Experts, Commissions and Market Power: Evidence from UK Mortgage Brokers*

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Abstract

Expert advisors often receive commission payments from upstream firms, especially in financial and healthcare markets. This paper empirically analyzes the effects on welfare and market structure of regulations restricting this form of experts' remuneration. Using loan-level data from the universe of UK mortgage originations, I present evidence suggesting that commissions paid by lenders to mortgage brokers can: 1) distort brokers' advice to households towards higher-commission products; and 2) increase upstream competition and efficiency by facilitating the entry of new, lower-cost lenders. To study the net effect of these forces in equilibrium, I estimate a structural model that features households' choice of mortgage products and sales channel (direct versus intermediated), lenders' optimal pricing decisions, and broker-lender bargaining over commissions. I then use the estimates of the model to evaluate the impact of policies restricting broker compensation. I find that a ban on commissions has unintended consequences in terms of prices and equilibrium outcomes, leading to a 25% fall in consumer welfare. Instead, a cap can increase consumer surplus by at least 10%. These results follow from the presence of both lender and broker market power.

JEL Codes: G21, G28, L14, M52, D12. **Keywords:** Expert advisors; intermediaries; mortgages; brokers; bargaining; vertical markets.

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1 Introduction

Many transactions nowadays occur via intermediaries acting as expert advisors. In financial and healthcare markets, households frequently rely on certified experts to provide information on complex products and help them decide which alternatives best fit their needs. When buying insurance, planning for retirement, or choosing a house (to name just a few), consumers often demand expert services and are willing to pay the fees charged by financial advisors and brokers. These −sometimes significant− charges are not the only source of revenue for experts. In many instances, they also receive commission payments from upstream firms when recommending their products. This form of compensation may influence experts' advice, causing them to steer consumers towards higher-commission, more expensive products. If so, upstream payments generate an agency problem between expert advisors and households, reducing consumer welfare in the market.

Motivated by the controversial nature of these widespread practices, regulators worldwide have recently restricted commission payments between providers and expert advisors. Examples of these initiatives include the Retail Distribution Review in the UK, which resulted in a ban on all upstream commissions for retail investment advice. The Netherlands and Australia have also introduced comparable bans on commission payments for complex financial products, and other countries such as Canada are currently considering the possibility of taking similar measures. The main objective of these policies has been to reduce distortions in advice by eliminating supply-side monetary incentives. However, despite the many restrictions on financial relationships between experts and upstream firms, there is scarce empirical evidence on the costs and broader effects of these regulations.

While outlawing commission payments to financial advisors and brokers might help align their incentives with those of consumers, such policies can also have supply-side equilibrium effects. In some markets, commissions allow new, smaller firms to introduce their products at a lower cost, e.g., less need for advertisement and infrastructure investment. A regulation restricting upstream payments would increase entry costs, decrease upstream competition and strengthen incumbents' market power. These effects are likely to result in higher prices for consumers. There can also be demand-side unintended consequences. After a ban on commissions, brokers will pass on some of the costs (previously compensated by upstream revenue) to consumers. The price of accessing advice and intermediation services will go up. In markets where search costs are large and households find it difficult to gather information about alternative products, an increase in the price of expert services will have a detrimental effect on consumers. Overall, there exists a trade-off when restricting upstream commissions. On the one hand, restrictions can alleviate the agency problem between experts and consumers. On the other hand, they can increase prices (via less competition) and reduce consumer surplus (via more expensive expert services). The net effect on welfare

of these forces is an empirical question that remains unanswered. In this paper, I address this gap in the literature by focusing on mortgage brokers and the commission payments they receive from lenders when recommending their products. Understanding the effects of restricting financial relationships between lenders and brokers is important both because of these restrictions' economic and policy interest and because of the central role mortgage markets have in the consumer credit landscape.

Using a novel transaction-level dataset for all mortgage originations in the UK, I empirically investigate the economic trade-offs affecting the interactions between lenders, brokers, and households in the presence of commission payments between brokers and lenders. Reduced-form evidence suggests that broker sales react to changes in lenders' financial incentives. After controlling for a rich set of fixed effects, I find that a product with a 13% increase in commission (£100) has, on average, a 2% higher share on a broker's sales portfolio. This result hints that, despite demand-side incentives that might discipline brokers to act in the best interest of households (e.g., repeated sales and reputation concerns), brokers are still responsive to supply-side monetary incentives. The data also suggest that brokers have preferences over product characteristics, other than commissions. For example, brokers recurrently recommend mortgage products for which borrowers have an incentive to refinance more frequently and are more likely to demand broker services in the future. Brokers also seem to have a preference across lenders. After accounting for observable characteristics, households originating their mortgage through a broker are 7% more likely to choose a product from smaller, challenger banks. These lenders pay, on average, higher commissions to brokers, but often offer the cheapest deals in the market. In an industry that is very concentrated upstream, brokers seem to improve competition by making households aware of better products that would otherwise not be discovered given challenger banks' limited advertisement and lack of extensive branch networks.

Despite the rise of price comparison websites and online sales, I find that nearby bank branches still matter for household choices. The number of branches in a given county is strongly correlated with lenders' share of non-intermediated sales, suggesting that borrowers using lenders' in-house distribution channels value proximity of the nearest branch. Moreover, in counties where lenders have a low branch density, they tend to pay higher commissions to brokers in order to increase their market share via intermediated sales. Brokers offer lenders a way to introduce their products in areas where it is very costly to set up a branch, and consumer take-up of online distribution channels remains low. However, in areas where lenders already have a high branch density, brokers can steal business from lenders' in-house distribution channels. These results suggest that brokers and bank branches are substitutes. Because households can bypass the intermediary and go directly to lenders, the relationship between brokers and lenders in this market is both vertical (brokers provide an alternative distribution channel for lenders) and horizontal (brokers compete downstream with lenders'

in-house distribution channels).

With this empirical evidence in mind, I develop a structural model of the UK mortgage market that I later estimate and use to quantify the net effect on welfare of restricting commission payments. The model features (1) utility-maximizing households in need of a mortgage for the purchase of a residential property, (2) heterogeneous multi-product lenders selling differentiated mortgage products and competing on interest rates, and (3) broker firms providing advice to households on available products and sorting out all application and origination paperwork. On the supply side, I endogeneize commission payments in this market by modeling negotiations between a broker and a lender as a Nash bargaining game. Each pair bargains over the lender's inclusion in the broker's network. In the event of an agreement, the pair sets a per-sale commission, and the broker can originate the lender's mortgages. Once all negotiations end, each lender chooses interest rates to maximize its expected profits. On the demand side, I model households' choice of distribution channel as a discrete binary choice between hiring a broker or going directly to lenders' in-house distribution channels (e.g., branches). This decision depends on the households' search costs and their expected payoffs from each channel. After choosing a distribution channel, the household needs to decide on a mortgage product. I model this part of demand as a discrete logit with households' preferences being a function of interest rates, product characteristics, and latent demand. Broker preferences over commissions and other product characteristics will also matter for those households that selected the intermediated channel.

Demand estimates show that brokers have downstream market power and can extract surplus from consumers. I can reject the hypothesis of benevolent brokers, confirming the existence of an agency problem between households and brokers. I also find that households going directly to lenders have a preference for nearby branches. This taste disappears for households hiring a broker. Consumers originating their mortgages via the direct channel face stronger lender market power (at the local level) than those choosing the intermediated channel. Thus, changes in competition across lenders have a differential impact on households depending on their choice of sales channel. Additionally, average household search costs account for almost 20% of consumer surplus, implying that the average household finds it very costly to originate a mortgage on its own. I also find that lenders' marginal costs are on average lower when originating a mortgage through a broker. These results show that brokers improve efficiency in the market by reducing costs both for lenders and households. Finally, the estimated bargaining parameters reject take-it-or-leave-it offers as a model for setting commission payments in this market.

Next, I use these estimates to simulate welfare effects of policies restricting commissions. In the counterfactual simulations, I consider a complete ban (motivated by recent regulations) and three different caps. Two countervailing forces largely determine my results: broker and lender market power. On the one hand, households choosing the intermediated channel face

broker market power, resulting from brokers' capacity to extract surplus from the household. On the other hand, households originating their mortgage directly with lenders experience local lender market power, driven mainly by the presence of nearby branches. When compared with the baseline with no restrictions on commissions, a ban reduces broker market power at the expense of increasing lender market power. In this situation, the price of expert services increases for households, causing 115% more households to choose lenders' in-house distribution channels and incrementing search costs by 83%. Due to the lack of extensive branch networks, the share of challenger banks goes down by 16% with the Herfindahl-Hirschman Index (HHI) increasing by 21%. Lenders' average marginal cost goes up by 7%, causing prices to rise by 11%. The net effect of these forces is a 25% fall in consumer surplus.

Results reverse when I simulate a counterfactual imposing a sufficiently large cap on commissions. I find that a cap equal to the average commission payment in the baseline case with no restrictions generates at least a 10% increase in consumer surplus. In this scenario, the fall on broker market power is sufficiently large to compensate for the increase in lender market power. The intuition is that a cap still allows brokers to get revenue from lenders, causing household broker fees to increase but not as much as in the case of a ban. Therefore, although the share of direct sales increases by 30%, the competition effect of challenger banks dominates and prices fall by 5%. Overall, these findings are evidence in favor of capping, rather than banning, commission payments in markets where consumers can access the good not only through intermediaries but also directly from upstream firms.

Contributions to the Literature. This paper contributes mainly to three strands of literature. First, it fits into a vast literature on the role of intermediaries. Intermediaries can create value by guaranteeing quality and certifying information (Biglaiser et al. 2017, Biglaiser & Li 2018), which can alleviate information asymmetries in many markets, such as labor markets (David 2008, Stanton & Thomas 2015) and insurance markets (Anagol et al. 2017). Intermediaries can also lessen trading frictions (Gavazza 2016), reduce search costs (Salz 2017), promote innovation and adoption of new technologies (Howells 2006), and facilitate entry (Ahn et al. 2011). This paper is closest to settings in which intermediaries take the form of expert advisors and adds to the growing empirical literature that examines agency problems in expert services. For example, in the prescription drug market, Iizuka (2007, 2012) and Ho & Pakes (2014) find that doctors react to financial incentives when dispensing generic drugs. Financial advisors are also not immune to conflicts of interest, with many of them having misconduct records and being repeat offenders (Egan et al. 2016). In the housing market, Levitt & Syverson (2008) show how real estate agents exploit their informational advantage to their financial benefit when advising clients on the timing and sales price of their houses. Similarly, Guiso et al. (2018) find evidence of distorted advice when analyzing lenders' in-house mortgage recommendations to borrowers. Financial incentives can

also amplify the effects of high search costs by inducing brokers to steer consumers towards inferior products (Egan 2018).

Though closely related, this paper differs from prior work on expert advisors in that it estimates welfare effects from a policy restricting supply-side financial incentives. There has been a recent theoretical literature that, in a similar spirit to this paper, analyzes market effects in the presence of commission payments to financial advisors (*e.g.* Inderst & Ottaviani 2009, 2012*a*,*b*,*c*; Inderst 2015; Heidhues et al. 2016; Martimort & Pouyet 2017). However, given the possible trade-offs in the market, the overall effect on consumers of banning such commissions is theoretically ambiguous. The empirical literature on the topic is almost inexistent. The closest paper is the recent work of Grennan et al. (2018) studying pharmaceutical firms' payments to physicians. They use a structural model to estimate the equilibrium response of prices and quantities to a ban on these financial incentives and find that the presence of such payments significantly lowers consumer welfare. This paper differs from their approach in that it analyses intermediation services in financial markets, which face different trade-offs than those in the healthcare sector. For example, in many financial markets consumers can directly access providers without the need to consult with an expert advisor; this is often not the case for medical treatments. Therefore, in market structures where consumers can bypass the intermediary, the exposure of households to market power from providers and intermediaries differs from settings similar to that in Grennan et al. (2018). These differences lead to contrasting welfare effects of policies restricting upstream payments.

This paper also complements existing approaches in household finance (Campbell & Cocco 2003; Campbell 2012; Best et al. 2015; DeFusco & Paciorek 2017) by analyzing the role that brokers play on borrowers' demand in mortgage markets (often dominated by intermediated sales). Woodward & Hall (2010, 2012) take into account broker fees when analyzing originations in the US mortgage market. They find evidence of significant price dispersion in broker fees and show that groups that are likely less informed pay higher brokerage fees. Jiang et al. (2014) also study the role of mortgage brokers on mortgage delinquency between 2004 and 2008. They find that brokers originated lower quality loans, which were 50% more likely to be delinquent than bank-originated loans. These papers focus on the interactions between brokers and borrowers, and how brokers' financial incentives can generate biased advice and be detrimental for consumers. My contribution is that I explicitly account for supply-driven equilibrium effects that may increase consumer surplus via more upstream competition, lower search costs and lower prices. This paper is also the first one to develop a structural model to quantify welfare effects from regulations imposing restrictions on brokers' financial incentives. In that sense, my work adds to the recent trend of using structural techniques to analyze markets with financial products, such as pensions (Hastings et al. 2017), insurance (Koijen & Yogo 2016), retail deposits (Egan et al. 2017), corporate

lending (Crawford et al. 2015), credit cards (Nelson 2017), and mortgages (Benetton 2018).

Finally, my analysis relates to the recent empirical literature on estimating bargaining games. Many of the existing papers focus on the healthcare sector and the interactions between hospitals, insurance companies, suppliers and firms (see, e.g., Grennan 2013, Gowrisankaran et al. 2015, Ho 2009, Ho & Lee 2017*a*, Ho & Lee 2017*b*, Grennan & Swanson 2016); and on the telecommunications industry and the relationships between television channels, programming distributors and viewers (see, e.g., Crawford & Yurukoglu 2012, Crawford et al. 2018). This paper is the first to introduce bargaining to analyze vertical payments in credit markets. Moreover, this work also contributes to the literature by modeling a bargaining game in markets where consumers have the option of bypassing the intermediary and directly purchase the good from providers via their in-house distribution channels. Therefore, when providers and intermediaries negotiate they take into account that their relationship is both vertical (intermediaries provide an alternative distribution channel for providers) and horizontal (intermediaries compete with providers' in-house distribution channels). I exploit this vertical-horizontal structure in a novel identification strategy using geographical and time variation in providers' in-house distribution channels and direct access to consumers.

The rest of the paper proceeds as follows. Section 2 describes the data and some stylized facts about the UK mortgage market. Section 3 shows motivating empirical evidence on potential trade-offs and conflicts of interests in the data, which I will later capture in the model. In Section 4 I develop a general equilibrium model for the mortgage market. In Section 5 I discuss estimation and identification of the demand and supply. Section 6 presents the estimation results. Section 7 performs counterfactual and welfare analysis of restricting upstream payments. Section 8 concludes.

2 Institutional Setting and Data

2.1 The UK Mortgage Market

The UK mortgage market has several institutional features that differentiate it from mortgage markets in the US, Canada and Continental Europe. For example, there are no long-term fixed-rate mortgages in the UK. Most products feature a relatively low (usually fixed) interest rate for an initial period of usually two, three or five years followed by a (usually floating) reset rate that is significantly higher. Reset rates last until the end of the mortgage term, unless borrowers decide to refinance. Additionally, most mortgage contracts include early repayment charges, which typically account for 5 or 10 percent of the outstanding loan and are in place until the end of the initial fixed period. Given the significant size of these charges and the jump in the reset rate, most borrowers refinance around the time when the initial

duration ends, making remortgaging a relatively frequent event in this market (see, e.g., Cloyne et al. 2017).

Another important aspect of the UK mortgage market is that there is no individual-based pricing or negotiation between the lender and the borrower. All borrowers purchasing the same mortgage product will pay the advertised rate. Lenders' pricing of default risk in this market seems to be driven by loan-to-values (see, e.g., Best et al. 2015), while pricing of refinancing risk is embedded in the duration of the initial fixed period (see, e.g., Benetton 2018). Therefore, products with the same maximum loan-to-value and initial fixed period should have very similar interest rates for a given lender. I test this assertion by regressing loan-level interest rates on an extensive set of dummy variables. Figure A.1 reports the adjusted R-squared that results from such regressions. I consider a product to be a triplet of maximum loan-to-value, initial period and lender, and I find that product-month fixed effects and the corresponding lender fees account for more than 90 percent of the variation in mortgage rates. The adjusted R-squared does not increase once I control for borrower characteristics (age, income, credit score, employment status) and location of the property. Moreover, the residual variation cannot be explained after including a dummy for the mortgage being originated through a broker.

In terms of market structure, the UK mortgage market is very concentrated upstream. The six largest lenders in the market account for more than 75% of mortgage originations. Panel A in Figure A.2 shows the consolidation process that these lenders, the so-called "Big Six," have experienced over the last decades. Through a series of mergers and acquisitions, they have been able to achieve significant market power at a national level. However, over the last years there has also been significant entry in the market from the so-called "Challenger Banks." Panel B in Figure A.2 presents the timeline for the main entrants in the mortgage market. Many of these entrants have a very limited branch network and promote their products mostly through on-line distribution channels and intermediaries. This strategy has proven successful partly because of the strong presence of mortgage brokers in the UK market. In 2017, more than 70% of first-time-buyers and 60% of home-movers originated their mortgage through an intermediary. Brokers also have a significant market share in the remortgaging market, especially for those borrowers who refinance with a different lender. Although there are many individual brokers in the form of one-person firms, the broker market is dominated by the largest twenty broker companies. These brokerage firms account for more than 60% of all new originations and have direct communication with lenders. I will discuss the relationship between lenders and broker companies in more detail when describing the data in the next subsection.

Table 1: Summary Statistics (All Borrowers).

	N	Mean	SD	Min	Max
Panel A: Loan Characteristics					
Interest Rate (%)	2,236,025	2.57	0.79	1.26	6.2
Lender Fee (£)	2,236,025	467	631	0	2405
Loan Value (£1000)	2,236,025	159	129	49	903
Loan-to-Value (%)	2,236,025	60.1	23	15	98
Maturity (Years)	2,236,025	25	8	2	45
Initial Period (Years)	2,236,025	3.2	2.4	1	10
Panel B: Borrower Characteristics					
First-Time-Buyers	2,236,025	0.19	0.39	0	1
Home-Movers	2,236,025	0.23	0.42	0	1
Internal Remortgagors	2,236,025	0.22	0.41	0	1
External Remortgagors	2,236,025	0.36	0.48	0	1
Gross Income (£1000)	1,506,724	62.1	48.2	10	523
Age (Years)	1,506,724	38	9.6	18	85
Loan-to-Income	1,506,724	3.1	1.2	1.3	5.2
Credit Score	984,471	482	66.3	250	765

2.2 Data

My main dataset is the Product Sales Database (hereinafter, PSD), which is a novel and comprehensive regulatory dataset containing the universe of residential mortgage originations in the United Kingdom. These data are collected quarterly by the Financial Conduct Authority (FCA) and are only available to restricted members of staff and associated researchers at the FCA and the Bank of England. For the purposes of this paper, I focus on the year 2015 and the first half of 2016. During this period, I observe for each mortgage origination details on the loan (interest rate, loan amount, initial fixed period, lender, fees), the borrower (income, age, credit score) and the property (value, location). I also have information on the distribution channel, that is, whether a broker intermediates the sale and, if so, the identity of the broker company. Table 1 summarizes the data. I observe more than 2 million contracts of which almost 90% are mortgages with initial fixed periods of two, three and five years. Given the importance of refinancing in this market, it is not surprising that more than 50% of borrowers in my sample are either external or internal remortgagors. The average interest rate is 2.6 percentage points, and lenders charge on average an origination fee of £467. The average loan is almost £160 thousands with a loan-to-value of 60%, a loan-to-income of 3.1 and an average maturity of 25 years. Borrowers are, on average, 38 years

old, have an annual income of £62 thousands and have a credit score of 480.

