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Staff Working Paper No. 819

Non-salient fees in the mortgage market

Lu Liu

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Abstract

This paper studies supply-side product pricing when consumers underreact to non-salient fees. Using comprehensive data on issued and offered mortgages in the UK, I document that lenders differ substantially in the fees they charge, and that borrowers appear less overall cost-sensitive to products with fees. In order to distinguish from demand factors such as unobservable preferences or product characteristics, I show that lenders pass on firm-specific funding cost shocks via fees, but not interest rates, consistent with strategic pricing of fees, and maintaining competitive prices in the salient price dimension, interest rates. I further find heterogeneity in pricing across lenders: those who rely on high fees tend to have higher funding cost, lower return on equity and larger branch networks, in line with a specialization equilibrium in which high-cost lenders are able to match with less cost-sensitive consumers.

Key words: Price dispersion, salience, strategic pricing, mortgages.

JEL classification: G21, G41, D12, D14, D18.

(1) Imperial College London, South Kensington Campus, London SW7 2AZ, and Bank of England. Email: l.liu16@imperial.ac.uk

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Bank of England, Threadneedle Street, London, EC2R 8AH

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1. INTRODUCTION

The “law of one price” fails to hold across a range of seemingly homogeneous consumer goods markets.¹ Existing work suggests that this may be due to demand-side factors, taking prices as given: consumers may have unobserved preferences, e.g. for specific brands that increase their willingness to pay; or alternatively, search and cognitive frictions may prevent them from finding the cost-minimizing product (Hortaçsu and Syverson, 2004, Choi et al., 2009). One such friction is how readily available and visible information on cost is to consumers. In many markets, one cost component is naturally more *salient* than others, e.g. used as reference category in price comparison websites, such as basic airline fares and hotel rates, with less visible cost components such as fees for luggage and usage of amenities, respectively, added on (Gabaix and Laibson, 2006, Ellison and Ellison, 2009). In order to find the cost-minimizing product, consumers have to correctly compute total cost as the sum of all relevant cost components. However, if one cost dimension is more salient to consumers and if consumers underreact to non-salient cost components (Chetty et al., 2009, Bordalo et al., 2013), recent theoretical work implies that firms have an incentive to adjust pricing of these cost dimensions differentially (Gabaix and Laibson, 2006, Carlin, 2009), suggesting a *supply-driven* mechanism behind price, or total cost dispersion, given demand-side frictions.

I study this mechanism in the context of the UK mortgage market, which provides a useful laboratory of a market with one highly salient cost component, the interest rate, and a less visible and non-optional cost component,² the origination fee.³ The market in itself is interesting as mortgage costs have significant implications for household finances (Campbell, 2006), while frictions in search, as documented by Bhutta et al. (2019) and Woodward and Hall (2012) for the US, are important for macroeconomic policy (Scharfstein and Sunderam, 2015).

Most mortgages in the UK have a limited set of product characteristics, namely the product type (fixed vs. adjustable rate), fixation period and loan-to-value (LTV) ratio, and are hence fairly standardized.⁴ However, even when holding fixed a given set of product characteristics, such as a 2-year fixed rate product with a maximum 75% LTV,⁵ there exists a range of products

¹As noted by Varian (1980), see Baye et al. (2006) for a review.

²The non-optionality is important as it allows for a simple and unique total cost comparison across consumers. In many of the examples given, some cost components are optional such that variation in realized cost may arise due to unobserved heterogeneity in preferences across optional components.

³In the UK context, fees are a pure price component required at origination in contrast to the US “points” system. Early repayment penalties are allowed and charged separately to fees.

⁴The homogeneous product benchmark is more likely to hold when consumers are sufficiently homogeneous and creditworthy, which is why the paper focuses on low risk mortgages, i.e. mortgages with an LTV smaller than 80%.

⁵Meaning *after* the optimal choice of mortgage type such as fixed vs. adjustable rate (Campbell and Cocco, 2003) and loan-to-value (LTV) (Bailey et al., 2017) have been made.

that differ purely in price terms, most commonly a high interest rate and low fee, and low interest rate and high fee variant of the same product by the same lender. Using a novel product-level dataset of the universe of mortgages on offer between 2009 and 2016, I document that more than half of all products on offer are significantly cost-dominated and more than £1000 more expensive than the cheapest alternative.⁶ In addition, I find substantial heterogeneity in fees charged across lenders which is much greater than the relative dispersion in interest rates.⁷ I hence find reduced-form evidence for substantially dominated offers and fee heterogeneity. However, these facts alone are insufficient to pin down the mechanism. The evidence could be fully driven by demand motives, if fees are for instance compensating for unobserved brand preferences or services. Furthermore, there could be multiple potential supply mechanisms behind differential fees and cost, such as screening or liquidity motives, in addition to strategic pricing.

In order to disentangle these mechanisms more formally, I propose a two-part analysis. First, I estimate a simple discrete choice framework on administrative data on mortgages originated in the UK, to test the cost-minimization benchmark on the demand side while controlling for observable demand factors. The model assumes that consumers treat both interest cost and fees as equally salient, i.e. they weigh both cost components in £s equally, and allows the consumer to choose across lenders and price-variants within lenders, for a given loan value and product category. Based on observed loan choices, I find that the total cost sensitivity is lower for products with fees than without, which is partially driven by borrowers who benefit from borrowing the fee to bunch just at the LTV threshold, as documented by [Best et al. \(2015\)](#).⁸ However, the high-fee product fixed effect remains significant and sizeable even when excluding borrowers who bunch. The model hence systematically under-predicts market shares for high fee products relative to the data, and vice versa, even when controlling for lender-level fixed effects. This suggests that there may be “unexplained” demand for products with low rates, but high fees, which is difficult to match in a model where consumers minimize total cost and dislike interest cost and fees equally. To the extent that unobserved demand factors such as preferences for other services or convenience vary across lenders and not across price-variants within a given lender, borrowers seem to indeed neglect fees.⁹

⁶Assuming an average loan size of £150,000, where £1000 is about 10 to 20% of the total cost of the mortgage over 2 years and approximately 4% of the median household’s annual disposable income in 2016.

