	63,413
Joinby 2 (postcode district, price, lender)	16,290
Drop duplicates and implausible matches	9,179
Total matched (joinby 1 + joinby 2)	72,592
3) Bringing back matched loans into mortgage originations data; creating treatment and control groups	
Loans with interest rate information	1,851,595
Only lenders doing EL mortgages	1,344,357
Only fixed-rate mortgages with 2, 3, 5 or unknown fixed period	1,151,455
Only new builds	185,604
Only properties with value below or equal to £600,000	180,886
Only LTVs between 70 and 76	69,832
Drop special mortgages, outliers, singletons	68,550
Drop if EL in London after January 2016	67,001
Drop if not EL and origination is after 30 June 2016	47,780

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