I complement the PSD data with additional information on broker companies that is also collected by the FCA. For each mortgage origination in PSD I observe commission payments (made by lenders to brokers for a given sale), broker fees (paid by borrowers) and supplementary details on contract agreements between lenders and brokers. Table 2 summarizes this data. Panel A compares the fraction of intermediated sales and the average per-sale broker remuneration across borrower types. More than 70% of first-time-buyers originate their mortgage through a broker company. Intermediation is also the most popular distribution channel in the home-movers and external remortgagors markets, with shares above 60%. Only 11 percent of internal remortgagors (those refinancing with the same lender) hired a broker when renewing their mortgage. On average, a broker will receive over £800 per mortgage, with most of the revenue coming from lenders' commissions and only a small fraction (if any at all) from broker fees. Figure A.3 plots the distribution of broker fees, revealing that most broker companies charge borrowers zero fees for their services. On the other hand, commissions from lenders are quite generous. Figure A.4 shows the distribution of commission rates across borrower types. There is no within-lender-broker variation for a given period, implying that commissions are the same for all products within each lender-broker pair. However, there is significant heterogeneity across brokers and across time, with commission rates ranging between 0.3 and 0.8% of the loan.

Panels B and C of Table 2 report the average number of agreements between brokers and lenders and the fraction that were formed or broken during my sample period. The average lender deals with thirteen broker companies, while the average broker company sells products from eight lenders. However, there is heterogeneity both across brokers and across lenders. For example, there is one lender with no dealings with brokers, while another lender has agreements with all brokers. Likewise, there are broker companies with very few lenders in their network, while others include almost every lender. There also exists variation in broker-lender networks across time. Throughout my sample period, there are 18% new agreements and 11% of links are broken.

Finally, I collect quarterly postcode-level data on all bank branches in the UK from Experian's Goad and Shop*Point datasets. This panel allows me to identify branch openings and closures for all lenders in my sample. Figure 1 plots time-series variation in the number of branches for the largest lenders. Aggregate total branches fall by almost 17% during my sample period. Despite the general downward trend, branch openings and closures are very heterogeneous across lenders and geographical areas (see Figure A.5). For example, London and other large urban conurbations experience large openings for some lenders, while some rural areas are essentially bank-branch deserts.

Overall, the combination of these three sources of data provides me with a very rich, loan-level dataset that is ideal to analyze the effects of broker remuneration on the market.

Table 2: Summary Statistics for Intermediated Sales and Broker-Lender Agreements.

PANEL A: Intermediated sales and broker payments.

	All Borrowers	First-Time Buyers	Home Movers	Internal Remortgagors	External Remortgagors
Intermediated	46%	72%	64%	11%	63%
Commission (£)	723	661	845	708	543
Commission Rate (%)	0.41	0.42	0.41	0.41	0.37
Broker Fee (£)	141	167	164	3	129
N	2,236,025	426,958	510,833	797,430	500,804

Panel B: Agreements between largest lenders and broker companies.

	Mean	SD	Min	Max
Number of Brokers per Lender	13	7	0	23
Number of Lenders per Broker	8	3	3	14

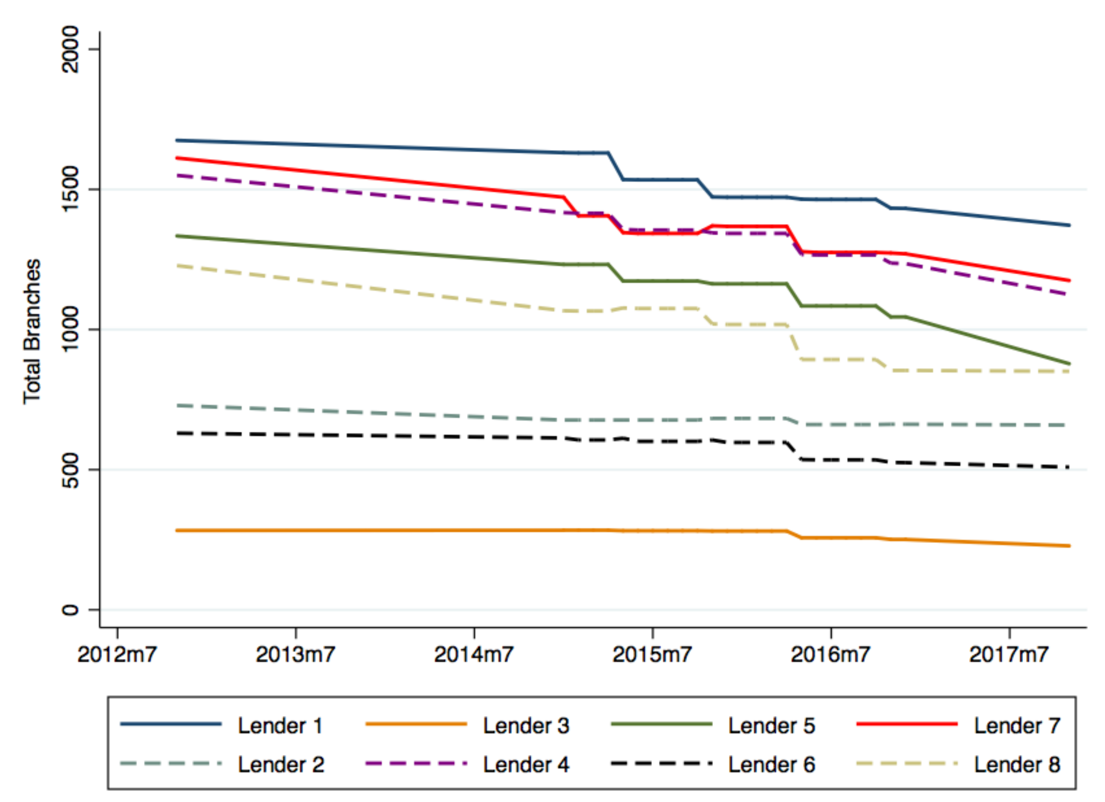
Panel C: Changes in agreements between 2015Q1-2016Q2.

Lender-Broker Links Broken	11%
Lender-Broker Links Formed	18%

Note: Panels B and C report all agreements between the largest 16 lenders and 23 broker companies, which account for 87% of the first-time-buyers market. These constitute the set of lenders and brokers that I will use later when estimating the model.

Note: Panel A summarizes the percentage of borrowers that originate their mortgage through a broker and the average per-sale revenue for brokers. Panels B and C report all agreements between the largest 16 lenders and 23 broker companies, which account for 87% of the first-time-buyers market. These constitute the set of lenders and brokers that I will use later when estimating the model.

Figure 1: Total Branches for largest lenders



Note: Data obtained from Experian Shop*Point and Goad datasets. Total branches account for both openings and closures during the sample period.

This paper is the first to exploit these combined datasets and the first one to address the role of brokers in this market.

3 Motivating Evidence

In this section, I document in more detail evidence in favor of the economic trade-offs and conflicts of interest that can potentially exist in the presence of commissions in this market. On the one hand, commissions may distort brokers' advice. On the other hand, they can increase competition and efficiency upstream, leading to overall lower prices. I now present motivating evidence suggesting that both sides of the trade-off are present in the UK mortgage market, and that the data supports the inclusion of these forces in the model.

3.1 Brokers' Advice and Commissions

Commissions from lenders can potentially bias brokers' recommendations towards high-commission products. This distortion can be detrimental for borrowers if products offering high payments to brokers are also more expensive. Figure 2 illustrates this concern with a conceptual example using two lenders offering one of the most popular products in the market: a two-year fixed, 75% loan-to-value mortgage. Lender B's product is always cheaper, but Lender A's product pays a higher commission to brokers. Despite being more expensive, Lender A's product has a higher market share via direct sales. Unobservable characteristics, such as more advertisement or lax screening, could explain this gap in direct sales between lenders A and B. The distortion that I would like to address in this section relates to the even larger difference in market shares observed for intermediated sales. In particular, in this subsection I provide evidence showing that differences in commission payments partly explain the gap in broker market shares.

It is not straightforward that commissions will influence brokers' sales choices. In the UK mortgage market, there are mechanisms in place that discipline brokers and help ensure they act in their customers' best interests. For example, given the high-frequency of remortgaging in the UK market, repeated sales can align borrowers' and brokers' incentives. Brokers may maintain a good relationship with households in order to ensure that they return for future mortgage transactions. Indeed, in recent consumer surveys 68% of households said that they were satisfied with their broker and would use the same intermediary in the future.[1] Brokers can also be motivated by reputation concerns. Consumer surveys find that 23% of borrowers chose their broker because it was suggested by a real estate agent and 29% because a friend or relative recommended it. Therefore, in a market where referrals seem to play a critical role, brokers are less likely to misconduct for fear of not getting recommended in the future. All in all, whether brokers are reacting to commissions despite repeated sales and reputation concerns remains an empirical question.

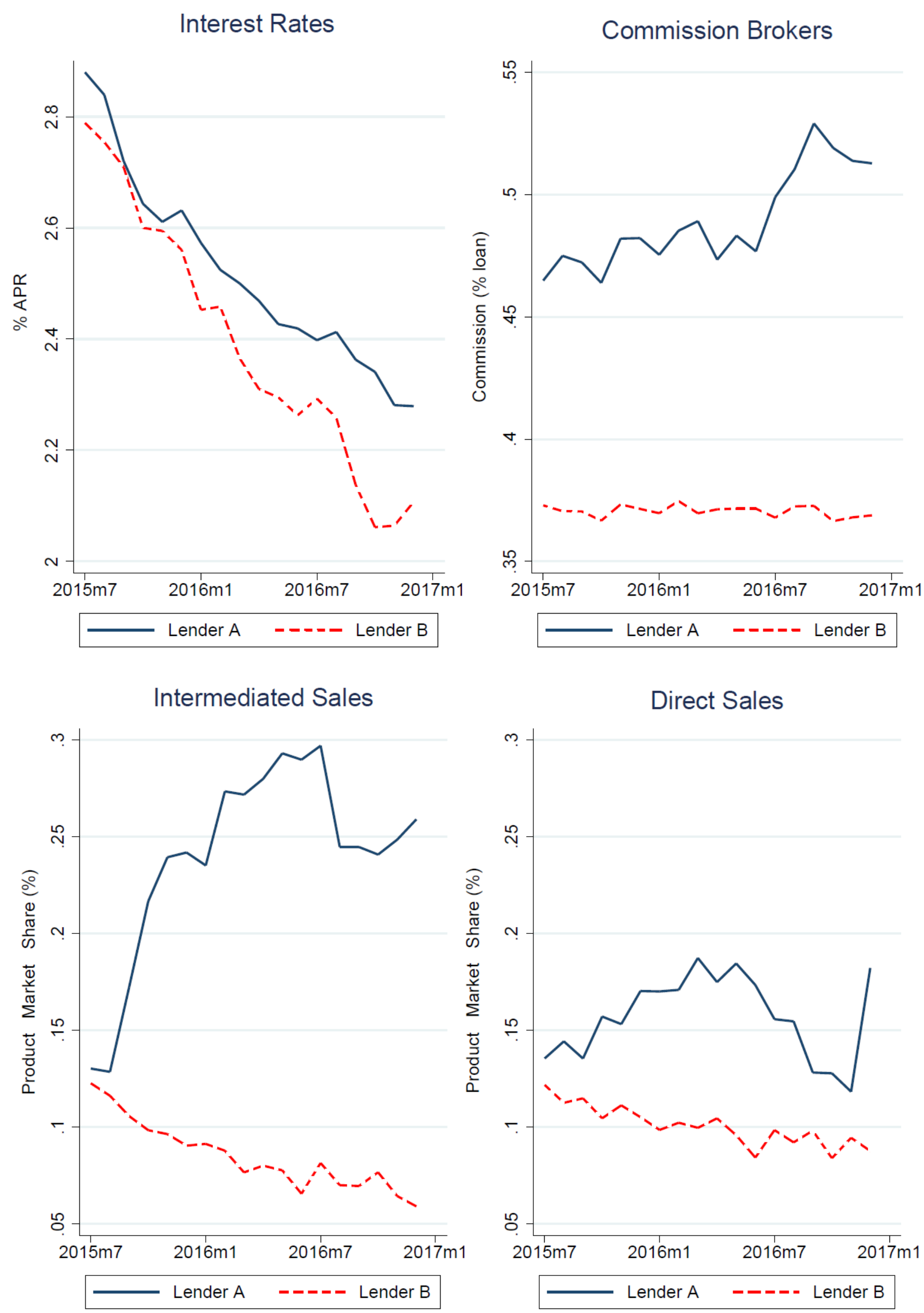
In an attempt to capture the effect of commissions on brokers' product choices I estimate the following fixed-effects specification at the product-broker-month-county level:

$$Share_{bjtc} = \alpha + \theta\, Commission_{bltc} + \delta_{jtc} + \gamma_{btc} + \psi_{blc} + \epsilon_{bjtc} \qquad (1)$$

where the dependent variable is the percentage share of product j in broker b's sales portfolio at month t in county c. The independent variable $Commission_{blt}$ is the per sale commission rate that broker b receives from lender l in month t in county c. In order to solve some of the endogeneity concerns when regressing product shares on commissions, I control for confounders by absorbing a rich set of fixed effects at the county level. I include product-

[1] See Question M56 in the FCA's consumer survey *Financial Lives Survey 2017*.

Figure 2: Example of (potential) distortion in a "Vanilla" Mortgage



Note: This figure illustrates prices, commissions and sales for two different lenders offering one of the most popular products in the market (2-year fixed, 75% LTV). Prices include interest rates and lender fees, and commission rates are expressed as a percentage of the loan.

Table 3: Product Market Shares and Commissions.

Dependent Variable: Product Market Share in Broker Sales (%)	All Borrowers (1)	Only FTBs (2)
Commission Rate	0.163*	0.271*
(% loan)	(0.097)	(0.180)
Product-Time-County FE	Yes	Yes
Broker-Time-County FE	Yes	Yes
Broker-Lender-County FE	Yes	Yes
Observations	327,750	153,416
Adjusted R-squared	0.953	0.937
Average Dependent Variable (%)	0.53	0.47
Average Commission Rate (%)	0.40	0.41
Average Total Commission per Loan (£)	776	802

Note: The dependent variable is the product share in a broker's sales portfolio each month in a county. The commission rate is the percentage of the loan paid by the lender to the broker for the sale of a product. Column (1) uses all borrowers, while Column (2) considers only first-time-buyers. Standard errors in parentheses are clustered at the broker and county levels, and (*) corresponds to a p-value lower than 0.1.

time-county fixed effects to account for time-varying product characteristics that could affect brokers' product preferences, such as interest rates, advertisement, and fees. I also add broker-time-county fixed effects to control for time-varying broker characteristics that could influence brokers' choices, such as their clientèle of borrowers. Finally, I also add broker-lender-county fixed effects to account for preexisting dealings between a broker and a lender that could result in preferential treatment. This triple-differences approach deals with the obvious endogeneity concerns; however, the estimate for θ could still be biased if there are broker-product-time-county-varying confounding variables. I will further discuss these endogeneity issues when estimating the model. At that stage, I will try to address these concerns using an instrumental variables approach exploiting time-variation in cost-shifters at the broker-lender level.

Table 3 presents estimates for equation 1. The first column uses the entire sample, while the second column focuses exclusively on first-time-buyers. Both specifications control for a rich set of fixed effects, resulting in a positive and significant coefficient with values of 0.163

for all borrowers and 0.271 for first-time-buyers. Doing a back-of-the-envelope calculation, I get that an increase of 13% (£100) in a product's commission leads, on average, to almost a 2% rise in the product's market share within a broker's portfolio. The statistically and economically significant coefficients show that after controlling for the obvious confounders brokers seem to be reacting to changes in commissions.

Estimates in Table 3 exploit within broker-product variation across time within a county. Results suggest that changes in a product's commission will, on average, increase the products' share within a broker's sales portfolio. However, a broker's advice can also be biased across different products. For instance, brokers may be more likely to recommend products with shorter fixed initial periods that will require households to refinance more frequently. Brokers get another commission payment each time borrowers need to remortgage. Brokers also have incentives to push borrowers towards higher loan-to-value products. Since commissions are expressed as a percentage of the loan amount, brokers may persuade households to borrow as much as possible.[2]

Both types of distortions are, however, difficult to identify empirically due to selection into intermediation. Indeed, the data shows brokers selling more two-year fixed mortgages (as opposed to three- and five-year fixed) and higher loan-to-value products than the direct sales channel. Still, unobservable (to the econometrician) borrower characteristics could explain these choices. Households originating their mortgages through brokers may have different preferences than those going directly to lenders, and brokers could be selecting the best products conditional on such (unobservable) preferences. To get a sense of any evidence in the data that might suggest selection into brokerage, I calculate borrowers' propensity scores for buying mortgages with (1) high loan-to-value and (2) short initial fixed period. I use as predictors borrower's characteristics (income, age, credit score, and whether is a joint application), property characteristics (house price and location) and month of the year. Figure A.6 plots these propensity scores separately for direct and intermediated sales. Based on observable characteristics, borrowers going through brokers are slightly more likely to buy a mortgage with high loan-to-value and short initial period. However, I cannot reject that distributions for both channels are statistically different. Unobservable product and borrower characteristics can be driving the observed differences in choices between direct and intermediated sales. Brokers' preferences over product characteristics could also be an explanation. In the model in Section 4 I explicitly account for borrowers' selection into

[2]In the US, there have been reports by media and consumer groups arguing that brokers advise to households to borrow beyond their means exacerbated the financial crisis. See, for example, Pleven and Craig, "Deal Fees under Fire Amid Mortgage Crisis; Guaranteed Rewards of Bankers, Middlemen Are in the Spotlight," Wall Street Journal, January 17, 2008; and "Steered wrong: Brokers, borrowers, and subprime loans", *Center for Responsible Lending*, 2008. Similar concerns have been raised in Europe by the Basel Committee on Banking Supervision's Report, "Customer suitability in the retail sale of financial products and services", 2008.

intermediation and brokers' incentives both within and across product types. I am able to separately identify the borrower and broker preferences over product characteristics, other than commissions.