⁷For instance, the cross-sectional standard deviation has risen from around £500 to £700 for fees, and declined from around 80 to 50 basis points for interest rates between 2009 and 2016, making cross-sectional fee dispersion much larger than interest rate dispersion relative to the respective average levels.

⁸This could be thought of as a “soft” borrowing constraint as interest rates rise discretely in 5 to 10% LTV steps ([Best et al., 2015](#)). In contrast, in this setting it is unlikely that borrowers demand different price-variants to achieve different payment profiles over time, as borrowers have the option to add the fee to the loan value and repay it over time, at no additional cost.

⁹There are no known differences in eligibility or services across price types (low fee or high fee), which is

However, possible concerns that remain are potentially time-varying confounding factors and that the demand analysis provides only indirect evidence for a supply-driven mechanism.

Hence as a second step, I study lender pricing directly. The UK market is particularly suited to study mortgage pricing as borrowers can directly obtain the interest rates and fees that are quoted and advertised. There is no ex post price discrimination based on borrower-specific characteristics such as credit scores or bargaining, and lenders operate fully flexible interest rate schedules instead of fixed tick sizes, in contrast to the US and other countries. Using the mortgage offer data, I build a quarterly panel from 2009 to 2016 of prices set by lenders across products and time. I then study price adjustment of lenders in response to firm-specific, time-varying shocks to wholesale funding cost, which I construct as a “shift-share” shock (Goldsmith-Pinkham et al., 2017, Borusyak et al., 2018) based on cross-sectional predetermined variation in loan-to-deposit ratios across lenders and aggregate instrumented variation in wholesale funding cost over time. I find that lenders respond to these firm-specific cost shocks by leaving interest rates broadly unchanged, but increasing fees for their lowest interest rate product. The increase in fees is economically large: given a one standard deviation increase in the funding cost shock, lenders raise fees for their lowest interest rate product by around £100, which is about 15 per cent of the average level of fees and corresponds to a 0.5 standard deviation change in fees. For this to be evidence for a supply-driven mechanism, the identifying assumption is that time-varying unobserved demand factors are uncorrelated with lender-specific cost shocks over time.¹⁰ This finding cannot be rationalized by time-varying preferences of lenders for fee income compared to interest income or a boost to current earnings alone, as they seem to increase total cost, instead of decreasing interest rates in line with the increase in fees. Instead, it would require a demand pattern that is somewhat less elastic to increases in fees, in line with a more strategic motive: in a market where (some) consumers narrowly focus on the salient cost dimension, interest rates, lenders may be able to use fees to improve their position in the interest cost ranking and appear cheap to consumers who neglect fees. This may affect search outcomes. In originated loans, I indeed find lower realized excess cost dispersion (accounting for borrower, product and regional characteristics) for products without fees, compared to products with fees, i.e. borrowers seem to come closer to the cost-minimizing benchmark in the class of products without fees than those with fees.

To illustrate the pricing incentives with non-salient fees, Table 1 shows a stylized example of a pricing table.¹¹ It illustrates two features in the data: first, lender L offers the cost-minimizing

confirmed in conversations with industry participants.

¹⁰This provides an alternative way to rule out that fees reflect compensation for unobserved demand factors, as it accounts for time-invariant unobservables such as branch distance, and assumes that variation in e.g. unobserved service quality does not vary at the frequency of cost shocks.

¹¹It provides a close approximation of popular price comparison tables such as MoneySupermarket.com, as

product 4 in the market, priced at 2% interest and zero fees, which I refer to as a low interest rate, high fee price type ($\{r_h, f_l\}$). Lender H who is more expensive than lender L can only attract less cost-sensitive consumers, and reprices its product at 1.95% interest and £495 fees, instead of a 2.23% interest and zero fee product,¹² which is dominated in the fee dimension, but not in the salient interest rate dimension (product 3). The same holds for lender L 's pricing of the low interest rate, high fee price type ($\{r_l, f_h\}$), and lender H 's product 1. Second, the interest-sorted price table shows low interest rate, high fee products more prominently than high interest rate, low fee products. In this example, the cheapest product is hence least visible on the interest rate ranking. The zero-fee interest column converts interest cost and fees into a zero-fee interest rate, which reveals the total cost ranking and makes more visible that product 4 would be the cost-minimizing choice.

TABLE 1: EXAMPLE OF A MORTGAGE PRICE TABLE

Product	Lender	Interest (%)	Fees (£)	Zero-fee interest*	Price type
1	H	1.34	1,700	2.32	$\{r_l, f_h\}$
2	L	1.44	1,000	2.02	$\{r_l, f_h\}$
3	H	1.95	495	2.23	$\{r_h, f_l\}$
4	L	2.00	0	2.00	$\{r_h, f_l\}$

*Assuming a loan value of £150,000, 2-year fixation and 25-year amortization period.

The findings suggest that a lender can use fees as an active margin of price adjustment to maintain its competitive position in terms of interest rates, in response to a relative (i.e. firm-specific) cost shock vis-à-vis its competitors. For this to be an optimal pricing strategy with fee heterogeneity in equilibrium requires two assumptions, and I discuss in turn why they appear valid in this context. First, there needs to be a significant fraction of the borrower population that does neglect fees. This does not seem far-fetched in the UK, where mortgage prices are commonly framed as part of “best buy” tables ranked by interest rates. Figure 1, a snapshot from one of the biggest price comparison websites, MoneySupermarket.com, illustrates that interest rates are the salient price dimension that price comparison tables coordinate on, while fees are shown separately, or, in this case, only specified in the footnotes. If borrowers are fully cost-minimizing, however, they should be indifferent between cost paid in fees and interest rates, and consider a total cost ranking. Offering cost-dominated products with high fees but low interest rates hence attracts borrowers who neglect fees, but not total-cost-minimizing borrowers.

Second, (some) lenders find it profitable to pass-through relative cost shocks via fees rather than interest rates, as shown in Figure 1.

¹²Assuming that the mortgage is repaid over an initial 2-year fixed rate period with a £150,000 loan value and 25 year amortization period, and is subsequently refinanced.

than interest rates, suggesting that demand is (locally) less elastic with respect to fees. I find that there is substantial heterogeneity in fees across lenders, in contrast to interest rates, pointing to heterogeneity across lenders where some lenders rely more on fees than others. For this to be an equilibrium requires that the marginal demand sensitivity to fees also varies across lenders,¹³ such that there is specialization across lenders. Hence one way to rationalize the results is that lenders with higher fees and overall cost need to be able to attract less cost-sensitive borrowers, while lenders with low overall cost attract cost-sensitive borrowers (Salop and Stiglitz, 1977, Carlin, 2009).

I provide further evidence for this type of specialization equilibrium by splitting lenders into pricing types based on terciles of the difference between their minimum total cost and interest rate ranking, as a measure of how much they skew their interest rate ranking using higher than prevailing average fees. The “high” pricing type, defined as the upper tercile of lenders, have a positive ranking difference of 6 on average, i.e. they have the $x+6$ th-highest position in the total cost ranking, but move up the interest rate ranking to the x th-highest position. As expected, they charge similar interest rates as their competitors, but higher fees, both for the high fee and low fee product. While they have similar size and funding structures as other lenders, they earn substantially lower returns on assets and equity and have higher funding costs. They also tend to have a higher branch density, measured as the number of households for whom a given lender operates one of the closest branches, and higher market share, suggesting that existing forms of market power based on branch networks (Drechsler et al., 2017) interact with those based on consumer mistakes and may make it easier for these lenders to acquire less cost-sensitive borrowers. Across lenders, fees do not seem to compensate directly for a greater branch density, however, meaning that both the financial necessity and ability to attract less cost-sensitive borrowers seem to affect lenders’ pricing decisions. I further find that high-skew lenders also adjust their fees by more in response to firm-specific cost shocks, which could be interpreted as an additional dynamic source of market power in line with anchoring effects (Bordalo et al., 2019) where consumers become less sensitive to bigger absolute fee changes if they are used to higher equilibrium levels of fees.

Next, I consider other supply motives such as screening that could drive pricing, and could be correlated with cost shocks. I find little evidence that fees are used to screen for borrower risk types. In contrast to the US, lenders frequently charge early repayment penalties in the UK, which are a more direct measure to screen for prepayment risk than fees.¹⁴ For

¹³This is also supported in the discrete choice analysis, where controlling for borrower-characteristics substantially increases the estimated cost sensitivity.

¹⁴In the US mortgage market, borrowers typically have the option to pay “points” (fees) upfront to obtain a lower interest rate, which decreases the refinancing incentive and signals lower prepayment risk (Stanton and

almost 90% of products in the sample, prepayment penalties do not vary across products within a given lender.¹⁵ This seeming lack of screening for heterogeneous prepayment risk could be explained by the relatively short initial fixation periods prevalent in the UK, with most borrowers refinancing at the end of a 2 to 5 year fixation period (Best et al., 2015).¹⁶ The pricing model by lenders implies, however, a consistent link between fees and loan size, as the benefit of a lower interest rate, the interest cost reduction, is greater for larger loan balances.¹⁷ For a given lender’s product offering of $\{r_l, f_h\}$, $\{r_h, f_l\}$ there exists a unique loan value at which a borrower should be indifferent between choosing the low or high fee product. From the perspective of a given borrower with a fixed loan size, she should only consider a single product by a given lender, such that price dispersion purely arises from choice across lenders. This does not seem to be the case in realized borrowing outcomes: I find substantial realized fee dispersion across the loan size distribution and even *within*-lender price dispersion, suggesting that consumers indeed make mistakes in the fee dimension, as unobservable preferences seem more likely to affect choice across lenders, and less so choice within.

These findings are important for two reasons. First, the paper provides empirical evidence that lenders price strategically in response to demand-side biases and document a supply-driven mechanism behind price dispersion. The framework provides testable predictions of firms’ pricing incentives in the presence of non-salient fees. This work is the first to empirically identify this supply-side channel using cost shocks, to the best of my knowledge. And second, fee dispersion may make total cost comparisons more difficult for consumers, pointing to an interaction mechanism with existing demand-side frictions.

The paper makes three contributions to the existing literature. First, recent work in household finance provides evidence of consumer mistakes (Bucks and Pence, 2008, Agarwal et al., 2009, Andersen et al., 2015), and firm behavior that exploits these (Henderson and Pearson, 2011, Ru and Schoar, 2016, Agarwal et al., 2017b, C  lerier and Vall  e, 2017). The first part of the analysis, that consumers seem to be less cost-sensitive to non-salient price components, is consistent with evidence from the credit card market (Agarwal et al., 2014), mutual fund (Barber et al., 2005, Anagol and Kim, 2012) and social security markets (Duarte and Hastings, 2012), as well as consumers underreacting to non-salient taxes (Chetty et al.,

Wallace, 1998).

¹⁵This extends to a regression setup, where prepayment penalties do not significantly affect the interest rate-fee trade-off within and across lenders.

¹⁶As another screening mechanism, lenders may use high fees to screen for liquidity risk, as liquidity-constrained borrowers may be less able to pay an upfront fee, or any other unobservable characteristics that may be correlated with default probabilities. The institutional framework in the market makes this less likely as borrowers are allowed to add the fee to the loan balance and repay it over the duration of the mortgage, at no additional cost, which is observed in the data.

¹⁷In that sense, fees can be thought of as very coarsely screening for loan size.

2009) and neglecting expected out-of-pocket costs in health insurance plan choice (Abaluck and Gruber, 2011). As a second step, I provide direct evidence that firms take into account these consumer frictions and set the non-salient price component jointly in order to compete in the salient price dimension.