3.2 Upstream Competition and Commissions

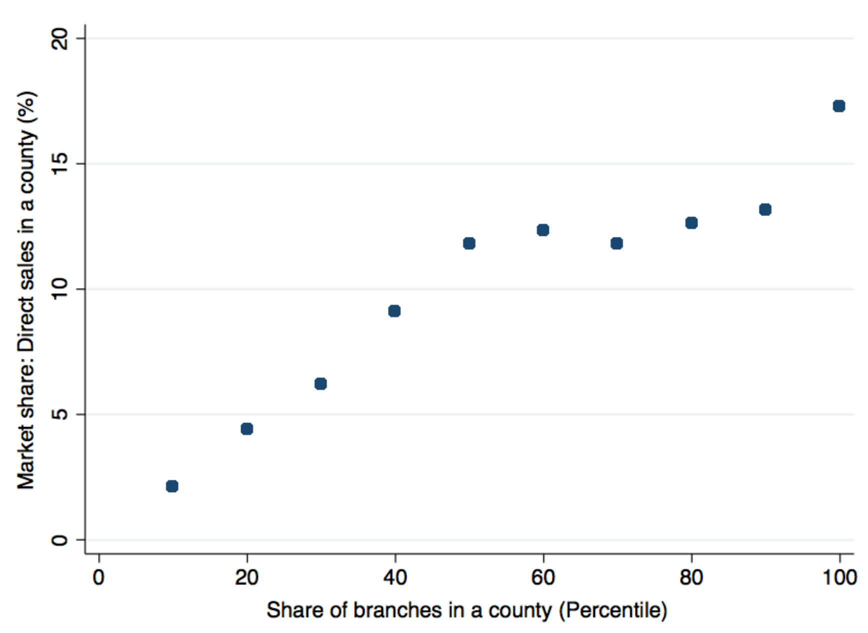
Despite the recent uptake of online distribution channels in many markets, bank branches still play a crucial role in mortgage originations in the UK. Panel A in Figure 3 shows that lenders with a more significant concentration of branches in a given county account for a higher share of direct sales in that same county. This strong positive correlation between direct sales and branch presence still holds after adding lender and area fixed effects to account for local demand and lender preferences. Moreover, recent changes in regulation implemented by the Mortgage Market Review (MMR) in April 2014 have intensified the importance of bank branches as a distribution channel. The MMR requires lenders to provide advice for all sales that require any "interaction" with borrowers. Lenders have been very conservative in their interpretation of these "interaction trigger" and now provide lengthy advice to almost all of their borrowers, except for internal remortgagors. Although some lenders give the option of speaking to an advisor over the phone, most borrowers are redirected to the nearest branch for an appointment with a specialized advisor to discuss their mortgage application. Both face-to-face and telephonic interviews take an average length of almost two hours. However, there is no such requirement for borrowers originating their mortgages via brokers. Lenders seem to be taking advantage of this and are using commissions to promote their products to intermediaries in areas where borrowers would have to travel a significant distance to their nearest branch for an interview. Panel B in Figure 3 shows that lenders are also more likely to pay higher average commission rates in counties where they have a lower concentration of branches. In such cases, commissions and brokers can increase welfare by (1) lowering lenders' distribution costs, (2) reducing borrowers' origination costs and (3) increasing households' available choice sets, especially in the so-called "bank-branch deserts."

Moreover, commissions also allow challenger banks to introduce and promote their products in the market without the need of setting up extensive (and expensive) branch networks. Panel A in Figure 4 plots average commission rates for challenger and non-challenger lenders over my sample period, while Panel B in Figure 4 shows the corresponding market shares for direct and intermediated sales channels. On average, challenger banks pay higher commissions and account for a higher market share in brokers' sales than in direct sales. To formalize this relationship between challenger banks and intermediated sales, I estimate the following specification:

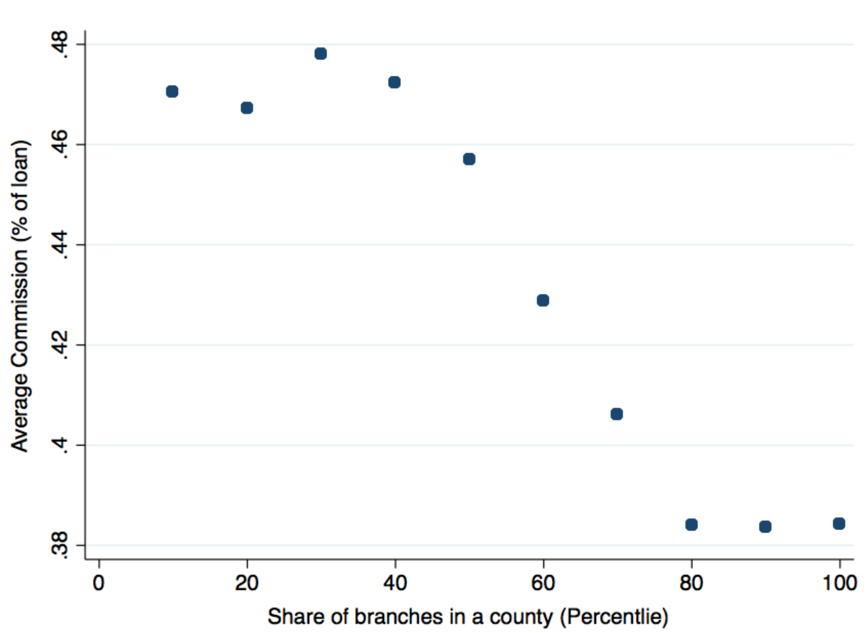
$$Challenger_{ijt} = \alpha + \delta \, Intermediated_{ijt} + \beta X_{ijt} + \epsilon_{ijt} \tag{2}$$

Figure 3: Branches, Direct Sales and Commissions

PANEL A: Correlation between branches and direct sales



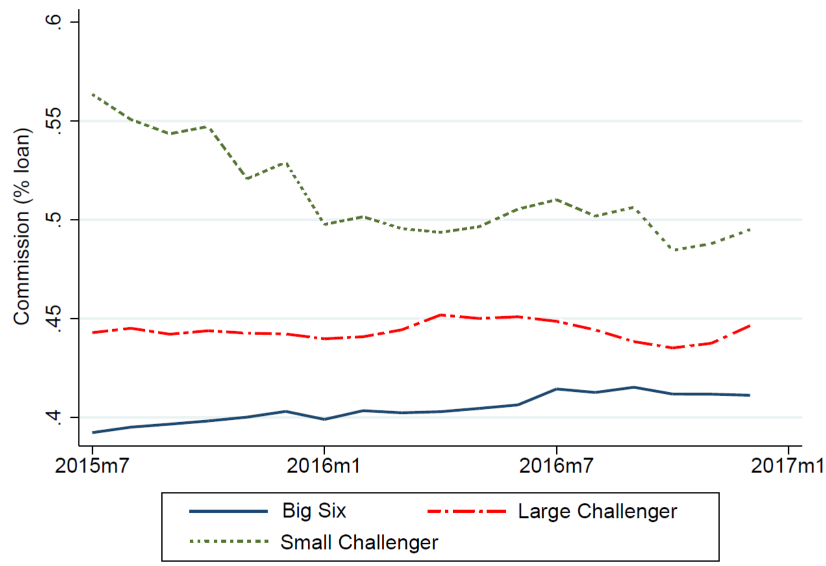
PANEL B: Correlation between branches and average commissions



Note: On the X-axes I sort all county-lender pairs according to the lender's concentration of branches in the county. In Panel A, I then average direct sales for each lender within a county. In Panel B, I calculate the average commission rates for each lender within a county.

Figure 4: Commissions and Market Shares across Lenders

PANEL A: Average commissions for challenger and non-challenger banks.



PANEL B: Market shares across lender types and distribution channels.

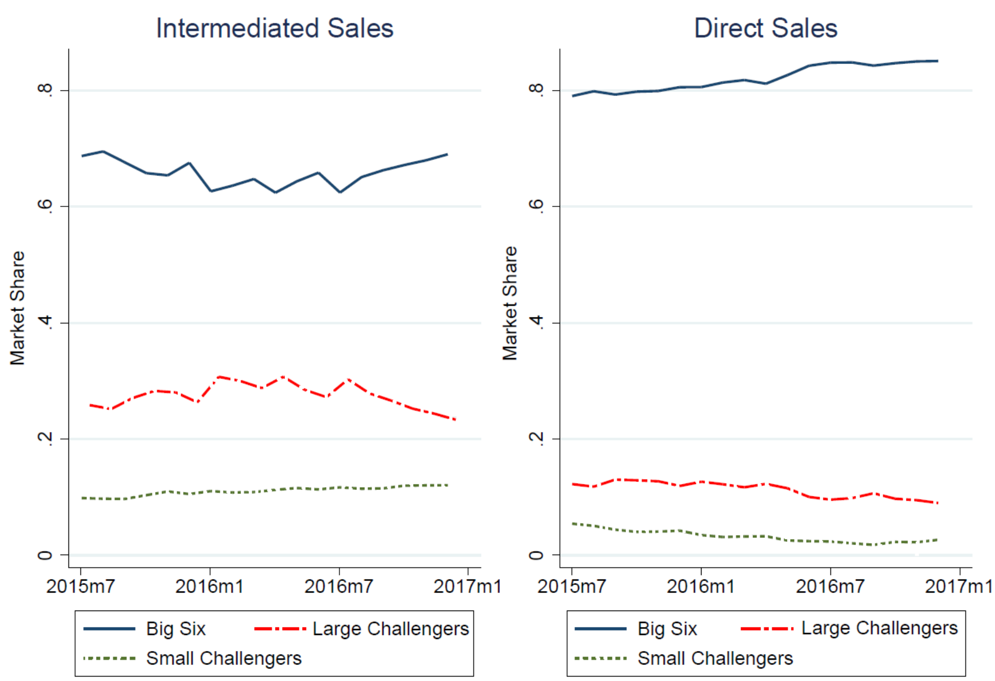


Table 4: Probability of Getting a Product from a Challenger Bank.

Dependent Variable: Challenger (0/1)	All Borrowers (exc. Internal Remortgagors) (1)	First-Time-Buyers Only (2)
Intermediated	0.0476***	0.0674***
	(0.001)	(0.003)
Max. LTV Band FE	Yes	Yes
Fixed Period FE	Yes	Yes
County FE	Yes	Yes
Year-Month FE	Yes	Yes
Borrower Characteristics (income, age, credit score)	Yes	Yes
Observations	489,352	159,486
R-squared	0.24	0.33

Note: Unit of observation is at the household level. Dependent variable is a dummy equal to one if the borrower chose a mortgage from a challenger bank. Robust standard errors in parentheses, such that *** p<0.01, ** p<0.05, * p<0.1

Note: The unit of observation is at the household level. Dependent variable is a dummy equal to one if the borrower chose a mortgage from a challenger bank. Robust standard errors in parentheses such that (***) corresponds to a p-value lower than 0.01.

where $Challenger_{ijt}$ is a dummy equal to one if household i at time t purchased mortgage product j from a challenger bank, and zero otherwise. The independent variable $Intermediated_{ijt}$ is a dummy variable equal to one if the household originated the mortgage through a broker, and zero if it used the direct channel instead. Covariates X_{ijt} control for observable borrower, product, geographical and time period characteristics.

Table 4 shows estimates from a probit specification of equation 2. Although the coefficients are not causal due to borrower selection into intermediation, first-time-buyers going to a broker seem to have a seven percent higher probability of originating their mortgage through a challenger bank, even after controlling for borrower and product characteristics and year-month and county fixed effects. Given that for many products in the market challenger banks offer better rates than the Big Six, commissions can benefit households via their allocative role in the broker channel, inducing higher matching rates between borrowers and challenger banks.

3.3 The Need for a Model

The results in the preceding subsections 3.1 and 3.2 point to a key trade-off emerging from the presence of commission payments from lenders to brokers. On the one hand, commissions

can create a misalignment of incentives between brokers and borrowers, distorting brokers' advice towards high-commission products, which could ultimately reduce consumer surplus. On the other hand, commissions allow challenger banks to introduce their products without the need to invest in an extensive branch network, increasing competition upstream and potentially leading to lower prices. Moreover, commission payments also allow established banks to promote their products in areas where they have limited branch density, reducing their distributional costs and eventually resulting in efficiency gains and lower prices. Finally, as shown in section 2.2, consumers currently pay very low fees (in many instances no fee at all) when hiring a broker. These low charges are possible only because brokers are getting most of their revenue directly from lenders. Commissions can, therefore, increase consumer surplus via a fall in the cost of purchasing valuable expert services that reduce household search costs and increase the information on available products. Overall, the net effect of commissions on consumer surplus depends on which of all these forces dominates in equilibrium.

In order to evaluate the overall impact of a policy restricting commission payments, it is necessary to empirically assess the relative sizes of these effects on consumer surplus. This may prove to be difficult for three reasons. First, there is no counterfactual scenario without commissions in this market. This precludes evaluating the performance of such a policy in this context. The second challenge arises due to selection into intermediation. Consumers decide whether or not to hire a broker based on observable and unobservable (to the econometrician) characteristics of both the borrower and the broker. Therefore, in the presence of this endogenous choice, reduced-form methods would require strong assumptions when evaluating such behavior, which could ultimately bias the resulting estimates. Finally, contract negotiations between lenders and brokers endogenously determine commission payments in this market. In order to evaluate the effects of a hypothetical cap or ban on such commissions, it is necessary to understand the incentives, and trade-offs lenders and brokers face when deciding whom to include or exclude from their sales networks and what commissions to set in such agreements.

In the rest of the paper, I present and quantify a structural model of the UK mortgage market that features all trade-offs discussed above. Such a framework will help overcome the empirical limitations described in this section and will enable me to evaluate the net effect on consumer surplus of restricting upstream commissions.

4 A Model of the UK Mortgage Market

4.1 Set-up

In this section, I develop a structural model of the UK mortgage market that predicts: (i) household demand for mortgage products, (ii) household demand for brokerage services, (iii)

interest rates offered by lenders, and (iv) negotiated lender-broker specific sales commissions. I will later estimate it and use it as a tool to simulate counterfactual policy analysis.

The model focuses on the interactions between the three principal economic agents in the UK mortgage market: lenders, brokers and households. Figure 5 describes the vertical and horizontal relations in this market between all main players. A *household* is comprised of one or two potential borrowers in need of a mortgage for the purchase of a residential property. A *lender* is a bank or building society selling differentiated mortgage products to households. A *broker* is a firm that helps households get a mortgage by providing advice on available products and sorting out application and origination paperwork with the lender. The timing of events is as follows. First, brokers negotiate with lenders for the terms of lenders' inclusion in the brokers' networks. If successful, these bilateral negotiations determine the set of commissions paid by lenders to brokers for the sale of any given product. Next, lenders set prices in the form of interest rates for all their mortgage products. Finally, households decide on a sales channel, that is, whether to hire a broker or use lenders' in-house distribution channels (e.g., branches). I will refer to the former as the intermediated channel and to the latter as the direct channel. Once households have chosen a sales channel, they acquire one of the available mortgage products through that channel. In this setting, lender-broker bargaining and lenders' mortgage pricing constitute the supply side of the market, while households' choice of sales channel and mortgage product captures the demand side.

4.2 Demand

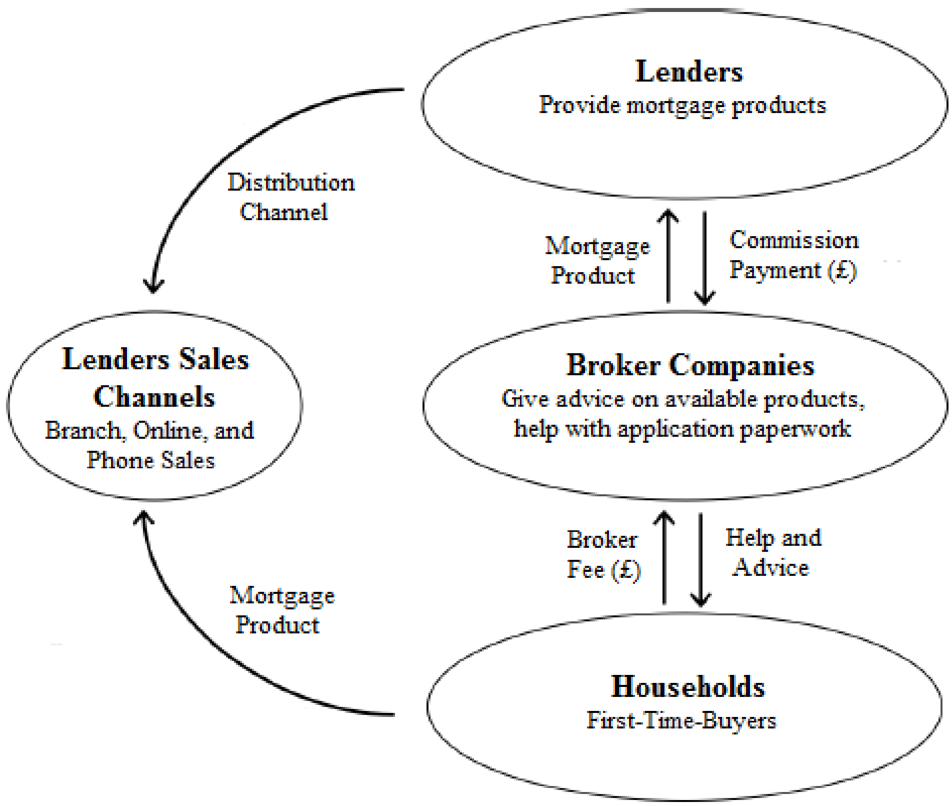
Assume that there are $t = 1, ..., T$ markets, each with $i = 1, ..., I_t$ rational and utility-maximizing households with heterogeneous search costs and preferences across product characteristics. I define a market as half-year in my data, and each household can only be active in one market and purchase only one product. In each market there are $l = 1, ..., L_t$ lenders, each selling J_{lt} horizontally differentiated mortgage products, indexed by $j = 1, .., J_{lt}$. Likewise, there are B_t brokers each market, indexed by $b = 1, ..., B_t$.

4.2.1 Mortgage Product Choice

In the last stage, after selecting a sales channel, households choose one of the available mortgage products. I follow the characteristics approach (Lancaster 1979) and assume households' mortgage demand is a function of observable household characteristics, random preferences, product attributes and a vector of preference parameters. I also assume that the problem faced by households when choosing a mortgage product will differ depending on their chosen sales channel, which is predetermined at this stage.

Direct Channel. Consider household i in market t that has opted for lenders' in-house

Figure 5: Vertical and Horizontal Relations in the UK Mortgage Market



Note: The diagram displays the main vertical relations in the UK mortgage market. Households in need of a mortgage can pay a fee and hire a broker company to provide them with advice on available products and help them with all paperwork involved in the application and origination of the mortgage. The broker will also receive a commission payment from the lender for each sale. Households can also bypass the broker and access the lender's distribution channels directly via bank branches and online and phone sales.

distribution channels. I make the parametric assumption that the indirect utility of such household has the following linear form:

$$V_{ijlt}^{D} \;=\; \alpha\, r_{jlt} + \beta\, X_{jl} + \xi_{jlt} \;+\; \lambda\, Branches_{ilt} + \;\epsilon_{ijlt} \tag{3}$$

where r_{jlt} is the interest rate of product j offered by lender l in market t; X_{jl} are time invariant product characteristics including lender, maximum loan-to-value and initial fixed period; ξ_{jlt} captures unobservable product-lender-market characteristics affecting household utility in a market (e.g., advertising, screening) ; ϵ_{ijlt} is an idiosyncratic taste shock. Finally, $Branches_{ilt}$ accounts for the number of branches that lender l has in household i's county, and λ is the associated preference parameter. By adding branches in the horizontal differentiation

dimension, I account for costs associated with application and origination processes that households may face, along the lines of Hastings et al. (2017) and Benetton (2018).