Second, the identification strategy also allows me to highlight the active role of the supply side for household finance problems (Foà et al., 2015), as firms dynamically respond to cost shocks to adjust their prices optimally, in response to a change in their competitive position. It thereby reveals a pricing strategy in line with search and cognitive frictions on the demand side, while making a preference-driven mechanism less likely, hence adding to the previous literature that has used experimental (Choi et al., 2009) and model-based approaches (Woodward and Hall, 2012, Alexandrov and Koulayev, 2018) to distinguish between these two channels. The findings further show that supply-side incentives play a role in understanding the drivers behind price dispersion in markets for homogeneous goods (Hortaçsu and Syverson, 2004, Ellison and Ellison, 2009, Stango and Zinman, 2015, Argyle et al., 2017) which could exacerbate existing search frictions. Alternatively, the degree to which this supply channel matters may also depend on the degree of existing frictions. The UK mortgage market appears to have relatively low search frictions as a market where prices are posted and can be directly obtained. In closely related work, Bhutta et al. (2019) find substantial price dispersion in US mortgage rates that varies with borrower types, highlighting the role of ex post price discrimination in a market where lenders post initial prices, but where final prices are subject to negotiation. This suggests that the market structure and ease of search may affect the relative role of supply and demand behind price dispersion.

Third, I provide an empirical framework with testable predictions for pricing to link to theoretical work on price obfuscation (Ellison, 2005, Gabaix and Laibson, 2006, Piccione and Spiegler, 2012, Chioveanu and Zhou, 2013)¹⁸ and show evidence for a specialization equilibrium (Salop and Stiglitz, 1977, Stahl, 1989, Carlin, 2009) in which high-cost lenders attract less fee-sensitive consumers, as observed in other retail finance settings (Egan et al., 2019).¹⁹

The remainder of this paper is organized as follows. Section 2 provides background on the UK mortgage market and the data used. Section 3 presents stylized facts and the mortgage pricing structure. Section 4 provides the borrower-level discrete choice analysis, and Section 5 describes the identification strategy and results based on the lender-level analysis. Section 6 discusses the mechanism and Section 7 concludes.

¹⁸See Grubb (2015) for a review.

¹⁹The findings are also consistent with the salience theory of Bordalo et al. (2013) in the sense that differences in interest rates are quoted in percentage points, while differences in fees are quoted in £s, which consumers may be less sensitive to due to diminishing sensitivity to price differences at higher price levels.

2. BACKGROUND AND DATA

2.1. BACKGROUND ON THE UK MORTGAGE MARKET

Mortgage borrowing accounts for around half of the median household’s liabilities in the UK, which is similar to the US and one of the highest levels across developed economies (Badarinza et al., 2015). Mortgage product choice in the UK can be summarized using four product characteristics: mortgage type (fixed vs. floating), fixation period, LTV band, and mortgage borrower type. The large majority of UK mortgages are short duration fixed-rate products, with 2 and 5 years the most common fixation periods. These revert to so-called Standard Variable Rates that tend to be substantially higher than prevailing rates in the market, such that most borrowers refinance at the end of the fixation period. Lenders have “full recourse”,²⁰ default rates are comparably low and default risk pricing takes place through a discrete interest rate schedule at maximum LTV bands in steps of 5 to 10% (Best et al., 2015). Most mortgages are available to first-time buyers, second-time buyers and refinancing borrower types, with some only available to a particular borrower type.

In contrast to the US (Bhutta et al., 2019) and Canada (Allen et al., 2014), UK borrowers can directly obtain the interest rates and fees that are quoted and advertised, i.e. there is no ex post price discrimination based on borrower-specific characteristics such as credit scores or bargaining. Prices are set UK-wide and hence not differentiated by branch location or region. Lenders also operate fully flexible interest rate schedules, in contrast to fixed tick sizes in the US, such that both interest rates and fees can be adjusted flexibly. These factors make the UK mortgage market an ideal laboratory to study lenders’ pricing strategies. I observe the full universe of mortgages and product characteristics that a borrower can shop from, and the prices reflect the final interest rates and fees that can be obtained.²¹

Similar to other countries, the market is relatively concentrated. The largest six UK lenders together account for around 75% of the stock and new flows of mortgage lending.²² The largest 27 lenders that I study together account for approximately 95% of new mortgage lending.

²⁰Meaning lenders can recover losses from defaulted borrowers through their assets and incomes for up to seven years, until the debt is paid (Aron and Muellbauer, 2016).

²¹In an earlier step, lenders will accept and reject loan applications based on a borrower’s credit history, such that prices are implicitly conditional on approval. The approval mechanism depends on lender-specific internal credit models, but these do not differentiate between a borrower who takes out a high fee product, compared to a low fee product, and so should not confound the analysis. This is likely to play a greater role for more risky mortgages, as demonstrated by Agarwal et al. (2017c).

²²Between 2010 and 2015, see former quarterly “Trends in Lending” reports from the Bank of England: <http://www.bankofengland.co.uk/publications/Pages/other/monetary/trendsinlending.aspx>.

2.2. DATA

I combine three datasets. First, my main data source is Moneyfacts which is one of the most commonly used financial price comparison websites in the UK,²³ and is accessed through the Bank of England. It comprises the universe of mortgage products on offer, with detailed product characteristics, since June 2008, by lender and at monthly frequency. The data used covers the time period from January 2009 to December 2016.

Since the focus of this paper is to study the consumer choice problem for a given set of product characteristics, the analysis focuses on 2-year fixed rate products that are low risk (maximum 70-75% LTV) and available for first-time buyers, and I assume that borrowers refinance at the end of the fixation period, such that they need to search anew after each fixation spell.²⁴ Fixed-rate mortgages available to first-time borrowers account for around 80% and 70% of the mortgages on offer, respectively. They also reflect respectively around 80% and 30% of mortgage issuance in the UK.

Table B.1 illustrates the product characteristics and a representative menu structure based on four products by Halifax, one of the largest UK mortgage lenders, as observed in April 2013. It shows that a borrower with a maximum 75% LTV ratio can choose between an annual interest rate of 3.39% and a total arrangement fee of £295, or “trade down” the interest rate to 2.69% by paying a higher fee, £1290. Further descriptive statistics are provided in Table 2, Panel 1.