Household i will purchase mortgage product jl if and only if it attains the highest utility among all available products in the household's consideration choice set, C_{it}, which I assume is household specific and restricted by household characteristics. That is, household i will choose product j from lender l if (1) it is part of the available choice set, and (2) $V^D_{ijlt} > V^D_{ikst}, \forall\, ks \in C_{it}$. Consider $V_{11}, V_{21}, ..., V_{jl}, ..., V_{JL}$ to be the utilities for all product-lender alternatives where J and L are the number of products and lenders in choice set C_{it}, respectively. Let $g(V_{11}, V_{21}, ..., V_{jl},\ ..., V_{JL})$ be the joint density function for them. Then, the probability that alternative jl is chosen at a purchase occasion is given by:

$$\begin{aligned} s_{ijlt} &= Pr\,(\,jl\ \ chosen \,|\, C_{it}) \;=\; Pr\,(\,V^D_{ijlt} > V^D_{ikst} \quad for\ \ all\ \ \ ks \in C_{it}) \\ &= \int_{-\infty}^{v_{jl}} ... \int_{-\infty}^{\infty} ... \int_{-\infty}^{v_{jl}} g(V_{11}, \ldots, V_{jl}, \ldots, V_{JL})\ dv_{11} ...\ dV_{jl}\ ...\ dV_{JL} \end{aligned} \tag{4}$$

Intermediated Channel. Consider now household i' has hired broker b in market t. Let $b(i')$ denote this broker-household pair. I assume that each broker-household pair $b(i')$ is a composite agent that maximizes the joint indirect utility, which I assume to be a weighted average of the indirect utility of the household, V^b_{ijlt}, and that of the broker, W_{bjlt}. Moreover, I make the parametric assumption that the indirect utility of the pair $b(i')$ for the purchase of product j from lender l in market t takes the following form:

$$\begin{aligned} V_{b(i')jlt} \;&=\; (1-\theta_b)\ \underbrace{(\beta\, X_{jl} + \alpha\, r_{jlm} + \xi_{jlt}\ +\ \epsilon_{ijlt}\,)}_{\text{Household's Utility } (V^b_{ijt})} \\ &+\ \theta_b\ \underbrace{(\ \gamma_1\, c_{lbt}\ \ +\ \gamma_2\, X_{jl} + \zeta_{blt})}_{\text{Broker's Utility } (W_{bjlt})} \end{aligned} \tag{5}$$

where the indirect utility of the broker includes a percentage commission c_{lbt} that broker b receives from lender l, as well as product characteristics over which the broker may have some preferences. For example, brokers may prefer products with shorter initial fixed periods. These type of products incentivize households to refinance more frequently, which in turn leads to more business (and commissions) for brokers. Moreover, brokers may prefer higher loan-to-value products since commissions are expressed as a percentage of the loan. I also account for the possibility of brokers' preference being affected by unobservable (to the econometrician) broker-lender-market characteristics, ζ_{blt}, such as preferential treatment. Parameter θ_b in equation 5 captures the average downstream market power of broker b and

the share of surplus a broker can extract from her average client. This parameter captures the magnitude of the agency problem households face when dealing with broker b and the influence/negotiation power the latter has over the consumer. If θ_b is equal to zero, then then the broker is fully benevolent in the sense that demand-side incentives are so large that brokers' and households' incentives are fully aligned. If, on the other hand, θ_b is equal to one, then supply-side incentives fully dominate, and the broker can extract all surplus from households. Finally, households indirect utility is analogous to that of equation 3 in the direct channel, with the exception that bank branches do not play a role when getting a mortgage through a broker.[3]

Each broker-household pair maximizes the joint indirect utility subject to their available choice set, $C_{b(i')t}$. These consideration choice set is broker-household specific, and it is restricted by household characteristics (as in the direct channel) but also by broker b's network of lenders. At this stage, a broker can only originate mortgages with lenders with whom she reached an agreement in the previous bargaining stage. I denote this subset of lenders N_{bt}. Therefore, broker-household $b(i')$ will choose product j from lender l in N_{bt} if (1) it is part of the available choice set $C_{b(i')t}$, and (2) $V_{b(i')jlt} > V_{b(i')kst}$, $\forall\, ks \in C_{b(i')t}$. Finally, the probability that product jl is chosen, $s_{b(i')jlt}$, conditional on the available choice set, $C_{b(i')t}$, is analogous to the one defined in equation 4 for the direct channel.

4.2.2 Sales Channel Choice

Before choosing a mortgage product, households need to decide whether to go directly to lenders' in-house distribution channels or hire a broker. I assume each household i as a search cost κ_i. This search cost is a fixed cost that households incur when gathering information on all products available to them in market t. I assume search costs are heterogeneous and assigned via i.i.d. draws from a distribution F_κ. If household i decides to use the direct sales channel, then it will incur the search cost κ_i to learn about available products and to deal with the administrative aspects of the application. Household i can also choose the brokerage option. In this case, the household is matched to broker b with probability π_{bit} and has to pay a broker fee f_{bit} for the broker's services. I assume that (1) households do not search across brokers, and (2) there is no competition among brokers. Therefore, I consider broker fees as exogenous.[4]

Household i will choose the sales channel that provides the highest (net) ex-ante expected

[3]Reduced-form evidence in Section 3.2 suggests that branch presence matters only for direct sales. Moreover, when adding this coefficient in the estimation for broker sales, the effect is small and not significantly different from zero. After controlling for commissions, branch proximity does not seem to play a role when originating a mortgage through a broker.

[4]As already presented in Figure A.3, broker fees in this market are significantly low with many broker companies offering their services at no cost for the borrower. Thus, households always have the option of hiring brokerage services at a zero fee.

utility, which depends on the household's search cost, broker fees and ex-ante expected maximum indirect utility from each sales channel. Let $\hat{\kappa}_i$ be the search cost that makes household i indifferent between both sales channels. This indifference cut-off value is determined by:

$$\underbrace{E\Big[\max_{jl}\ V_{ijlt}\left(\eta\right)|Direct\Big] - \hat{\kappa}_i}_{\text{Direct Channel}} \;=\; \underbrace{\sum_{b\in B_t}\pi_{b(i)t}\Bigg(E\Big[\max_{jl}\ V_{b(i)jlt}\left(\eta\right)\mid b\Big] - \alpha_i f_{ibt}\Bigg)}_{\text{Broker Channel}} \tag{6}$$

where η is a vector of all household preferences parameters; $E\big[\max_{jl}\ V_{ijlt}\left(\eta\right)|Direct\big]$ and $E\big[\max_{jl}\ V_{b(i)jlt}\left(\eta\right)\mid b\big]$ are the ex-ante expected household utilities of household i going directly to the lender and hiring broker b, respectively; $\pi_{b(i)t}$ is the probability that household i is matched to broker b; f_{ibt} is the broker fee paid by household i when hiring broker b. I multiply the fee by the price coefficient, α_i in equations 3 and 5, to transform money into utils and make the fee comparable to the expected utilities. This indifference condition in equation 25 implies that, if household i has a search cost draw κ_i that is greater than $\hat{\kappa}_i$, then it will choose to hire a broker. Similarly, if it has a search cost draw κ_i smaller than $\hat{\kappa}_i$, then it will opt for the direct sales channel and search for a mortgage across lenders' in-house distribution channels.

4.3 Supply

4.3.1 Lender Mortgage Pricing

In each market t there are L_t lenders that are for-profit organizations selling mortgage products to households. They maximize expected profits by setting interest rates (prices) for each of their products. I define the set of products offered by lender l in market t as J_{lt}. Lender l's profits from a direct sale of product j in market t are given by:

$$\Pi^D_{jt} \;=\; t_j\left(r_{jt} - mc^D_{jt}\right) \tag{7}$$

where t_j is the initial fixed period for product j; r_{jt} is the initial rate for that product in market t; and mc^D_{jt} is the "perceived" marginal cost of selling product j in market t through a direct distribution channel. Similarly, lender l's profits from selling product j in J_{lt} in market t via an intermediated sale from broker b are defined as:

$$\Pi^b_{jt} \;=\; t_j\left(r_{jt} - mc^B_{jt}\right) - c_{lbt} \tag{8}$$

where c_{lbt} is the commission paid to broker b in market t for the sale of product j from lender l, and mc^B_{jt} is the "perceived" marginal cost of selling product j in market t through

the broker channel. I allow for marginal costs to vary across sales channels, because there could be ways in which brokers reduce lenders' origination costs (e.g., screening, income verification). I am also implicitly assuming that a household's loan quantity choice is equal to one, and it is not affected by changes in the interest rate. That is, a change in the interest rate will affect households' choice probabilities across products, but not the associated loan amount (conditional on the loan-to-value bands). Therefore, I am only accounting for households discrete choice in lenders' profits, as opposed to previous work that also endogeneizes households' choice of loan amount (see Benetton 2018). Finally, I am assuming all households remortgage at the end of the initial period (see Cloyne et al. 2017) and no default.

Using demand choice probabilities as defined by equation 4 and cut-off search costs as characterized in equation 25, lender l's expected profits from serving household i in market t are given by:

$$\Pi^l_{it} = \underbrace{F_\kappa(\hat{\kappa}_i) * \sum_{j \in J_{lt}} \left(s_{ijlt} * \Pi^D_{jt}\right)}_{\text{Revenue from Direct Sales}} \;+\; \underbrace{\left[1 - F_\kappa(\hat{\kappa}_i)\right] * \sum_{j \in J_{lt}} \sum_{b=1}^{B} \left(\pi_{b(i)t} * s_{b(i)jt} * \Pi^b_{jt}\right)}_{\text{Revenue from Broker Sales}} \tag{9}$$

where s_{ijlt} and $s_{b(i)jt}$ are choice probabilities for household i choosing product jl conditional on choice channel; $F_\kappa(\hat{\kappa}_i)$ represents the probability that household i will choose to go directly to the lender's distribution channel and $1 - F_\kappa(\hat{\kappa}_{it})$ is the probability that it will decide to hire a broker. Conditional on other lenders' interest rates, lender l will decide in each market t the initial rate for each product j in J_{lt} that maximizes the sum of equation 9 across all households in each market. Thus, in each market, lender l solves the following maximization problem:

$$\max_{r_{jt}\ \forall j \in J_{lt}} \quad \Pi^l_t \;=\; \sum_{i \in I_t} \Pi^l_{it}(r_{1t}, ..., r_{J_l t}) \tag{10}$$

with the corresponding first order conditions with respect to interest rate of product j in market t being given by:

$$
\begin{aligned}
\frac{\partial \Pi_t^l}{\partial r_{jt}} = & \sum_{i \in I_t} \Bigg[F_\kappa(\hat{\kappa}_{it}) * s_{ijlt} * t_j \\
& + F_\kappa(\hat{\kappa}_{it}) \sum_{k \in J_{lt}} \frac{\partial s_{iklt}}{\partial r_{jt}} * \left[t_k \left(r_{kt} - mc_{kt}^D \right) \right] \\
& + f_\kappa(\hat{\kappa}_{it}) * \frac{\partial \hat{\kappa}_{im}}{\partial r_{jt}} \sum_{k \in J_{lt}} s_{iklt} * \left[t_k (r_{kt} - mc_{kt}^D) \right] \\
& + \left[1 - F_\kappa(\hat{\kappa}_{it}) \right] \sum_{b=1}^{B} \pi_{b(i)t} * s_{b(i)jlt} * t_j \qquad (11) \\
& + \left[1 - F_\kappa(\hat{\kappa}_{it}) \right] \sum_{b=1}^{B} \pi_{b(i)t} \sum_{k \in J_{lt}} \frac{\partial s_{b(i)klt}}{\partial r_{jt}} * \left[t_k \left(r_{kt} - mc_{kt}^B \right) - c_{lbt} \right] \Bigg] \\
& - f_\kappa(\hat{\kappa}_{it}) * \frac{\partial \hat{\kappa}_{it}}{\partial r_{jt}} \sum_{b=1}^{B} \pi_{b(i)t} \sum_{k \in J_{lt}} s_{b(i)klt)} * \left[t_k \left(r_{kt} - mc_{kt}^B \right) - c_{lbt} \right] \Bigg] \\
& = \; 0, \qquad \forall j \in J_{lt}
\end{aligned}
$$

In (11), the first and fourth terms capture the extra profits for both direct and intermediated sales due to a higher interest rate. The second and fifth terms show the effect of higher rates on choice probabilities for all products from lender l. Finally, the third and last terms capture the change in the probability of households choosing the direct channel due to higher interest rates. Solving for the interest rate in (11) gives (I omit the market subscript for simplicity):

$$
r_j^* = \sum_{i \in I_m} \Bigg[\underbrace{mc_j^D \; \rho_j^D + \sum_{b=1}^{B} \pi_{b(i)} (mc_j^B + \frac{c_{lb}}{t_j}) \; \rho_j^b}_{\text{Effective average marginal cost}}
$$

$$
\underbrace{- F_{\hat{\kappa}} \; s_{ijl} \; \frac{\rho_j^D}{F_{\hat{\kappa}} \; \frac{\partial s_{ijl}}{\partial r_j} \; + \; f_{\hat{\kappa}} \; \frac{\partial \hat{\kappa}_i}{\partial r_j} \; s_{ijl}} \; - \; (1 - F_{\hat{\kappa}}) \; \sum_{b=1}^{B} \pi_{b(i)} \; s_{b(i)jl} \; \frac{\rho_j^b}{(1 - F_{\hat{\kappa}}) \; \frac{\partial s_{b(i)jl}}{\partial r_j} \; - \; f_{\hat{\kappa}} \; \frac{\partial \hat{\kappa}_i}{\partial r_j} \; s_{b(i)jl}}}_{\text{Full mark-up}}
$$

$$
\underbrace{- \sum_{k \neq j \in J_l} \frac{1}{t_j} \left(F_{\hat{\kappa}} \; \frac{\partial s_{ikl}}{\partial r_j} \; + \; f_{\hat{\kappa}} \frac{\partial \hat{\kappa}}{\partial r_j} s_{ikl} \right) \; \frac{\Pi_k^D \rho_k^D}{F_{\hat{\kappa}} \; \frac{\partial s_{ijl}}{\partial r_j} \; + \; f_{\hat{\kappa}} \; \frac{\partial \hat{\kappa}_i}{\partial r_j} \; s_{ijl}}}_{\text{Other products via direct}}
$$

$$
\underbrace{- \sum_{k \neq j \in J_l} \frac{1}{t_j} \; \sum_{b=1}^{B} \pi_{b(i)} \left((1 - F_{\hat{\kappa}}) \; \frac{\partial s_{b(i)kl}}{\partial r_j} \; - \; f_{\hat{\kappa}} \frac{\partial \hat{\kappa}}{\partial r_j} s_{b(i)kl} \right) \frac{\Pi_k^B \; \rho_k^b}{(1 - F_{\hat{\kappa}}) \; \frac{\partial s_{b(i)jl}}{\partial r_j} \; - \; f_{\hat{\kappa}} \; \frac{\partial \hat{\kappa}_i}{\partial r_j} \; s_{b(i)jl}}}_{\text{Other products via brokers}} \Bigg] \tag{12}
$$

where ρ_j^D is the effective probability of household i going direct and purchasing product j. Likewise, ρ_j^b is the effective probability of household i going to broker and purchasing product j. Expressions for both ρ_j^D and ρ_j^b are given by:

$$
\rho_j^D = \frac{F_{\hat{\kappa}} \; \frac{\partial s_{ijl}}{\partial r_j} \; + \; f_{\hat{\kappa}} \; \frac{\partial \hat{\kappa}_i}{\partial r_j} \; s_{ijl}}{\left[F_{\hat{\kappa}} \frac{\partial s_{ijl}}{\partial r_j} \; + \; f_{\hat{\kappa}} \; \frac{\partial \hat{\kappa}_i}{\partial r_j} \; s_{ijl} + (1 - F_{\hat{\kappa}}) \sum_{b \in B} \pi_{b(i)} \frac{\partial s_{b(i)jl}}{\partial r_j} - f_{\hat{\kappa}} \; \frac{\partial \hat{\kappa}_i}{\partial r_j} \; \sum_{b \in B} \pi_{b(i)} \; s_{b(i)jl} \right]} \tag{13}
$$

$$
\rho_j^b = \frac{(1 - F_{\hat{\kappa}}) \; \frac{\partial s_{b(i)jl}}{\partial r_j} \; - \; f_{\hat{\kappa}} \; \frac{\partial \hat{\kappa}_i}{\partial r_j} \; s_{b(i)jl}}{\left[F_{\hat{\kappa}} \frac{\partial s_{ijl}}{\partial r_j} \; + \; f_{\hat{\kappa}} \; \frac{\partial \hat{\kappa}_i}{\partial r_j} \; s_{ijl} + (1 - F_{\hat{\kappa}}) \sum_{b \in B} \pi_{b(i)} \frac{\partial s_{b(i)jl}}{\partial r_j} - f_{\hat{\kappa}} \; \frac{\partial \hat{\kappa}_i}{\partial r_j} \; \sum_{b \in B} \pi_{b(i)} \; s_{b(i)jl} \right]} \tag{14}
$$

Note that if there were no brokers in the market and all lenders offer only one product, then expression (12) collapses to the standard mark-up pricing formula:
$r_j^* = \sum_{i \in I_m} \left(mc_j^D - s_{ijl} \times \left(\frac{\partial s_{ijl}}{\partial r_j} \right)^{-1} \right)$.

4.3.2 Broker-Lender Bargaining over Commissions

In each market t, before setting prices and making any sales brokers and lenders bilaterally meet and bargain á la Nash to determine whether to form an agreement. If successful, they set a per sale commission that is expressed as a percentage of the final loan amount. There are $L_t \times B_t$ potential contracts, and brokers and lenders have complete information about all payoff functions. I assume that the negotiated commission for each contract solves the Nash bargaining solution for that contract. Thus, the equilibrium commission vector maximizes the Nash product of each pair's gains from trade, conditional on agreements reached by all other pairs. Moreover, given that the agreement value for a broker dealing with a given lender may change depending on whether she has reached an agreement with another lender with similar mortgage products, I also assume that each contract remains the same even if negotiation for another contract fails. Thus, all negotiations within market t are simultaneous and separate, such that commissions set in other meetings are not known but conjectured. This setting is motivated by the model presented in Horn & Wolinsky (1988), and it is commonly used by other empirical papers (see, e.g., Crawford & Yurukoglu 2012, Grennan 2013, Gowrisankaran et al. 2015, Ho & Lee 2017*a*,*b*, Crawford et al. 2018).[5] Despite these assumptions, lenders and brokers' payoffs will still depend on outcomes of bilateral negotiations for which they are not party to. I start by considering the ex-ante payoff structures for brokers and lenders, and their resulting participation constraints. I then show the Nash bargaining solution to each contract.

Each broker seeks to maximize his ex-ante expected payoff from serving all households who hire her services. Given lenders' expected rates and households' expected mortgage and sales channel choices, the ex-ante expected utility for broker b in market t, as a function of commissions and network structure N_{bt}, is given by:

$$W_{bt}(\boldsymbol{c}_{bt}, N_{bt}) \;=\; \sum_{i \in I_t} \Big(1 - F_\kappa[\hat{\kappa}_{it}(\boldsymbol{c}_t)]\Big) * \pi_{b(i)t} * \sum_{j \in J_{b(i)t}, N_{bt}} s_{b(i)jlt}(\boldsymbol{c}_{bt})\; W_{bljt}(c_{lbt}) \tag{15}$$

where $\boldsymbol{c}_{bt}$ is all commissions payments of broker b and $W_{bjlt}(c_{lbt})$ is the broker's utility from originating product j with lender l in market t as defined in equation 5. Brokers' ex-ante utility also depends on households' probability of choosing the brokerage channel, $(1 - F_\kappa[\hat{\kappa}_{it}(\boldsymbol{c}_t)])$, which is a function of commission payments for all brokers in market t. Similarly, the ex-ante expected profits to lender l in market t, conditional on commissions

[5] Recently, Collard-Wexler et al. (2018) have provided a non-cooperative foundation for this bargaining solution based on Rubinstein's model of alternating offer bargaining.

and network structure N_{lt}, are given by:

$$\Pi_t^l(\boldsymbol{c}_{lt}, N_{lt}) = \sum_{i \in I_t} \Bigg(\underbrace{F_\kappa[\hat{\kappa}_{it}(\boldsymbol{c}_t)] \sum_{j \in J_{lt}} \left(s_{ijlt} * \Pi_{jt}^D\right)}_{\text{Revenue from Direct Sales}} \\ + \underbrace{\left[1 - F_\kappa[\hat{\kappa}_{it}(\boldsymbol{c}_t)]\right] \sum_{j \in J_{lt}} \sum_{b \in N_{lt}} \left(\pi_{b(i)t} * s_{b(i)jt} * \Pi_{jt}^b(c_{lbt})\right)}_{\text{Revenue from Broker Sales}} \Bigg) \tag{16}$$

where $\boldsymbol{c}_{lt}$ is a vector with all commissions paid by lender l to all brokers, and lender profits are defined by equations 7 and 8.