Second, I augment the Moneyfacts dataset with data on lender characteristics and funding cost. Data on lender characteristics for the 27 largest lenders in the UK is obtained from SNL Financial. These contain lender characteristics from balance sheet and income statement data (Table 2, Panel 2). Data on wholesale funding cost are based on daily 2-year LIBOR and USD swap rates and CDS premia averaged by quarter for the largest six lenders, and are obtained from Bloomberg and the Bank of England.

Third, in order to study choice outcomes, I use the Financial Conduct Authority’s Product Sales Database (PSD) which collects data on all regulated mortgage originations in the UK, and is accessed through the Bank of England via a data sharing agreement. The data used covers mortgage originations between 2015 and 2016. Each loan contains detailed loan and borrower characteristics such as the mortgage type, fixation period, LTV, interest rate, fees paid, LTI, age, income and postcode of the borrower. I further use a 2016 snapshot from SNL Financial on all UK bank branch locations to compute the distance from a given lender’s nearest branch

²³Recommended by the formerly government-led Money Advice Service on its “Mortgage comparison checklist”, see <https://www.moneyadviceservice.org.uk/en/articles/your-mortgage-comparison-checklist>

²⁴I abstract from dynamic dependencies that may give lenders different pricing incentives - I do not find a relation between fees and Standard Variable Rates, which is likely explained by the fact that borrowers tend to refinance consistently at the end of their fixation period, as documented by Best et al. (2015).

to a given borrower.

I use loan-level data from the PSD for the borrower-level analysis. For the lender-level analysis, I construct a panel with lender characteristics and pricing statistics, in particular changes in interest rates and fees for the low rate, high fee, and high rate, low fee product on offer at the lender level, and a lender-specific funding shock, at quarterly frequency between 2009Q1 to 2016Q4. Data selection and variable construction are further described in the Appendix A.

3. STYLIZED FACTS AND MORTGAGE PRICING

This section documents two stylized facts in the data: first that there is evidence for substantial price dispersion in the UK mortgage market, and second that this is accompanied by large heterogeneity across fees. It then describes how supply-side mortgage pricing could be related to price dispersion, and why fees could be interpreted as a non-salient cost component.

Price dispersion in the mortgage market. From the perspective of a borrower with an approximately average loan demand of $L = \text{£}150,000$, who refinances the mortgage after the end of the fixation period d (2 years, i.e. 24 months) and amortizes the mortgage over 25 years ($T = 300$ months), the total cost C of the mortgage with monthly interest r and origination fee f over time period d is

$$C_d = \underbrace{\frac{r}{1 - \frac{1}{(1+r)^T}} \cdot L \cdot d}_{\text{interest cost}} + f. \quad (1)$$

When the borrower searches for a mortgage in the universe of products on offer in a given month, there is substantial dispersion in total cost and the majority of products on offer at any one point in time is cost-dominated by more than $\text{£}1000$.²⁵ Table 3 shows the share of cost-dominated products by fee categories. Overall, only 14.5% of products are within $\text{£}500$ of the cheapest product in a given month. While about half of all products with a low to medium (up to $\text{£}1000$) fee are strongly cost-dominated, this is true for more than 90% of all products with higher fees.²⁶

Fee heterogeneity. Next, I examine the pricing patterns that underlie the cost dispersion. Figure B.1a shows the share of products on offer, by double-sorting all products by interest

²⁵The total cost measure abstracts from time discounting as the fee can be amortized over the duration of the loan, and does otherwise not affect the preference ranking across products.

²⁶Figure B.2 in the appendix demonstrates that this pattern holds across the loan size distribution. And Table B.2 shows that a large share of products with fees remains cost-dominated even for borrowers with a high loan value of $\text{£}250,000$ (around the 90th percentile of the loan size distribution). One notable difference is that the share of low fee cost-dominated products also increases for high loan values, as the interest rate differential gets magnified at higher loan values.

and fee quintile in a given month. It gives a sense of the most common type of products on offer. Similar to the illustrative example above, there are two product clusters in general: one with low interest rates (lowest interest quintile, bottom row), but with medium to high fees (third to fifth fee quintile), and another with relatively low fees (lowest two fee quintiles), and medium-level interest rates. The prices show a pattern of horizontal differentiation along the fee dimension, reflecting products with similar interest rates, but higher fees.²⁷ Figure 2 illustrates the heterogeneity across fees based on a histogram of fees for 2-year fixed rate, 75% LTV products, with clusters at £0 and £1000 and substantial variation in between and beyond £1000, with the largest fees at around £3000 to £4000. Overall, this illustrates that mortgage products on offer tend to have similar interest rates, but appear differentiated along the fee dimension.

Mortgage pricing. The above pattern reflects that in the UK market, each lender typically offers product variants with different price types based on an interest rate-fee trade-off, e.g. a high interest rate (r_h) and low fee (f_l), compared to a low interest rate (r_l) and high fee (f_h) product. The average and median lender offers around 2 of these products, and the analysis focuses on the case of two price types for simplicity, but can be easily generalized.²⁸ For a given borrower with a fixed loan size, the pricing scheme hence implicitly defines loan value cut-offs L^* at which a borrower should be indifferent between the $\{r_h, f_l\}$ and $\{r_l, f_h\}$ product, i.e. is indifferent between paying the higher fee to obtain the interest cost reduction, which is greater for larger loan balances, or paying a lower fee but higher interest rate. L^* is obtained by solving for the loan value for which $C^{(r_h, f_l)}$ is equal to $C^{(r_l, f_h)}$ using the total cost equation (1) from above, which gives

$$L^* = \frac{-(f_h - f_l)}{d \cdot \left(\frac{r_l}{1 - \frac{1}{(1+r_l)^T}} - \frac{r_h}{1 - \frac{1}{(1+r_h)^T}} \right)}.$$

This suggests that a given borrower with a fixed loan size should only consider one product per lender, and that the products available for a given borrower should be segmented according to loan size. However, this does not seem to be reflected in the way the product market is structured in practice. The implied loan value cut-offs vary strongly across lender and over time, and products appear marketed with an overall interest rate ranking in mind. That is,

²⁷Figure B.1b further gives a sense of how expensive these products are compared to the cheapest product in a given month. The cost differential is naturally lowest close to the left lower corner where both interest rates and fees are low, and increases most visibly along the fee dimension. High fee products command a £3000 to £4000 premium on average, compared to the cheapest product.

²⁸The minimum lender-quarter observation has only one product on offer, while the maximum is 5 products.

prices in the UK mortgage market tend to be prominently framed in terms of the cheapest interest rates available in the market, e.g. via “best buy” tables, and many price comparison websites sort products by interest rate cost by default, as shown in Figure 1. So while interest rates are made visible as the most salient price dimension, fees are often shown as separate price category, and in this example, are only specified in the footnotes.²⁹ The emphasis on the overall interest rate ranking leads to products with higher fees being more visible in the market overall, as illustrated in the following. Figure 3a shows the set of available products in a particular month, first as a pure interest rate ranking, and then in interest rate and fee-space (Figure 3b). The top 10 products with the lowest interest rates are clustered very tightly together when considering just the interest rate dimension, but all belong to the group of products with “higher fees”, with some having fees up to £2000.

Hence the pricing structure may allow cost-dominated products (with fees) to compete with cost-minimizing products in the salient price dimension, interest rates, even though these products would not be intended to compete if borrowers correctly ruled out dominated products by applying the cut-off rule based on their loan size. Figure 3b also illustrates the interest rate-fee combinations that yield the same total cost for the borrower (with average loan value \bar{L}) as isocost curves $\bar{C}^{\bar{L}}$. It shows that for an average borrower, focusing narrowly on the interest rate ranking tends to be misleading as the cost-minimizing choice tends to be a product without fees (green squares). The excess total cost paid for a given product compared to the cost-minimizing product can be read as the distance from the cost-minimizing isocost curve, which is at least £500 and up to £2000 for most of the interest-rate minimizing products in this example from the data.³⁰ Over the sample period more generally, only a relatively small sample of borrowers with large loan values should consider products with fees, in particular high fees, in the first place, if they minimize total cost rather than interest rate cost.

Within-lender price dispersion. One immediate consequence of the pricing structure is that the product alternatives by price types can be a source of price dispersion even *within* a given lender. Figure 4 shows the log-distance of the total cost of the product chosen, and the cheapest alternative, for the same lender at the same point in time. If price dispersion only arose from choice across lenders, this distribution would be degenerate and collapse to zero. In the data, the average within-lender price dispersion is around £400, with substantial variation across lenders.

²⁹Composite cost measures are not necessarily readily available. The APR, for instance, is measured over the full amortization period (usually 25 to 30 years), which is often not representative of a mortgage that is refinanced after the end of the initial fixation period.

³⁰I verify that this tends to hold more generally and over time, the loan value cut-off from which it is worthwhile to pay a medium fee (up to £1000) is at around the 75th percentile of the actual loan value distribution, while a loan value needs to be at around the 90th percentile for it to be worthwhile to pay a high fee (greater than £1000).

This confirms the idea that borrowers with a fixed loan size are free to pick any of the products by a given lender, and may overpay in that process. Within-lender price dispersion reflects variation in prices paid while holding constant any lender-specific unobservable preferences as there are no known services or other unobserved product characteristics and eligibility criteria that differ between a product with a low or high fee within a given lender. This provides some suggestive evidence that consumers do not pick across lenders according to the loan value threshold rule, and may not fully consider total cost as the sum of interest cost and fees. I test this idea more formally in the following two sections.

4. BORROWER-LEVEL ANALYSIS

This section develops the first part of the analysis, which is to study consumer choice as a cost-minimization problem based on observed interest rates and fees (taking choice of product characteristics and loan demand as given), and controlling for other lender and borrower-specific factors. I use a discrete choice model to create a simple empirical benchmark for predicted choice which I compare to observed market shares. The approach has recently increased in prominence to study mortgage market demand ([Buchak et al., 2018](#), [Benetton, 2017](#)).

4.1. DISCRETE CHOICE MODEL SETUP

Suppose borrower i 's utility from a mortgage that is homogeneous in terms of observable product characteristics, but differentiated by lender and borrower-level factors, by lender j with mortgage pricing type k is

$$U_{ijk} = \underbrace{-\gamma C_{jk} + \beta X_{ij} + \xi_j + \eta_{ij} + \epsilon_{ijk}}_{\delta_{ijk}},$$

where $k \in \{1, 2\}$ denotes the type of mortgage: $k = 1$ if the consumer chooses the low rate, high fee combination $\{r_l, f_h\}$, and $k = 2$ if the consumer chooses $\{r_h, f_l\}$. Utility decreases in total cost C_{jk} which is the sum of interest rate cost and fees, and increases in observable borrower-lender-specific variables captured by X_{ij} , most notably the (negative) distance to the nearest branch of lender j based on borrower i 's location, and ξ_j , η_{ij} and ϵ_{ijk} are respectively lender, borrower-lender and borrower-lender-type-specific unobservables. As is common in the literature, the random utility shock ϵ_{ijk} is assumed to be i.i.d and follows a type 1 extreme

value distribution (Berry, 1994).³¹ I define choice indicators as

$$y_{ijk} = \begin{cases} 1, & \text{if } i \text{ chooses product } k \text{ by lender } j, \\ 0, & \text{otherwise.} \end{cases}$$