Brokers and lenders' ex-ante expected profits are key in the Nash bargaining model, as they determine the agreement and disagreement payoffs. Using equations (15) and (9), the exponentiated product of the net payoffs from agreement is given by:

$$NP_t^{lb}\left(c_{lbt} | \boldsymbol{c}_{-lbt}\right) = [\, \underbrace{\Pi_t^l(c_{lbt}|\boldsymbol{c}_{-lbt}) - \Pi_t^l(0\, |\boldsymbol{c}_{-lbt})}_{\text{Gains from trade for lender } l} \,]^{\,\beta_{lb}} \\ \times [\, \underbrace{W_{bt}(c_{lbt}|\boldsymbol{c}_{-lbt}; N_{bt}) - W_{bt}(0\, |\boldsymbol{c}_{-lbt}; N_{bt} \setminus J_l)}_{\text{Gains from trade for broker } b} \,]^{\,1-\beta_{lb}} \tag{17}$$

where β_{lb} is the bargaining power of lender l when negotiating with broker b. Setting $\beta_{lb} = 0.5$ assumes symmetric Nash bargaining, and setting $\beta_{lb} = 0$ assumes Nash-Bertrand pricing behavior by lenders. Disagreement payoffs imply that all commissions for broker b for the sale of all products from lender l are set to zero. That is, I treat products for each lender as an indivisible block, meaning that if bargaining breaks down between a lender and a broker, then the broker cannot originate any of the lender's products and the lender will not be part of the broker's network. Moreover, I assume lenders face no capacity constraints. Hence, in the event of a disagreement between a lender and a broker, the broker can originate a mortgage with his ex-post second choice of lender without facing any restrictions on the lender's side.

I define the Nash bargaining solution as the commission vector $\boldsymbol{c}_t^*$ that maximizes equation (17) for each Nash bargaining contract, conditioning on the outcomes of all other contracts.

Therefore, each c^*_{lbt} in $\boldsymbol{c}^*_t$ solves the following maximization problem:

$$\max_{c_{lbt}} \quad NP^{lb}_t\,(c_{lbt}|\boldsymbol{c}^*_{-lbt}) \quad \textit{such that}$$

$$(1)\;\; \Pi^l_t(c_{lbt}|\boldsymbol{c}^*_{-lbt}; N_{lt}) - \Pi^l_t(0\,|\boldsymbol{c}^*_{-lbt}; N_{lt} \setminus b) \;\geq\; 0 \;\; (\textit{Lender Participation Constraint})$$

$$(2)\;\; W_{bt}(c_{lbt}|\boldsymbol{c}^*_{-lbt}; N_{bt}) - W_{bt}(0\,|\boldsymbol{c}^*_{-lbt}; N_{bt} \setminus J_l) \;\geq\; 0 \;\; (\textit{Broker Participation Constraint})$$

where $\boldsymbol{c}^*_{-lbt}$ is the equilibrium commission vector, excluding the commission of the lender-broker pair in the negotiation. Participation constraints (1) and (2) need to be imposed since an agreement is not mandatory and either broker or lender can unilaterally walk away. Expanding the participation constraint of lender l dealing with broker b, I get:

$$\begin{aligned}
\Delta\Pi^l_t(c_{lbt}|\boldsymbol{c}^*_{-lbt}) = &\sum_{i\in I_t}\Bigg[\underbrace{\Big(1 - F_\kappa[\hat{\kappa}_{it}(c_{lbt}|\boldsymbol{c}^*_{-lbt})]\Big)\sum_{j\in J_{lt}}\pi_{b(i)t}\;\, s_{b(i)jlt}(c_{lbt}|\boldsymbol{c}^*_{-lbt})\;\,\Pi^b_{ijt}(c_{lbt})}_{\text{Expected profits from dealing with broker } b} \\
&+ \underbrace{\Big(\,F_\kappa[\hat{\kappa}_{im}(c_{lbt}|\boldsymbol{c}^*_{-lbt})] - F_\kappa[\hat{\kappa}_{it}(0|\boldsymbol{c}^*_{-lbt})]\,\Big)}_{\text{Change in sales channel choices}} * \\
&* \underbrace{\sum_{j\in J_{lm}}\Big(s_{ijlt}\,\Pi^D_{ijt} - \sum_{b'\neq b}\pi_{b'(i)t}\,s_{b'(i)jlt}(\boldsymbol{c}^*_{-lbt})\,\Pi^{b'}_{ijt}(\boldsymbol{c}^*_{-lbt})\Big)}_{\text{Gains/losses from other sales channels}}\Bigg] \\
&\geq 0
\end{aligned} \tag{18}$$

Equation 18 implies that, for the lender's participation constraint to be non-binding, commission payments need to be below a certain threshold, $\bar{c}_{lbt}$. Similarly, I can expand

the participation constraint of broker b dealing with lender l:

$$\begin{aligned}\Delta W_{bt}(c_{lbt}|\boldsymbol{c}^*_{-lbt}) = \sum_{i\in I_t}\pi_{b(i)t}\Bigg[& \underbrace{\left(1 - F_\kappa[\hat{\kappa}_{im}(c_{lbt}|\boldsymbol{c}^*_{-lbt})]\right)\sum_{j\in J_{lt}} s_{b(i)jlt}(c_{lbt}|\boldsymbol{c}^*_{-lbt})\, W_{b(i)jt}(c_{lbt})}_{\text{Profits from selling products from lender } l} \\ & + \underbrace{\left(1 - F_\kappa[\hat{\kappa}_{it}(c_{lbt}|\boldsymbol{c}^*_{-lbt})]\right)\sum_{\substack{k\notin J_{lt}\\ l'\neq l}} s_{b(i)kl't}(c_{lbt}|\boldsymbol{c}^*_{-lbt})\ W_{b(i)jt}(c_{l'bt})}_{\text{Gains/losses from other product sales + changes in sales channel choices}} \\ & - \overbrace{\left(1 - F_\kappa[\hat{\kappa}_{it}(0|\boldsymbol{c}^*_{-lbt})]\right)\sum_{\substack{k\notin J_{lt}\\ l'\neq l}} s_{b(i)kl't}(0|\boldsymbol{c}^*_{-lbt})\ W_{b(i)jt}(c_{l'bt})}\ \Bigg] \\ & \geq 0 \end{aligned} \tag{19}$$

Equation 19 shows that, for the broker's participation constraint to be non-binding, commission payments need to be above a certain threshold, $\underline{c}_{lbt}$. Therefore, for a broker and a lender to begin negotiations, it must be that the maximum commission a lender is willing to pay is higher than the minimum commission a broker is willing to accept, that is, $\bar{c}_{lbt} > \underline{c}_{lbt}$. A lender's decision to reach an agreement with a broker is affected by downstream competition between brokerage services and the lender's in-house distribution channels (e.g., branches). A lender may decide to exclude brokers operating in areas where it has an extensive branch network and his outside option (i.e., direct sales) is much higher. On the other hand, a broker may decide to exclude a lender from her network if the profits she gets from selling other products is sufficiently larger. The intuition is that when jointly agreeing on a mortgage with households, brokers need to split the surplus as given by equation 5. When distortion parameter θ_b is very low (e.g., the broker has limited bargaining power), the household's utility dominates the broker's utility and mortgage choices for the pair are driven by households preferences. However, if brokers refrain from including low-commission lenders in their networks, then households' will be forced to choose among choice sets that are beneficial for brokers. The downside is that households will anticipate the more restricted network and may decide to switch to direct sales instead. The latter effect may be small for some lenders, causing brokers to exclude them from their network if their commission is not sufficiently high.

Given each pair's maximization problem, there are three possible outcomes in terms of agreement and optimal commission. First, if $\bar{c}_{lbt} < \underline{c}_{lbt}$, then no agreement is reached and the broker is not allowed to originate mortgages with that lender. Second, if, on the

other hand, $\bar{c}_{lbt} \geq \underline{c}_{lbt}$ and both participation constraints are not binding, then each pair chooses an optimal commission rate, c^*_{lbt}, such that the first-order conditions are equal to zero, $\partial log\ (NP^{lb}_t)\ /\ \partial c_{lbt} = 0$. Finally, if at least one of the participation constraints is binding, then the optimal commission is either $\bar{c}_{lbt}$ or $\underline{c}_{lbt}$.

5 Estimation and Identification

5.1 Demand

5.1.1 Household Preference Parameters

I assume that demand taste shocks, ε_{ijlm} and $\epsilon_{b(i)jlm}$, in the indirect utilities are identically and independently distributed across households, products and lenders with a type I extreme value distribution. Conditional on going through the direct channel, the probability of household i choosing product j from lender l in market t is given by:

$$s_{ijlt} \equiv Pr\ (\ jl\ \ chosen \mid C_{it}) = \frac{exp\left(\bar{V}_{ijlt}\right)}{\sum_{ks=0}^{C_{it}} exp\left(\bar{V}_{ikst}\right)} \tag{20}$$

where $\bar{V}_{ijlt}$ is household indirect utility in equation 3 excluding the error term ε_{ijlt}. Similarly, if household i hires broker b, then the probability of choosing product j from lender l in market t is given by:

$$s_{b(i)jlt} \equiv Pr\ (\ jl\ \ chosen \mid C_{b(i)t}) = \frac{exp\left(\bar{V}_{b(i)jlt}\right)}{\sum_{ks=0}^{C_{b(i)t}} exp\left(\bar{V}_{b(i)kst}\right)} \tag{21}$$

where $\bar{V}_{b(i)jlt}$ is broker-household indirect utility as defined in equation 5 without the error term $\epsilon_{b(i)jlt}$. Given these choice probabilities, the log-likelihood for direct and intermediated channels is defined as:

$$ln\ (L_i|\eta_i, \delta^G_{jlt}, \delta_{blt}) \ \ = \ \sum_{jl=0}^{C_i} \mathbb{1}_{ijlt}\Big(\mathbb{1}^D_i\ s_{ijlt} + \sum_{b\in B_t} \mathbb{1}^b_i\ s_{b(i)jlt}\Big) \tag{22}$$

where η_i is a vector of all demand parameters, $\mathbb{1}_{ijlt}$ is a dummy equal to one if household i buys product j from lender l in market m; $\mathbb{1}^D_i$ is a dummy equal to one if household i chooses the direct channel; $\mathbb{1}^b_i$ is a dummy equal to one if household i hires broker b. Similarly, I include product-lender-market-group fixed effects, δ^G_{jlt}, account for product mean utility in a income-region group (G), that is, the part of utility obtained from product j from lender l in market t which is common across all households i in group G. Similarly, I

add broker-lender-market fixed effects, δ_{lbt}, to control for broker-lender mean utility, that is, the part of the utility obtained from originating a product with lender l which is common across all households going to broker b in market t.

Identification.– One of the limitations of having transaction data is that households' choice sets and lenders' affordability criteria are unobserved. In order to identify preference parameters, I create a household-specific counterfactual choice set depending on their observable characteristics. First, I divide households into groups based on geographical regions and year-quarter. I assume that households in each group can access all products sold in that region during that quarter, but not those sold in other regions or other quarters. The geographical restriction affects mostly building societies and smaller banks since they often have limited coverage. The time restriction is needed to account for the entry and exit of products. Next, I consider all households that purchased a given product and select those with the lowest credit score, the highest loan-to-income, and the highest age. I do this for every product. I then assume that a household will not qualify for that product if (1) it has a credit score smaller, (2) a loan-to-income larger, or (3) is older than the cut-off values. The rationale for these restrictions is based on lenders' most common set of affordability criteria, which rely on credit scores, loan-to-income, and age. Finally, for the intermediated sales channel, I further restrict the choice set of the household-broker pair to products sold by lenders with whom the broker has reached an agreement in the bargaining stage.

After constructing a consideration choice set for each household, I proceed to estimate demand parameters in the log-likelihood described in equation 22. To identify household preferences over product characteristics (α, β) I use a two-step instrumental variables approach to explicitly account for possible correlations between interest rates (r_{jlt}) and unobservable product characteristics (ξ_{jlt}). I use a similar two-step approach to identify broker preferences over commission payments and broker downstream market power (θ_b). This approach allows me to account for correlations between commissions (c_{lbt}) and unobservable broker-lender relationships varying over time (ζ_{blt}). In a first step, I maximize the log-likelihood and recover estimates for household preferences over branches (λ), broker preferences over product characteristics other than commissions (γ_2), product-lender-market-group fixed effects (δ^G_{jlt}) and broker-lender-market fixed effects (δ_{lbt}). I can separately identify broker and household preferences as long as household preference parameters for product characteristics remain constant across sales channels. I can identify the coefficient on bank branches as long as household value nearby branches only when originating their mortgage directly through lenders. That is, for households going through brokers, branches do not play a role.

In a second step, I regress the estimated product-lender-market fixed effects ($\hat{\delta}^G_{jlt}$) on

interest rates and product characteristics:

$$
\begin{aligned}
\hat{\delta}^{G}_{jlt} \;&= [\, \alpha_G \, r_{jlt} + \psi_G \, High\, LTV \,] \times \mathbb{1}[i = Income\text{-}Region\, G] \\
&+ \, Lender\, FE + \, Market\, FE \, + \varepsilon_{ijlt}
\end{aligned}
\tag{23}
$$

where $High\, LTV$ is a dummy equal to one if LTV is 85% or higher. Since interest rates are potentially correlated with unobservable product characteristics included in the error term, I use an instrumental variable approach in order to get consistent estimates of demand parameters α_G and ψ_G. In particular, I use two cost shifters as instruments for the interest rate. I use risk weights associated with capital requirements, which vary across time, lender and loan-to-value bands. I also use the rate for Euro interest rate swaps for two, three and five years. Swap rates vary across time and type, and are a hedging instrument used by lenders when selling mortgages with fixed periods of two, three and five years, respectively. Both instruments allow me to exploit variation across markets, lenders and products. For identification, I am assuming that these instruments are uncorrelated with unobserved product characteristics once I control for lender and market fixed effects.

Moreover, I regress the estimated broker-lender-market fixed effects ($\hat{\delta}_{lbm}$) on commissions and broker dummies:

$$
\begin{aligned}
\hat{\delta}_{lbt} = &\sum_{b} \mathbb{1}[i = Broker\, b] \left(\frac{\theta_b}{1-\theta_b} \, \gamma_1 \;\, c_{lbt} \right) + \\
&+ \, Lender\, FE \, + \, Broker\, FE \, + \, Market\, FE \, + \; \varepsilon_{lbt}
\end{aligned}
\tag{24}
$$

where $\mathbb{1}[i = Broker\, b]$ is a dummy equal to one for broker b. I normalize γ_1 to one, and I use instrumental variables in order to control for possible correlations between the broker-lender commissions and unobservable (to the econometrician) broker-lender relationships that might affect brokers' choices. I use "BLP-type" instruments, i.e., commissions from other brokers and lenders. As a robustness check, I also use cost shifters for lenders and brokers: business rates (taxes) in counties where the lender has its headquarters and the broker has its principal place of business. These instruments exploit variation across markets, lenders and brokers. For identification, I assume that these instruments are uncorrelated with unobserved time-varying broker and lender characteristics once I control for lender, broker and market fixed effects.

5.1.2 Household Search Cost Distribution

I assigned households to groups, G, based on their income quartile q, region g and market t. I assume a household i in group G knows the average ex-ante expected maximum utility

that households in the same group get from each sales channel.[6] These ex-ante expected utilities can be computed using choice probabilities as given by equation 4 for both direct and intermediated sales. Let $\hat{\kappa}_G$ be the search cost that makes household i in group G indifferent between both sales channels. This indifference cut-off value is determined by:

$$\underbrace{\left(\sum_{i \in G}^{I_G} E\big[\max_{jl} \ V_{ijlt}(\eta)\,|Direct\big] \right) - \hat{\kappa}_G}_{\text{Direct Channel}} = \underbrace{\sum_{b \in G} \pi_{b(G)t} \sum_{i \in G}^{I_G} \left(E\big[\max_{jl} \ V_{b(i)jlt}(\eta)\,|\,b\,\big] - \alpha_G f_{Gbt} \right)}_{\text{Broker Channel}} \tag{25}$$

where η is a vector of all preferences parameters estimated in the mortgage choice problem; $E\big[\max_{jl} \ V_{ijlt}(\eta)\,|Direct\big]$ and $E\big[\max_{jl} \ V_{b(i)jlt}(\eta)\,|\,b\,\big]$ are the ex-ante expected household utilities of household i in I_G going directly to the lender and hiring broker b, respectively; $\pi_{b(G)t}$ is the probability that a household in group G is matched to broker b; f_{Gbt} is the broker fee paid by households in group G when hiring broker b. I multiply the fee by the price coefficient, α_G, in equation 23 to transform money into utils and make the fee comparable to the expected utilities. This indifference condition in equation 25 implies that, if household i in group G has a search cost draw κ_i that is greater than $\hat{\kappa}_G$, then it will choose to hire a broker. Similarly, if it has a search cost draw κ_i smaller than $\hat{\kappa}_G$, then it will opt for the direct sales channel and search for a mortgage across lenders' in-house distribution channels.

To estimate the mean and standard deviation of the search cost distribution across subgroups, I use equation 25 and the preference parameters estimated in the previous subsection. First, it is necessary to compute for each household the average expected ex-ante utility that it will receive from each sales channel. For the direct channel, following Small & Rosen (1981), household i will get an ex-ante expected maximum utility equal to:

$$E\big[\max_{jl} \ V_{ijlt}(\hat{\eta})\,|Direct\,\big] = ln\left[\sum_{ks \in J_{it}} exp\,\left(V_{ijlt}(\hat{\eta}, Direct)\right) \right] \tag{26}$$

where $\hat{\eta}$ is the vector of demand preference parameters estimated in the previous subsection.

For broker sales, each broker-household pair maximizes the joint utility as defined by equation 5. Therefore I need to split the ex-ante expected maximum utility of the pair into that of the broker and that of the household. In order to do so, I first simulate draws from

[6] Recent consumer surveys at the Financial Conduct Authority have shown that 67% of borrowers only consulted one broker when originating their mortgage. In another survey for UK financial products, citetfinney2008consumer find that most consumers only consulted at most one source of information before making a purchase. citetchater2010consumer reach similar conclusion after studying several European countries. Moreover, the FCA's Financial Lives Survey 2017 indicates that 23% of borrowers chose their broker because they were suggested by an estate agent and 29% because it was recommended by a friend or relative. This indicates that this referral is influential for some consumers. Given households' limited search for a broker and the importance of referrals, it seems like a reasonable assumption that households only know the average utility similar households got when choosing the brokerage channel.

the distribution of the household's error term for each product assuming a type I extreme value distribution. For each draw, I compute the utility of the broker-household pair for each product in the pair's choice set and select the product that gives the pair the highest utility. I then compute the household's utility for that choice. Finally, I take the average of the maximum household utilities across draws, which will give me a numerical approximation of the household's expected ex-ante utility from that broker.

After computing all ex-ante expected maximum utilities for all channels and all income-region groups, I can rewrite equation 25 as:

$$\hat{U}_G^{Direct} - \hat{\kappa}_G = \hat{U}_G^{Broker} \tag{27}$$

where $\hat{U}_G^{Direct}$ is the estimated expected maximum indirect utility of going direct, and $\hat{U}_G^{Broker}$ is estimated average expected net maximum indirect utility of choosing the broker channel (after subtracting broker fees and multiplying by probability of being pair with that particular broker). The probability of household i choosing the direct channel will depend on whether its search cost κ_i is smaller than $\hat{\kappa}_i$:

$$\begin{aligned} P_i^{Direct} &= Prob\,(\,\kappa_i < \hat{\kappa}_G) \\ &= \int \mathbb{1}(\kappa_i < \hat{\kappa}_G)\, f(\kappa) d\kappa \end{aligned} \tag{28}$$

Likewise, the probability that household i will choose the broker channel is given by:

$$\begin{aligned} P_i^{Broker} &= Prob\,(\,\kappa_i > \hat{\kappa}_G) \\ &= \int \mathbb{1}(\kappa_i > \hat{\kappa}_G)\, f(\kappa) d\kappa \end{aligned} \tag{29}$$

I assume that search costs κ follow a normal distribution with mean μ and standard deviation σ, so that the probability density of κ is given by:

$$f(\kappa \mid \mu, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} exp - \frac{(\kappa - \mu)^2}{2\sigma^2} \tag{30}$$

Therefore, the log-likelihood function is defined as:

$$Ln\,[L(y_i, \hat{\kappa}_G; \mu, \sigma^2)] = \sum_i ln\Bigg(\Big[F(\hat{\kappa}_G \mid \mu, \sigma^2)\Big]^{y_i} \Big[1 - F(\hat{\kappa}_G \mid \mu, \sigma^2)\Big]^{1-y_i}\Bigg) \tag{31}$$

where $F(.)$ is the cdf of κ, which is obtained by integrating equation 30, and y_i is a dummy variable equal to one if the household chose to go directly to the lender and zero if it hired a

broker. The value $\hat{\kappa}_i$ is determined by equation 27.

Identification.– Identification of the search cost distribution parameters, μ and σ, comes from variation in consumer choices and their expected utilities.

5.2 Supply

5.2.1 Lender Marginal Costs

The estimation of lenders' marginal costs is based on the optimal pricing formula derived in Section 4.3.1. Using the estimated preference parameters and cut-off search costs, I can back out from equation 12 the average effective marginal costs (AMC_{jt}), which are a weighted average of the marginal costs from direct and intermediated sales. I then assume that marginal costs from intermediated sales are a function of product characteristics and an error term, while marginal costs from direct sales are the same as those of intermediated sales plus a premium. Using equations 12, 13 and 14, I can rewrite average effective marginal costs as:

$$\begin{aligned} AMC_{jt} &= mc^D_{jt}\,\rho^D_{jt} + \sum_{b=1}^{B} \pi_{bt}(mc^B_{jt} + \frac{c_{lb}}{t_j})\,\rho^b_{jt} \\ &= \Big[(\varphi_1+\varphi_2)X_{jt} + \epsilon_{jt}\Big]\,\rho^D_{jt} + \sum_{b=1}^{B} \pi_{bt}(\Big[\varphi_1 X_{jt} + \epsilon_{jt}\Big] + \frac{c_{lb}}{t_j})\,\rho^b_{jt} \\ &= (\varphi_1+\varphi_2)\tilde{X}^D_{jt} + \varphi_1 \tilde{X}^B_{jt} + K + \varepsilon_{jt} \end{aligned} \tag{32}$$

where $\tilde{X}^D_{jt}$ is a vector of product characteristics, namely loan-to-value band and initial period, multiplied by ρ^D_{jt}, and $\tilde{X}^B_{jt}$ is the same vector of product characteristics times ρ^B_{jt}; K is a function of observed data on product characteristics, commission payments, ρ^D_{jt} and ρ^B_{jt}. I get estimates for φ_1 and φ_2 by regressing the effective marginal costs I have retrieved from equation 12, $A\hat{M}C_{jt}$, on $\tilde{X}^D_{jt}$ and $\tilde{X}^B_{jt}$. Then, I can use $\hat{\varphi}_1$ and $\hat{\varphi}_2$ from this two-step estimation approach to predict the marginal costs of both direct and intermediated sales.

Identification.– I recover effective average marginal costs comes by inverting lenders' optimal first-order conditions. Then, to separately identify direct and intermediated marginal costs, I exploit variation across product choice probabilities conditional on sales channels and changes in household choices of direct versus intermediated channels. I also use that for intermediated sales the lender has to pay an additional commission to brokers.

5.2.2 Broker-Lender Bargaining Parameters

The bargaining parameters depend on the protocol of the bargaining game and the outside options of both lenders and brokers, as defined in section 4.3.2. Given estimates for demand preferences, household search costs and marginal costs, I choose the values of β_{bl} that minimize the distance between observed equilibrium commissions and the estimated optimal commissions from the model, as determined by the first-order conditions in the bargaining game.

Identification.– For each broker-lender pair, I invert the first-order conditions in each pair's bargaining problem. At this stage, the only unknowns are the bargaining parameters. In order to identify them, I exploit the horizontal and vertical structure of the market. In particular, I use the fact that households can bypass intermediaries and originate their mortgage directly through lenders. Therefore, brokers and lenders also compete downstream for customers. I exploit geographical and time variation in lenders' branch networks that affects lenders' outside options, but not their bargaining parameters. Moreover, since demand realizations and changes in branch networks are observed more frequently than commission renegotiations, I am able to identify bargaining parameters separately from changes in outside options. I also use variation on commission payments both across lenders, brokers and time.

6 Estimation Results

6.1 Demand Parameters: Preferences and Search Costs

For estimating the demand parameters described in subsection 5.1, I use a 25% random sample as a training sample, and then use the remaining 75% of the data for cross-validation. Panel A in Table 5 reports the estimated demand parameters of the households' mortgage choice problem for the 25% random sample.

The average point estimate of the coefficient on interest rates across all income-region groups is significant and equal to -0.91, implying that borrowers dislike more expensive mortgages. The corresponding average own-product demand elasticity is equal to 3.34, and the cross-product demand elasticity equals 0.02. That is, on average, a one-percent increase in the interest rate decreases the market share of the mortgage by 3 percent, while the shares of other mortgages increase by 0.02 percent. I also find that first-time-buyers value more mortgages with higher leverage, as captured by parameter $\bar{\gamma}_{21}$. These type of borrowers are often credit constrained, and a higher loan-to-value allows for lower down-payments. Borrowers also value the fraction of branches in nearby postcodes when purchasing the mortgage directly from lenders. This effect disappears when borrowers originate the mortgage through a broker.

Table 5: Demand Estimates

PANEL A: Mortgage Choice Parameters

	Interest Rate (α)	High LTV (ψ)	Branches Direct (λ)	Commission Broker ($\bar{\theta}$)	High LTV Broker ($\bar{\gamma}_{21}$)	2-Year Fixed Broker ($\bar{\gamma}_{22}$)
Estimate	-0.91	0.45	0.33	0.37	0.14	0.27
SE	0.39	0.10	0.09	0.11	0.02	0.08
N Likelihood	7,493,244	7,493,244	7,493,244	7,493,244	7,493,244	7,493,244
N Borrowers	91,137	91,137	91,137	91,137	91,137	91,137
N 2nd Stage	5,208	5,208	-	483	-	-
Lender FE	Yes	Yes	-	Yes	-	-
Market FE	Yes	Yes	-	Yes	-	-
Broker FE	-	-	-	Yes	-	-
F-stat	102	102	-	26	-	-

PANEL B: Sales Channel Choice Parameters

	All Borrowers	London	Other Regions	Q1 Income	Q2 Income	Q3 Income	Q4 Income
SEARCH COSTS							
Mean (μ)	3.3	2.9	4.1	3.1	3.3	3.9	5.0
Stand. Dev. (σ)	0.5	0.4	0.7	0.8	0.7	0.5	0.2

Note: Panel A shows the structural demand estimates of the logit model for demand for mortgage products. The model is estimated for a 25% random sample. Standard errors are computed by bootstrapping. The F-stat is the F statistics for the excluded instrument in the second stage instrumental variable regressions for both product-market and broker-lender-market estimated fixed effects. N likelihood is the total number of observations in the first stage (borrower-product pairs). N second stage is the number of observations in the second stages. N borrowers in the total number of borrowers in the 25% random sample. Panel B presents the estimates for the search cost distributions. I use the entire sample for this part of the estimation.

Panel A in Table 5 also presents estimates for brokers' distortions to households' choices (brokers' downstream market power). The average distortion is equal to 0.37, as captured by parameter θ. Figure 6 shows the distribution of θ across broker companies, with values ranging between 0.28 and 0.45. Although brokers are heterogeneous in their influence on borrowers, I can reject the null hypothesis of benevolent brokers (θ equal to zero) at a 5% significance level for all broker companies. Besides, brokers seem to have a preference for products with shorter initial fixed periods (2-year mortgages) and higher leverage. This preference is not surprising given the financial incentives brokers face. As already described in section 3, brokers get fees and commission payments every time households remortgage. Thus, it is in their best interest to make this event happen as often as possible. Considering that the commission payment is a percentage of the loan amount, brokers can nudge households towards higher loan-to-value products. Results also show evidence of lender geographical market power. The estimate for household preferences for bank branches (λ) is positive and significant. Moreover, it is 30% of the size of the average estimate for interest rates, implying that households going directly to lenders have a strong preference for nearby branches.

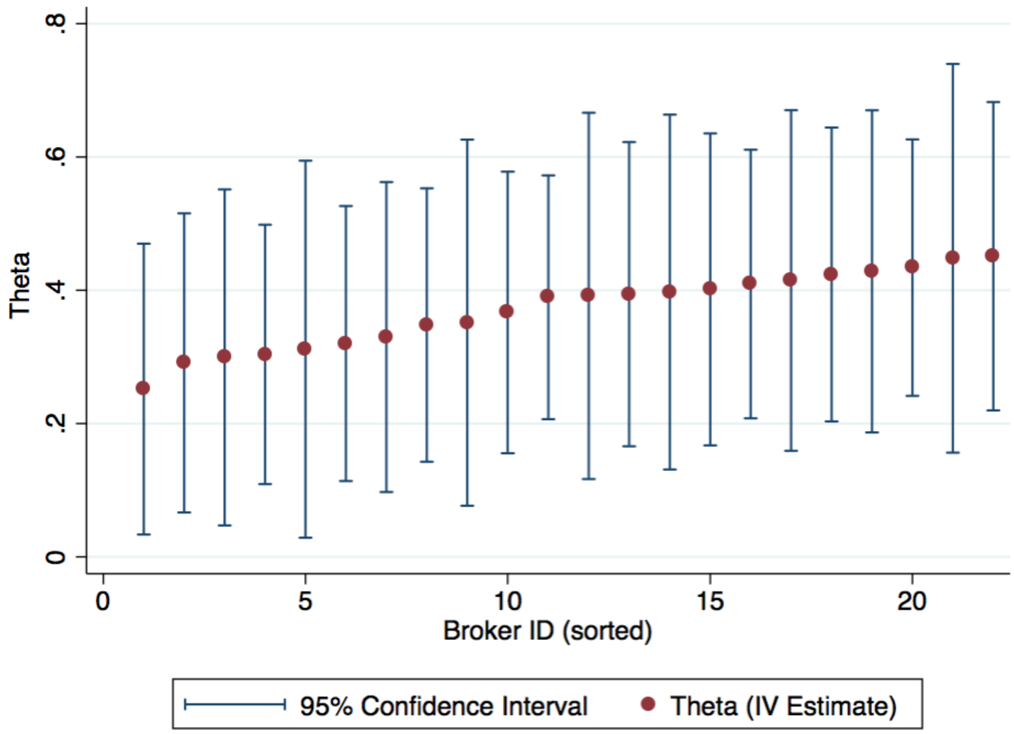
In terms of the fit of the model, Figure B.1 compares the distribution of estimated and observed market shares for both training and cross-validation samples. The model fits the out-of-sample data quite well, both in terms of mean and variance. The fit is also good when accounting for product characteristics, namely lender, initial period and loan-to-value band. Figure B.2 plots estimated and observed market shares across these dimensions. The main limitation is that the model over-predicts the share of shorter initial period mortgages and has a higher variance for products with loan-to-value bands above 85%.

Panel B in Table 5 presents estimates for the mean and standard deviation of borrowers' search cost distributions across income-region groups, as described in section 5.1.2. I use the entire sample to estimate these parameters. I find that the average search cost for all first-time-buyers is equal to 3.3, with a variance of 0.5. Panel A in Figure C.1 shows how borrowers in London have a lower average search cost than those in other regions in the UK. Similarly, Panel B in Figure C.1 shows that average search costs increase with income, while the variance decreases.

6.2 Supply Parameters: Marginal Costs and Bargaining

The first column of Table 6 presents average estimates for marginal costs. The average marginal cost is 1.82 percentage points. Small banks have the highest average marginal costs, resulting partly from higher funding costs. Mortgages with longer initial deals and higher loan-to-values are also more expensive on average. The second and third columns of Table 6 differentiate between average marginal costs for direct and intermediated sales, with intermediated sales being, on average, 7% less costly to originate than direct sales.

Figure 6: Broker Market Power Estimates



Note: The graph shows estimates of distortion parameter θ_b for the largest 20 broker companies in the market and two categories of small and medium brokers. These parameters are obtained after regressing the estimated broker-lender-market fixed effects on commissions interacted with broker dummies. I also control for market, broker and lender fixed effects. To account for endogeneity concerns, I use as BLP-type instrumental variable for commissions. Standard errors are computed by bootstrapping.

Figure C.2 plots marginal cost distributions for both origination channels, illustrating the lower mean and higher variance of broker sales' marginal costs. This differential in marginal costs across sales channels is higher for the Big Six, for whom intermediated sales are 12% cheaper. Challenger banks face similar marginal costs, regardless of sales channel, while both small banks and building societies find it more costly to originate mortgages through intermediaries rather than through in-house distribution channels. This heterogeneity can be partly driven by the Big Six having intermediary-only online platforms that facilitate the application process and take advantage of economies of scale, which can ultimately reduce the cost of originations via brokers, e.g. through quicker income verification. Intermediated sales also have a lower marginal cost for low loan-to-value products.

Given marginal costs, I compute average mark-ups and find that average mark-up is 22%, which is close to the range that other papers studying the UK mortgage market have reported (see, e.g., Benetton 2018). Table 7 shows the existing variation in mark-ups across lender

Table 6: Marginal Costs

	Total	Direct Sales	Intermediated Sales
All	1.82	1.93	1.79
Lender Type			
Big Six	1.80	1.95	1.71
Challengers	1.84	1.87	1.83
Small Banks	2.31	2.16	2.40
Building Societies	1.87	1.78	1.93
Initial Period			
2-Years	1.73	1.75	1.73
3-Years	1.94	2.02	1.89
5-Years	1.98	2.10	1.84
LTV Band			
LTV $\leq$ 80	1.60	1.79	1.50
LTV >80	2.03	2.04	2.03

Note: Marginal costs are expressed in percentage points and computed for direct and intermediated sales. I report total average marginal costs taking into account direct and intermediated sales for each product in each time period. I also report marginal costs by different product characteristics: lender, initial period and loan-to-value band.

types and other product characteristics. Most importantly, once I differentiate between mark-ups for direct and intermediated sales (accounting for commission payments), intermediated sales are estimated to be 37% less profitable for lenders than their in-house direct sales. This is the case for all lenders and all product types, implying that brokers have some market power when negotiating with lenders and are able to extract surplus from lenders given borrowers' preferences for the brokerage channel. Finally, given demand and cost estimates, Table 8 reports my estimates for bargaining parameters, as described in section 5.2.2. Higher values indicate relatively more bargaining power for lenders. Bargaining parameters are heterogeneous and range between 0.19 and 0.72. These values reject the hypothesis of take-it-or-leave-it offers since bargaining parameters are neither one, which would imply lenders choose mutually agreeable commissions that make brokers' participation constraints binding, nor zero, which would imply brokers offer commissions that make lenders' participation constraints binding. I find that large brokers have a 50% lower bargaining power when facing the Big Six and building societies than when negotiating with challengers and small banks. Small brokers, on the other hand, are able to equally split the surplus when negotiating with

Table 7: Mark-ups

	Total	Direct Sales	Intermediated Sales (Pre-Commission)	Intermediated Sales (Post-Commission)
All	22%	28%	32%	18%
Lender Type				
Big Six	22%	26%	36%	20%
Challengers	19%	30%	33%	17%
Small Banks	13%	27%	20%	7%
Building Societies	24%	36%	31%	16%
Initial Period				
2-Years	19%	29%	31%	15%
3-Years	24%	28%	34%	19%
5-Years	25%	27%	37%	23%
LTV Band				
LTV $\leq$ 80	23%	26%	38%	21%
LTV >80	17%	20%	20%	16%

Note: Mark-ups are expressed as a percentage of the interest rate. I report average mark-ups for all products and by different product characteristics: lender, initial period and loan-to-value band. I also differentiate between direct and intermediated sales mark-up. For the latter, I consider separately mark-ups before and after commission payments.

all types of lenders. Among lenders, the Big Six have a bargaining power of 0.72 when dealing with large brokers, but that situation is reversed when negotiating with small brokers. The same happens to building societies. Challengers, however, only have a bargaining power of 0.28 when facing large brokers, but are able to extract 50% of the surplus against small brokers. Similarly, small banks a higher bargaining parameter in negotiations with small brokers.

Table 8: Lender Bargaining Parameters

	Large Brokers	Small Brokers
Big Six	0.72	0.41
Challengers	0.28	0.50
Building Societies	0.61	0.47
Small Banks	0.19	0.51

Note: This table reports estimated bargaining parameters for lenders versus large and small broker companies. Larger values of the bargaining parameters indicate relatively more bargaining power for lenders.

7 Counterfactual Scenarios

In this section I use the estimates from the model to simulate counterfactual scenarios. Fist, I implement a ban on brokerage services to estimate the gains from having brokers in the market. Next, I consider equilibrium effects from policies that impose restrictions on commission payments. In all simulations, I make assumptions consistent with a short-run analysis. I assume that lenders do not change their available products and that there is no entry or exit in the market. I also impose that preferences remain invariant and that lenders' marginal costs are not affected by the policy change. I recognize that some of the assumptions underlying the results in the simulations are strong, but...

7.1 Restrictions on brokerage services and commissions

The reduced form evidence in Section 3 suggests that brokers react to supply-side incentives. Similarly, estimates for brokers' distortion parameters θ_b in Section 6 also reject the hypothesis of benevolent brokers, indicating that brokers' choices respond to commission payments. In order to align households' and brokers' incentives, regulators have imposed restrictions on upstream payments to intermediaries. To address the effects of such policies, I use the estimated model to explore the equilibrium impact of changes in commission payments.