This yields a closed-form solution for choice probabilities and market shares of logit form for each product type by lender:

$$s_{jk} = \frac{\exp \delta_{jk}}{\sum_{m=1}^M \exp \delta_m}.$$

Borrowers choose from the largest lenders J , where I group the 27 largest lenders that I study as the big six and three other lender groups, and the remaining lenders as the outside option. I aggregate the choice set and matched observed choices such that each lender offers a high ($\{r_l, f_h\}_j$) and low fee ($\{r_h, f_l\}_j$) product, which is a simplification for some lenders, but matches the average and median menu. Each borrower chooses the utility-maximizing product from the resulting choice set M in a given quarter, with $M = 2 \times J = 20$. Note that I am mainly interested in choice across pricing types, so I assume for identification that any unobserved variation in product characteristics that may jointly affect pricing and choice is at the lender level (ξ_j), such as an unobserved brand preference for a given lender that I can control for, and that unobserved borrower-lender-specific unobservables (η_{ij}) are i.i.d. mean zero when controlling for observed borrower-lender-specific nearest branch distance.³²

I estimate the model on a main sample of all borrowers with a 2-year, maximum 70 to 75% LTV loan between 2015 to 2016, who fulfil a set of standard characteristics (age 25 to 45, loan-to-income-ratio ≤ 4.5 , amortization period ≤ 30 years) in order to come as close to the homogeneous product choice benchmark as possible. I also do robustness checks on a subsample of borrowers who do not bunch at the 75% LTV threshold, as that may be an additional demand factor behind products with fees in order to borrow the additional fee amount, and results are also robust to both using an unrestricted or more restricted sample.

4.2. DISCRETE CHOICE MODEL RESULTS

I estimate alternative-specific logit models with results shown in Table 4. Columns (1) to (5) show results based on the main sample. Column (1) estimates a simple model only including

³¹This implicitly assumes that the odds ratio between any two product types does not depend on the number of products available and poses restrictive assumptions on cross-product substitution patterns. These could be alleviated using a nested logit or random coefficients logit approach.

³²In addition, while it would be possible to include interest rate cost and fee components separately to estimate demand elasticities for both price components, the price components are not set independently in this context in contrast to other settings, e.g. comparing salient and non-salient taxes as in Chetty et al. (2009).

total cost, which yields a coefficient of -0.20. This can be understood as a baseline cost sensitivity, indicating that borrowers indeed dislike total cost. Columns (2) to (5) estimate alternative model specifications. Column (2) estimates a model that accounts for the borrower-specific distance to the nearest branch of a given lender directly, which is significantly negative and picks up part of the total cost sensitivity. This suggests that borrowers indeed have a preference for convenience or familiarity. Column (3) includes lender fixed effects, with results similar to the baseline cost sensitivity, suggesting that cost sensitivity for choice within a given lender is not more sensitive than when choosing across lenders. Column (4) includes an indicator for the low interest, high fee product type which is significantly positive and the coefficient on total cost increases (in absolute terms) to -0.26, suggesting that borrowers have significant additional demand for high-fee products. Lastly, column (5) includes borrower-specific controls for age and income, which increases the cost sensitivity coefficient to -0.32, consistent with the idea that there is substantial heterogeneity in cost sensitivity across borrowers. One additional demand-driven reason why borrowers may have a preference for high fee products is that they can borrow the fee, allowing them to bunch just at the LTV threshold as the fee is not counted towards the LTV balance (as discussed in [Best et al. \(2015\)](#)). The intuition is confirmed by re-running the analysis with a subset of borrowers who do not bunch at the LTV threshold (Columns (6) to (10)).³³ But while the positive demand coefficient for high-fee products decreases by a factor of around 2/3, it remains sizeable and significantly positive.

One way to illustrate the results for demand across price types is to compare the fit of model-predicted market shares with realized market shares, by price types. I hence compute the model prediction error e_{jk} as the difference between the actual and predicted market shares ($s_{jk} - \hat{s}_{jk}$) using different model estimates of \hat{s}_{jk} , as discussed above. I then average these across lenders for the low fee and high fee products ($k = 1$ and $k = 2$) in Figure 5. In the Figure, Model (1) to (4) correspond respectively to columns (1) to (4) in Table 4. The model seems to systematically over-predict low-fee market shares compared to the data (negative prediction error), and under-predict high-fee market shares (positive prediction error). It shows that borrower-lender specific variables such as distance to nearest branch (2) and lender-specific fixed effects (3) cannot explain the systematic prediction errors across lenders. The average difference in errors only disappears once explicitly controlling for product-type fixed effects (4). The findings seem indicative of an “unexplained” demand for products with high fees that cannot be explained in the data if consumers weigh interest costs and fees equally, as is the assumption in the model. The caveat is that these results should be considered in the spirit of a calibration exercise, as it does not yet take into account any further challenges to identification,

³³Excluding borrowers who bunch at the LTV threshold which are about 23% of borrowers in the main sample.

for instance if fees are differentially related to unobserved preferences and product characteristics than interest rates. However, to the extent that these unobservables do not vary within a given lender, the specification with lender fixed effects remains a puzzling result.

Overall, the demand analysis provides indirect evidence for fees being a less salient price component than interest rates, and does not account for more complex challenges to identification, such as time-varying variation in unobserved preferences. In order to address these concerns, the following section studies lender pricing directly.

5. LENDER-LEVEL ANALYSIS

There are a number of competing explanations behind lender fee pricing. In order to distinguish supply-side pricing strategies from demand-driven mechanisms such as unobservable preferences or product characteristics, and to differentiate behind different supply-driven explanations, this section studies lender pricing in response to lender-specific time-varying funding cost shocks. I provide evidence that a lender-specific cost shock, i.e. a relative deterioration in the competitive position of the lender, is associated with significantly higher fees, in particular for the high fee, low interest rate product, while interest rates remain broadly unchanged.