First, I simulate an equilibrium without any brokerage services. Column (1) in Table 9 reports estimates of a counterfactual in which households can only originate their mortgages via lenders' in-house distribution channels. Prices go up by almost 25%, and search costs increase by more than 150%. Consumer surplus falls by 51% and lender profits increase by 12%. This scenario shows that brokers do provide a service to households by reducing search costs and increasing competition upstream. The fact that marginal costs also increases by

Table 9: Counterfactual Restrictions on Commission Payments

	Ban on Brokerage %Δ	Ban on Commissions %Δ	Cap on Commissions %Δ
Market Structure			
HHI	35%	21%	5%
Share Big Six	19%	12%	3%
Pass-Through			
Prices	24%	11%	-5%
Marginal Cost	13%	9%	-1%
Lender Profits	12%	7%	-2%
Demand			
Share Direct	357%	115%	30%
Search Costs	156%	83%	13%
Consumer Surplus	-51%	-26%	9%

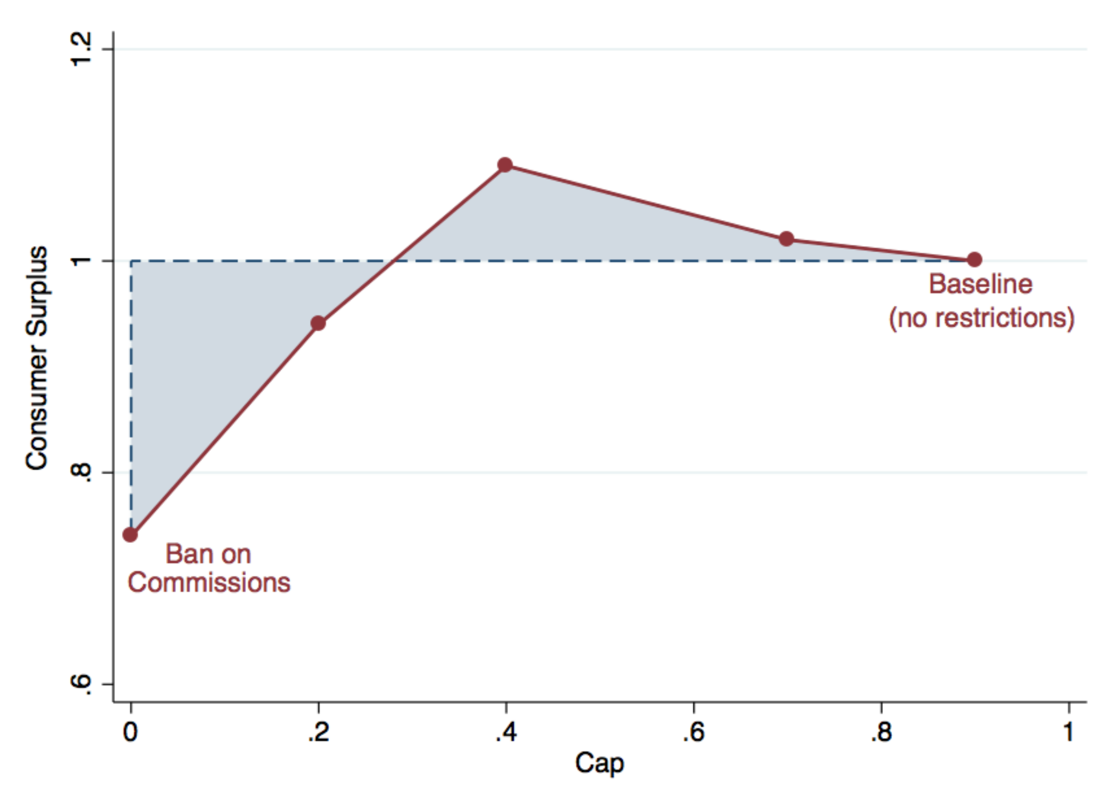
Note: Column (1) reports estimates of restricting brokerage services, so that all mortgages are originated through lenders' in-house distribution channels. Columns (2) and (3) show estimates for policies imposing a ban and a cap on commissions, respectively. Column (4) presents results for setting an homogenous fixed fee as commission payment for all brokers and lenders.

13% indicates that brokers also play a role improving efficiency in the market.

Next, I consider the equilibrium effects of imposing a ban on commissions, while keeping per-sale broker profits constant. In this counterfactual, I assume that broker fees to households' increase such that the average per-sale profit each broker company gets is the same as in the estimated baseline model.[7] Column (2) in Table 9 shows how market concentration and prices go up, as well as marginal costs and search costs. Consumer surplus falls by more than 25% and profits for the Big Six increase by more than 27%. To illustrate the mechanism that seems to dominate in this equilibrium, consider a household with large search costs. In the baseline model, this household chooses the brokerage channel. However, since broker fees to households significantly go up in this counterfactual, this household now decides to originate its mortgage via lenders' in-house distribution channels. As shown in

[7] I need to make an assumption on broker pass-through since my model does not endogeneize broker fees to households. Since most broker companies in the baseline charge zero fees, it would be unrealistic not to change fees in the counterfactual. Broker companies need to make money, and, if lenders are no longer making payments, it seems reasonable to assume household fees will go up.

Figure 7: Consumer Surplus and Maximum Commission Rates



Note: A ban on commissions is equivalent to imposing a cap equal to zero. No restrictions on commissions is equivalent to imposing a (non-binding cap) equal to 0.9%. The y-axis plots consumer surplus as defined in subsection 5.1.2.

the estimated model by the coefficient on nearby branches λ, lenders' with extensive branch networks are able to get a higher market share from households going direct. When setting interest rates, the Big Six anticipate this increase in direct sales and increase prices, resulting in lower consumer surplus. Given the relevance of branches and other in-house distribution channels in the new equilibrium, challenger banks are likely to invest in their own channels in the long-run. It is also possible that some broker companies would be forced to exit the market given the fall in their market share as a result of higher household fees. I do not capture these long-run equilibrium effects in my estimates.

An alternative policy to align households' and brokers' incentives is to impose a cap on commission payments. I assume this cap to be equal to the average commission in the baseline model (0.4% of the loan amount). This regulation allows brokers to still get some revenue from lenders and, therefore, broker fees to households do not increase as much as in the case of a ban. This policy also has implications for the network of broker-lender pairs. For some pairs, their new optimal commission, c^*_{lbt}, as defined in Section 4.3.2, is below the cap, c^{cap}_t.

For these cases, nothing changes and the link still holds. For other pairs, the cap violates the broker's participation constraint and the link is broken. Finally, it can also be the case for some pairs that the cap is binding, and the link holds with an equilibrium commission equal to c_t^{cap}. Column (3) in Table 9 reports estimates for a regulation imposing a cap. Direct sales increase only by 30% and search costs only go up by 13% (both significantly less than in the case of a ban). Prices fall by 5%, and the overall impact on consumer surplus is positive, with an increase of almost 10%. These results are driven because, despite brokers having narrower networks of lenders and household broker fees going up, households that do hire brokers get, on average, a much better deal than the baseline model.

Figure 7 plots the relationship between consumer surplus and different levels of caps on commissions. This non-monotonic relationship results from a trade-off between broker market power and lender local market power. Households originating their mortgages via brokers face broker market power in the sense that brokers can extract surplus from them (positive values of θ). On the other hand, households going directly to lenders prefer nearby branches. This preference gives lenders local market power, which they can exploit when setting interest rates. A very restrictive cap reduces broker market power at the expense of increasing lender market power. In the case of a ban, the gains of reducing broker market power do not compensate the welfare loss of increasing lender market power.

8 Conclusion

Work in progress.

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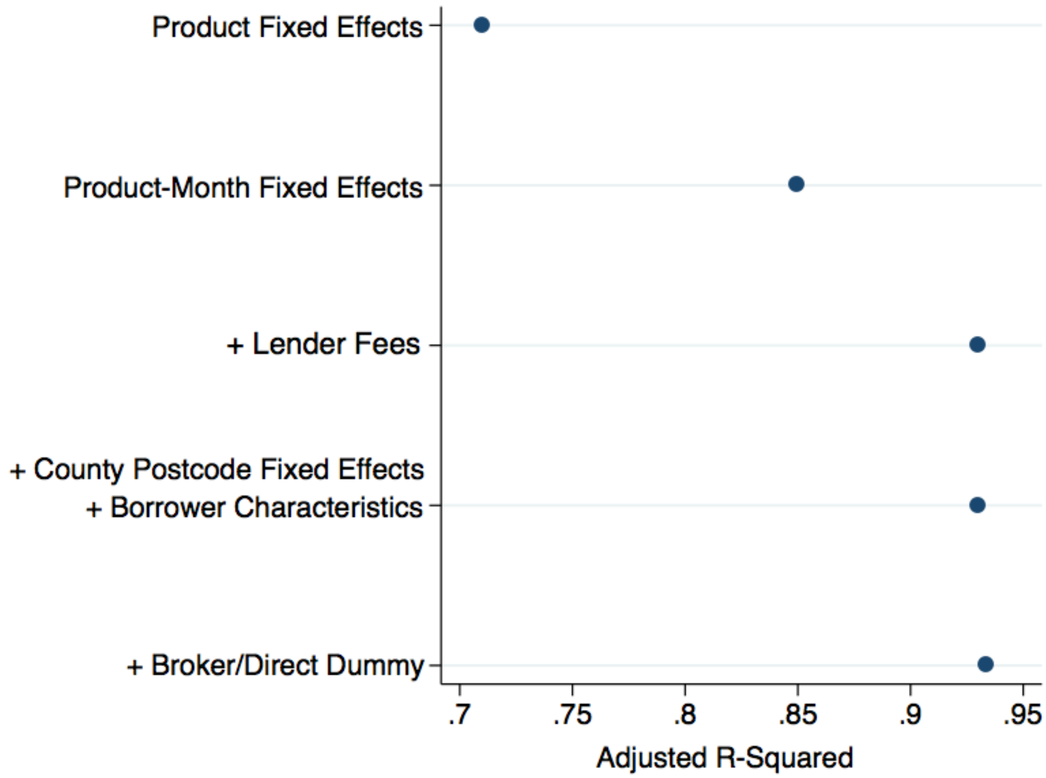
Appendix A Facts: Additional Material

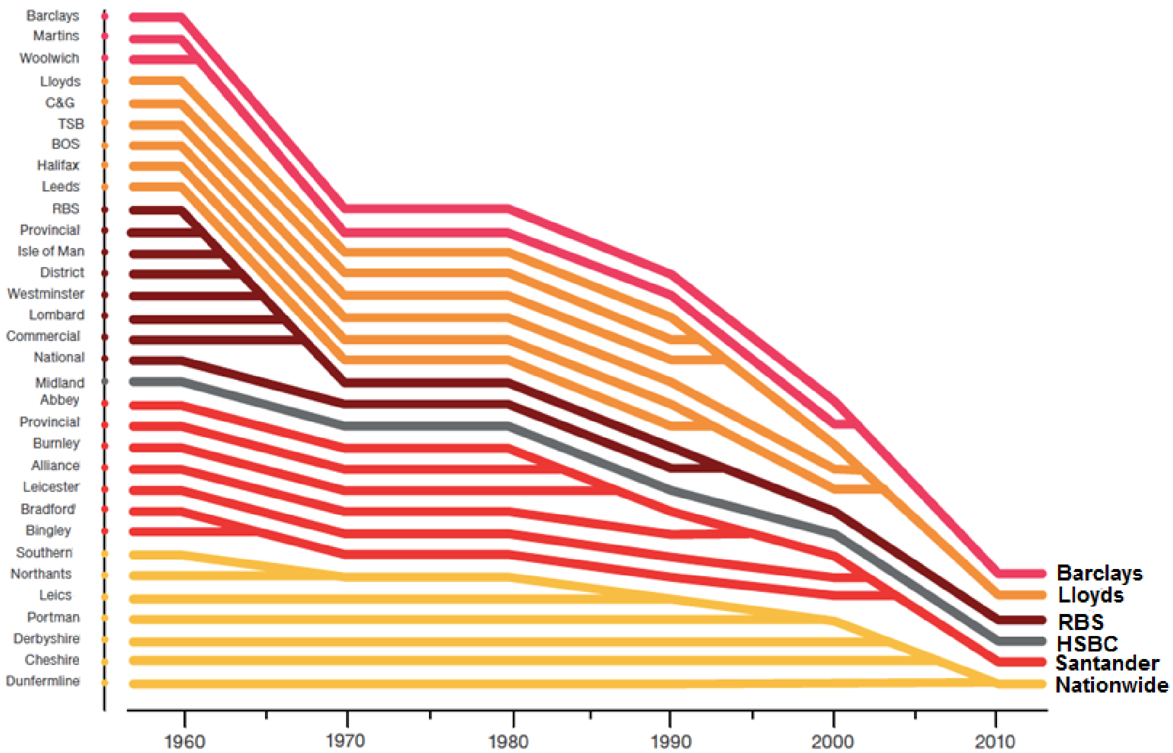
Figure A.1: Explained variation in mortgage pricing



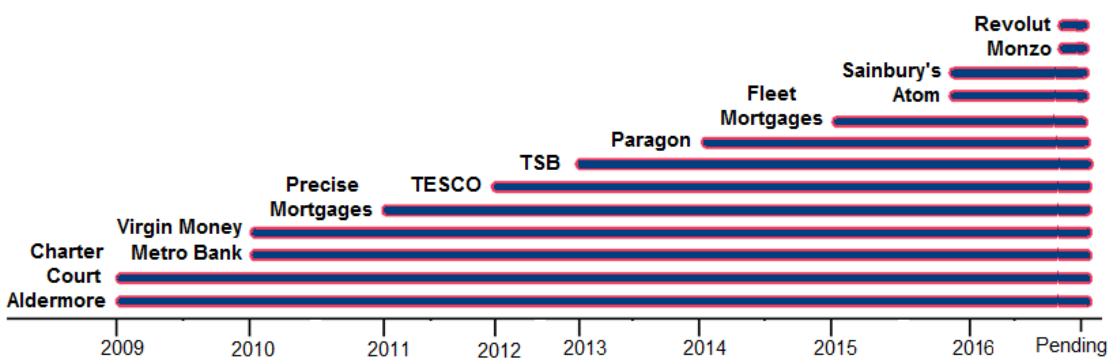
Note: the chart reports the adjusted R^2 of regressions of household level interest rates and fees on a set of dummy variables. First row includes only dummies for the product (interaction of lender, maximum loan-to-value band and initial fixed period). Second row adds fixed effects for each month. Third row adds dummies for lender fees (other price). Fourth row includes dummies for the location of the house and borrower characteristics (income, age, credit score). Finally, fifth row adds a dummy accounting for whether the mortgage was originated by a broker or directly through the lender's in-house distribution channels.

Figure A.2: Consolidation and Entry in the UK Mortgage Market

PANEL A: Consolidation in the UK banking sector over the last 50 years

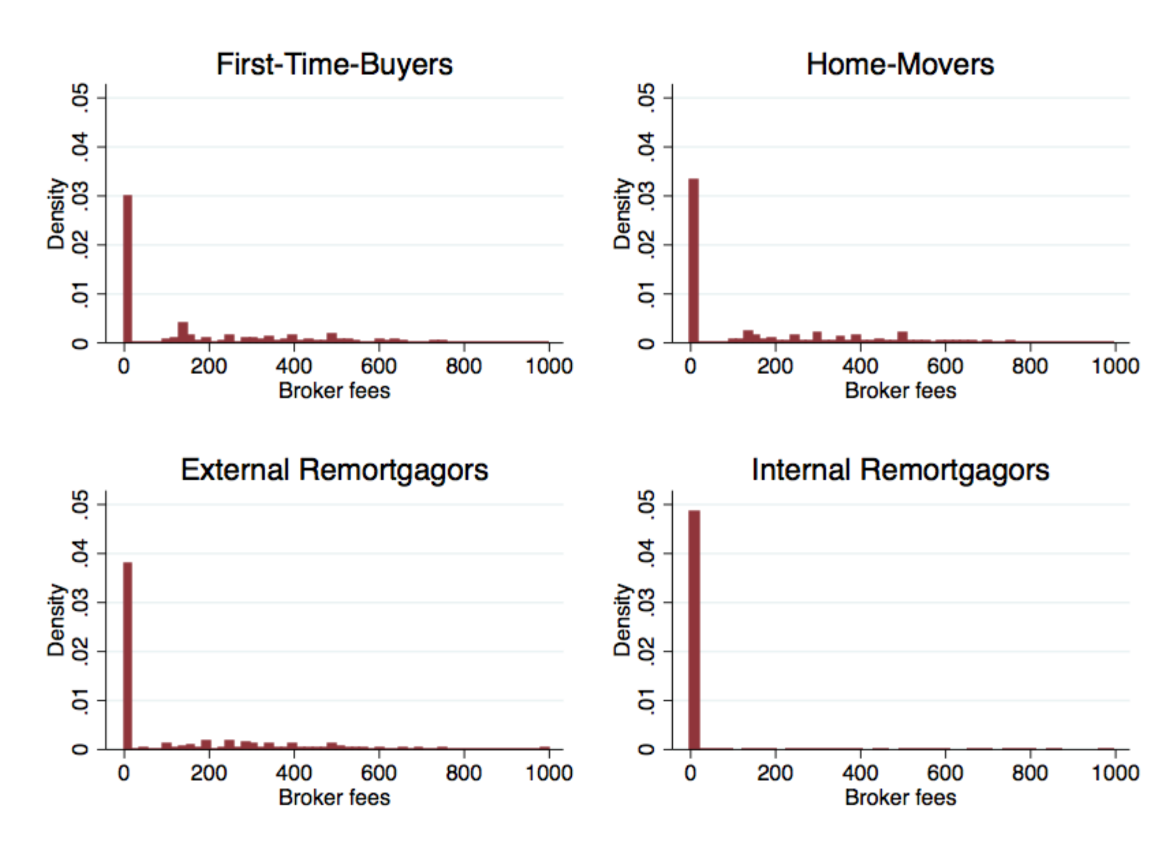


PANEL B: Entry in the UK banking sector over the last 10 years (not exhaustive)



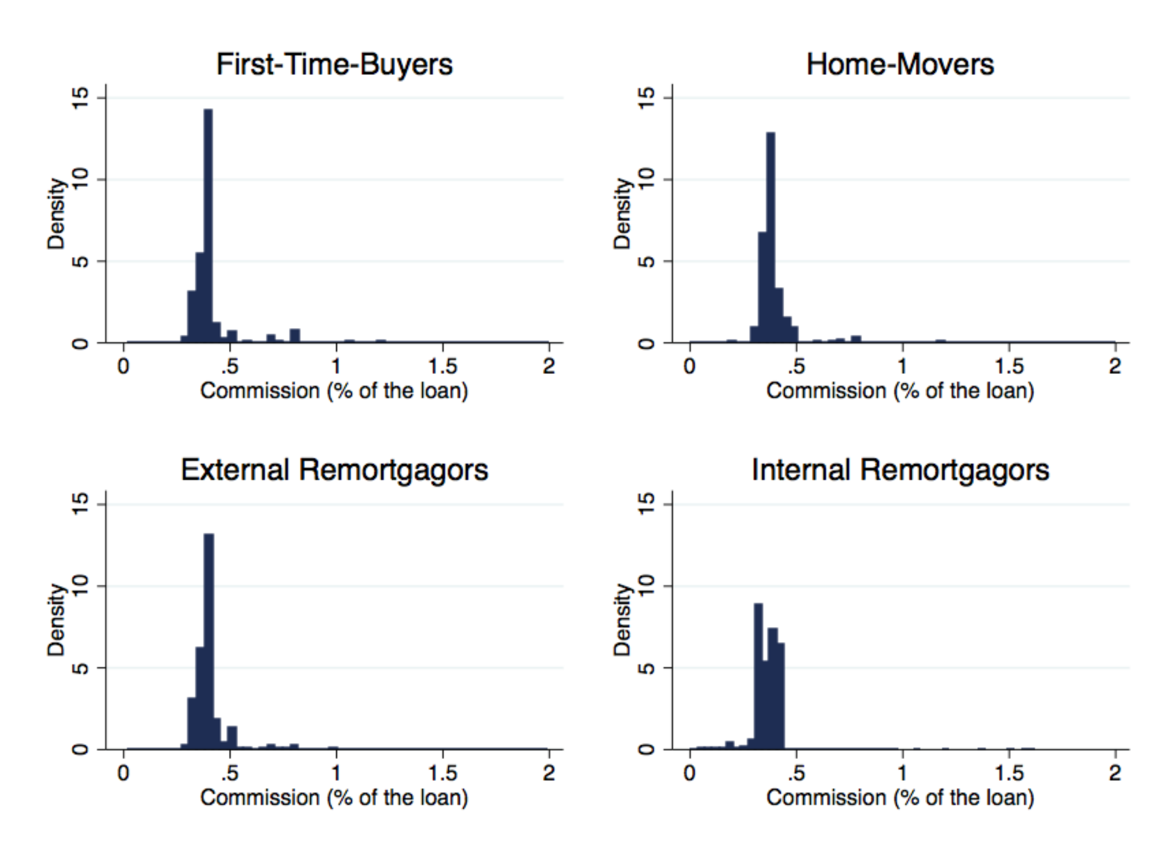
Notes: Panels A shows mergers and acquisitions for the Big Six lenders in the UK. Panel B presents a non-exhaustive timeline of recent entrants in the UK mortgage market. Graphs use data adapted from PwC Report "Who are you calling a challenger?", Bankers Magazine, and Quarterly Bulletin, Q4, Bank of England, 2010, plus additional dates from lenders' own websites.

Figure A.3: Distribution of Broker Fees Across Borrower Types



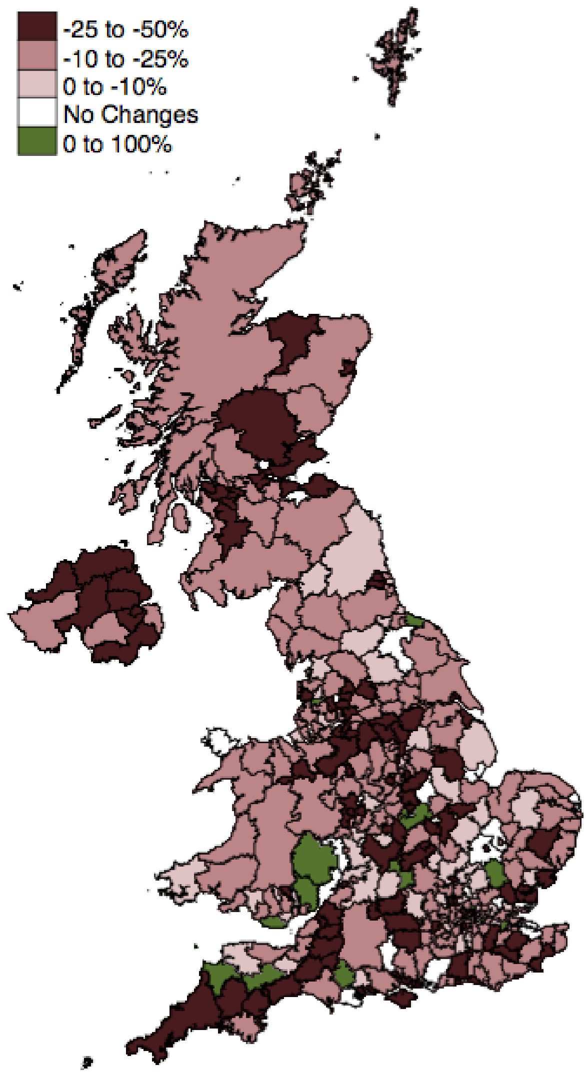
Note:

Figure A.4: Distribution of Commissions Across Borrower Types



Note:

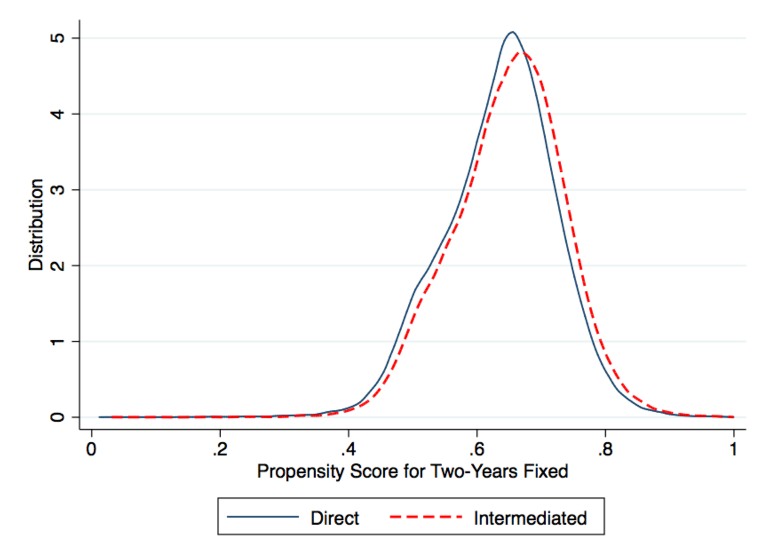
Figure A.5: Branch closures and opening at the local authority level.



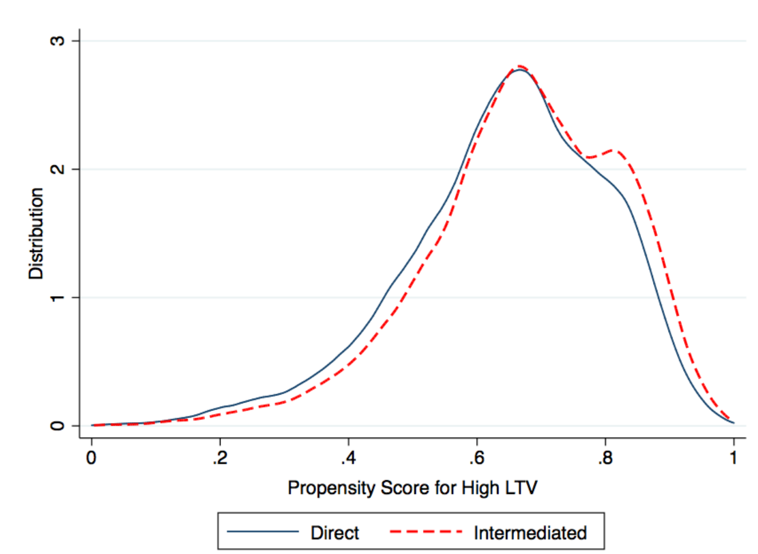
Note: Percentage change in total branches within a local authority district between December 2014 and January 2017. Data gathered from Experian Goad and Shop*Point datasets.

Figure A.6: Selection into Intermediation

PANEL A: Probability of Getting a 2-Year Mortgage



PANEL B: Probability of Getting a High Loan-to-Value Mortgage

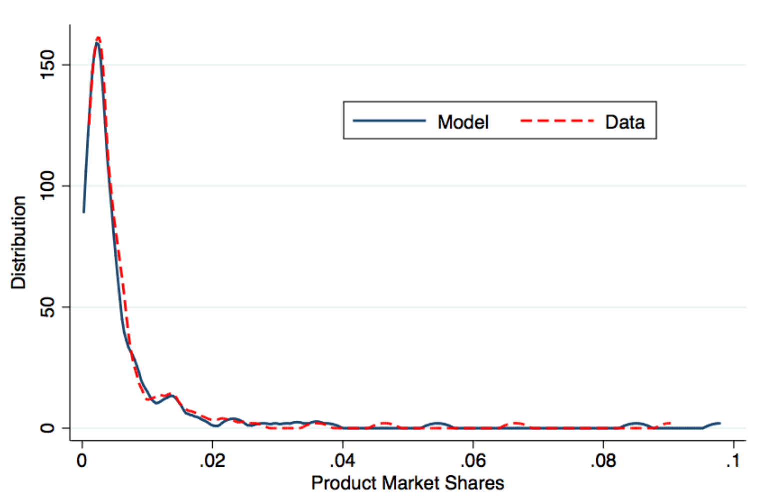


Notes: Panel A shows for each sales channel the probability that a first-time-buyer get a two-year mortgage based on its observable characteristics (age, income, credit score, partner, house price, location) and month dummies. Panel B plots the analogous probability for choosing a mortgage with a loan-to-value greater than 85%.

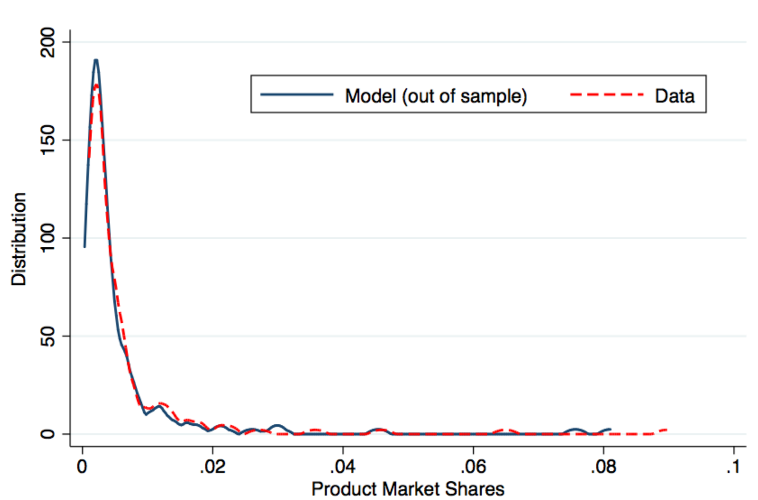
Appendix B Fit: Additional Material

Figure B.1: Model Fit

PANEL A: Training Sample (25% random sample)

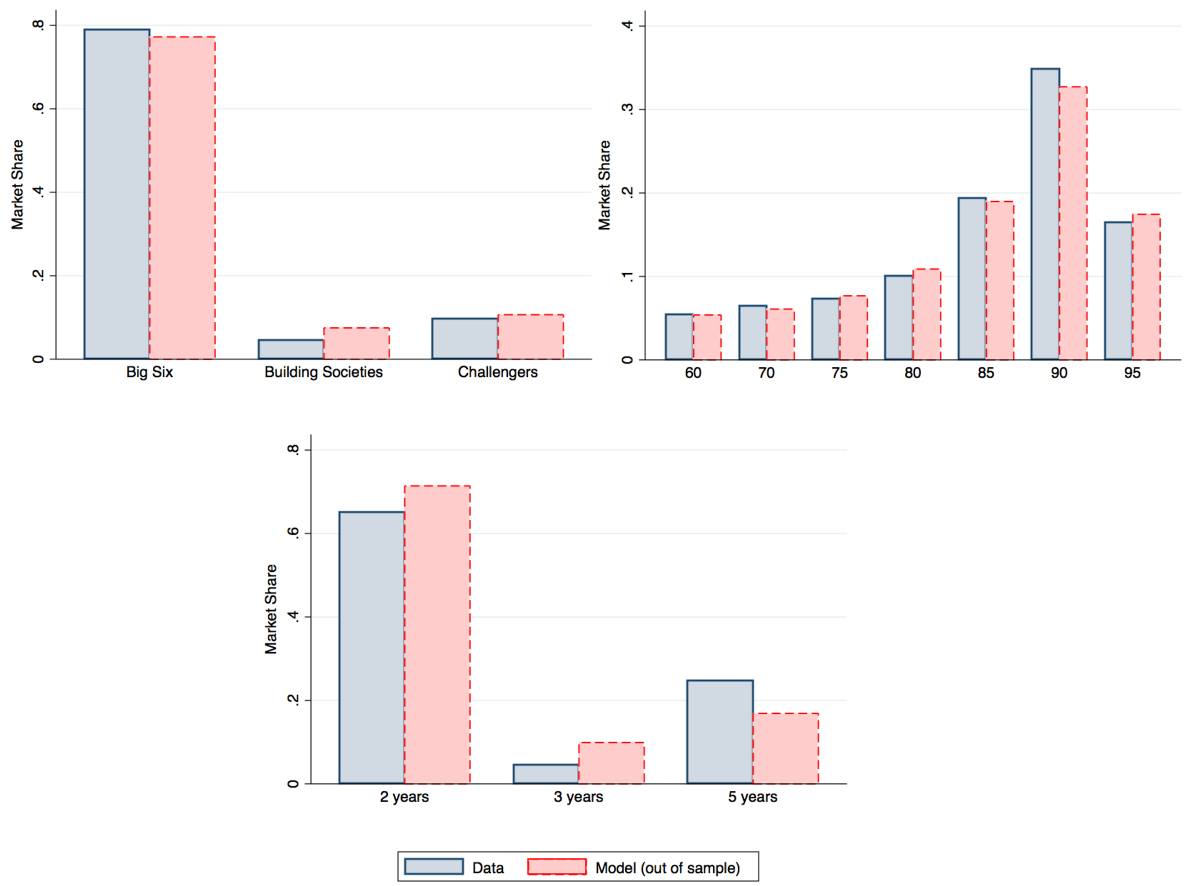


PANEL B: Cross-Validation Sample (Out-of-Sample Fit)



Note: The red solid lines are the observed market shares in the data computed as the sum of originations for each product in each market divided by the total number of households. The blue dashed lines represent the estimated market shares from the model calculated as the sum of the individual predicted probabilities. Panel A uses a 25% random sample, while Panel B is based on the remaining 75% that was not used in the estimation.

Figure B.2: Out-of-Sample Fit: Product Characteristics

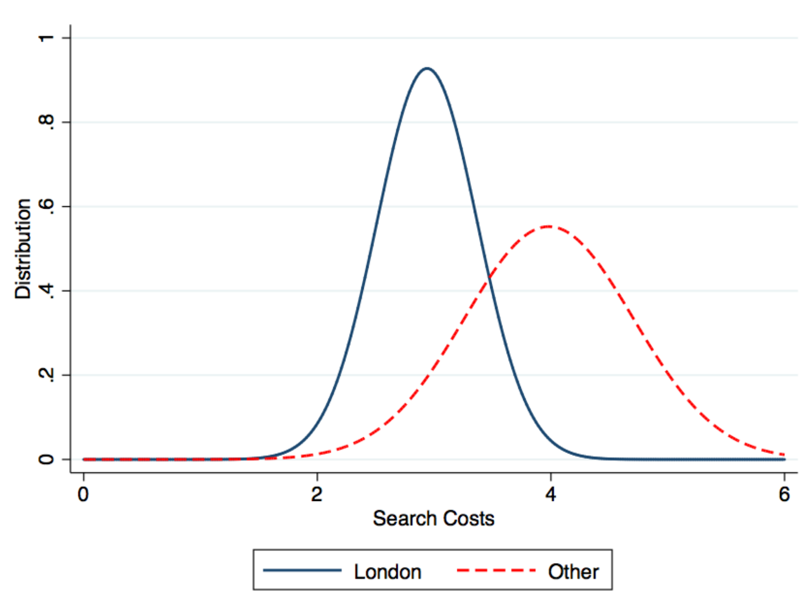


Note: I compare observed (solid line) and predicted (dash line) market shares across different product characteritsics. The upper left panel shows market shares for the Big Six, Building Societies and Challenger Banks. The upper right panel presents them across loan-to-value bands. Finally, the lower panel plots market shares across initial period deals.

Appendix C Estimates: Additional Material

Figure C.1: Search Cost Distributions Across Subpopulations

PANEL A: Geographical Variation



PANEL B: Income Variation

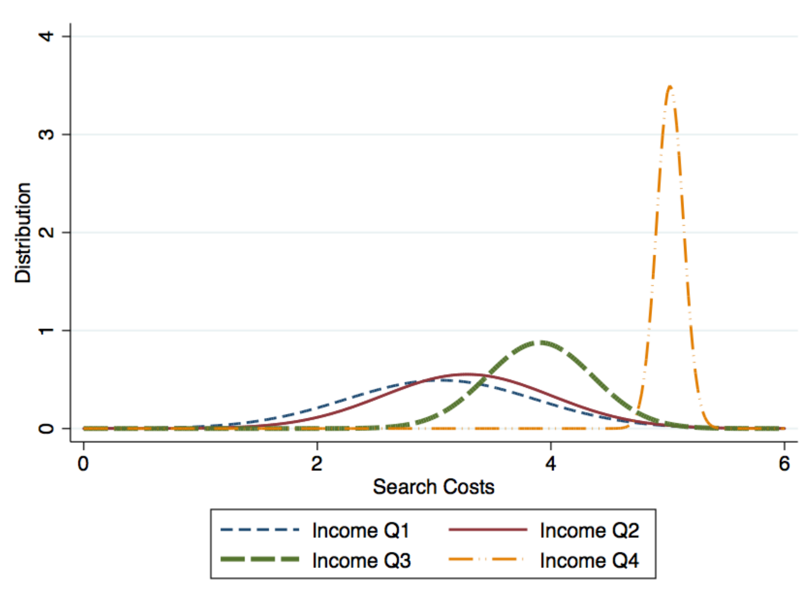
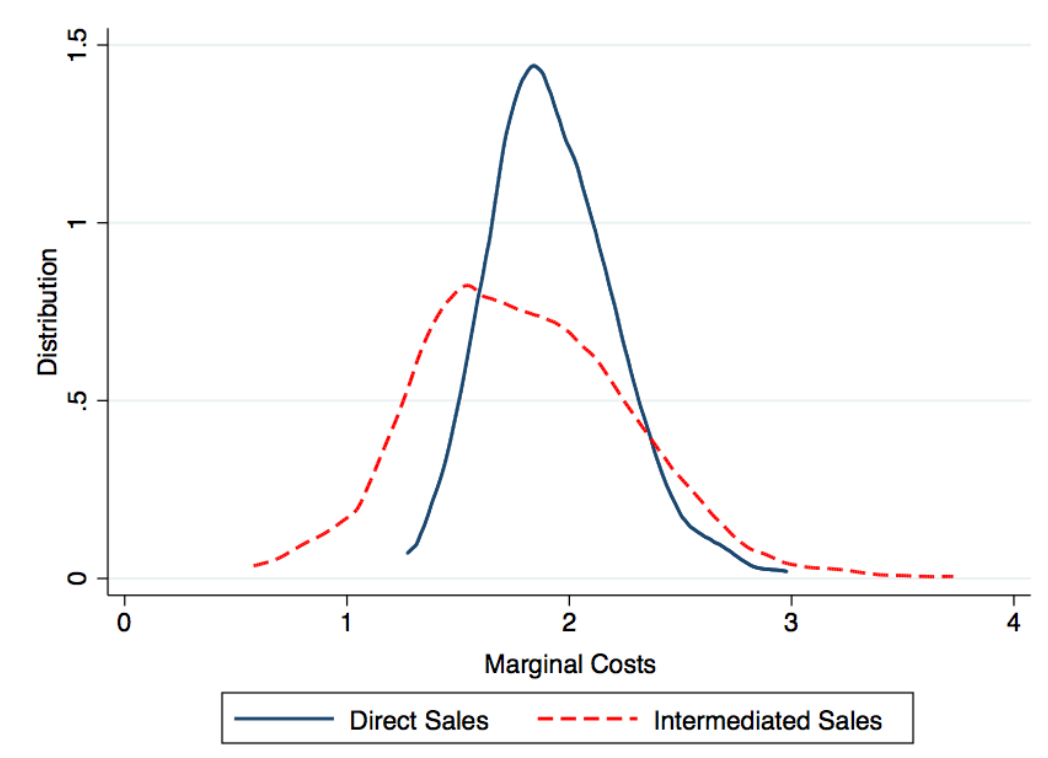


Figure C.2: Marginal Cost Estimates



Note:

Appendix D Counterfactuals: Additional Material