5.1. PRICING INCENTIVES WITH NON-SALIENT FEES

If consumers underreact to fees but emphasize a lender’s position in the interest cost ranking, lenders have an incentive to adjust pricing accordingly. The pricing incentives are illustrated in Figure 7. More specifically, suppose lender j receives a shock to its funding cost, which rise from isocost level \bar{C}^1 to \bar{C}^2 , where $\bar{C}^2 > \bar{C}^1$, while prevailing average market interest rates and fees $\{r_l^{avg}, f_h^{avg}\}$ remain at \bar{C}^1 , meaning it is a firm-specific shock. It decides how to reprice its products following the shock from \bar{C}^1 to \bar{C}^2 . If consumers emphasize the interest cost ranking, its lowest interest rate product (r_l, f_h) is particularly relevant. It can reprice the product by raising interest rates, raising fees, or a combination of both. However, if consumers neglect fees, it is as if they narrowly consider “iso-interest-cost” curves \bar{R} , where $\bar{R}^2 > \bar{R}^1$, which are flat across the fee dimension, instead of considering total cost and hence iso-(total)-cost curves. The lender hence has an incentive to reprice its products to dominate in the non-salient price dimension fees (f_h') , while maintaining a competitive low interest rate r_l^{avg} at iso-interest-cost level \bar{R}^1 , if sufficiently many consumers neglect fees.

This strategic pricing prediction in response to firm-specific cost shocks is further useful to differentiate it from a different plausible mechanism, which is that lenders may have time-varying preferences for fee income, for instance to boost their reported current earnings. This would

predict that lenders move “along” the same isocost curve to increase fee income, while decreasing interest income, all other things equal. Since total cost is held constant, this would attract the same borrower base and increase current fee income while decreasing interest income, for all products, not just the $\{r_l, f_h\}$ product, and is hence distinct from the prediction for strategic pricing.

5.2. IDENTIFICATION STRATEGY

In order to test these predictions and study pricing in response to supply shocks, I require a supply-side cost shifter. Work by [Button et al. \(2010\)](#) illustrates that the largest marginal cost component for mortgages in the UK is funding cost, where long-term wholesale debt is typically considered the marginal source of funding due to its more elastic supply compared to retail deposits. Based on this, I construct a *lender-specific* funding shock using a lender’s pre-determined past loan-to-deposit ratio as a measure of its dependence on wholesale funding,³⁴ interacted with aggregate (exogenous) changes in wholesale funding costs.³⁵

The exogeneity of this so-called “shift-share” shock can be assured in two ways: first, as suggested by [Goldsmith-Pinkham et al. \(2017\)](#), lender-specific exposures to wholesale funding need to be relatively sticky and as-good as randomly assigned after controlling for observables, i.e. loan-to-deposit ratios need to be uncorrelated with lender-specific characteristics conditional on controls. One way to do such a balance test is to regress the funding shock on lagged levels and changes of lender characteristics, which is reported in the appendix.³⁶ None of the lender characteristics (including size, return on assets, net interest margin and leverage) seem systematically correlated with the funding shock, especially not when measured in changes.³⁷ Second, recent work by [Borusyak et al. \(2018\)](#) suggests that this assumption can be relaxed as long as the aggregate shock is exogenous, with exposure sufficiently dispersed. Based on this idea, I further instrument aggregate variation in UK long-term wholesale funding cost, 2-year LIBOR swap rates (ρ_t^{UK}), using 2-year US dollar swap rates (ρ_t^{US}), and construct the aggregate funding cost shock using the fitted values from a regression of ρ_t^{UK} on ρ_t^{US} , denoted $\hat{\rho}_t^{UK}$. This

³⁴As a related application, [Jensen and Johannesen \(2017\)](#) use pre-crisis variation across lenders in the loan-to-deposit ratio in a difference-in-differences setup to compare banks which are relatively more exposed to the wholesale funding shock of the 2007-2008 financial crisis to those that are relatively less dependent on wholesale funding.

³⁵This is akin to a [Bartik \(1991\)](#) shock, originally using local industry employment shares \times national industry employment growth rates as an instrument for labour demand ([Goldsmith-Pinkham et al., 2017](#)), commonly used in the trade and labor literatures.

³⁶Table B.4 shows results for this exercise, based on individual years.

³⁷In addition, another concern could be that lenders who are dependent on wholesale funding differ systematically from lenders who are not, in terms of both depositor and borrower characteristics. The results show substantial variation even within lender types (e.g. large universal banks with similar business models and funding structures), suggesting that the pre-determined difference in loan-to-deposit ratios is not the primary driver of the main findings, further discussed in Section 6.3.

ensures that aggregate variation comes from changes in US wholesale funding markets that are plausibly exogenous to UK mortgage market dynamics. Following [Harimohan et al. \(2016\)](#), long-term wholesale funding cost are then approximated as 2-year swap rates plus senior CDS spreads (s_{jt}) where I use lender-specific CDS spreads for the largest six lenders, and for all other lenders, I use the average CDS spread (\bar{s}_t).

The lender j , time t -specific funding cost shock, denoted ϕ_{jt} , is then constructed as the lender-specific loan-to-deposit ratio in 2008 (one year prior to the start of my analysis), $ltd_{j,2008}$, based on annual balance sheet data, interacted with instrumented wholesale funding cost:

$$\phi_{jt} = ltd_{j,2008} \times (\hat{\rho}_t^{UK} + \bar{s}_t) \quad (2)$$

Identifying variation comes from cross-sectional variation in wholesale funding shares, cross-sectional variation in wholesale funding cost for the largest six lenders, and variation in instrumented aggregate wholesale funding cost over time.

One possible concern is that CDS spreads may not be fully exogenous to contemporaneous mortgage pricing strategies. As explained in [Button et al. \(2010\)](#), banks' operations may usefully alleviate links between funding and mortgage markets within a given bank. Lenders usually centralize their funding operations within a treasury department across the institution, which makes funding available to other business units, who further decide on business-specific lending margins (known as "transfer pricing"). That makes it more likely that for instance the risk strategy chosen for the mortgage market is at the most an outcome of shocks to funding cost, but not the other way round.³⁸ This is in line with the idea that banks can be considered as "price takers" in wholesale funding markets, in particular from the perspective of the mortgage business unit over the main sample period.

The identifying assumption for the overall identification strategy is

$$E[\epsilon_{jt} \mid \phi_{jt}, \gamma_t, \theta_j] = 0, \quad (3)$$

i.e. time-varying unobservables such as lender-time-specific demand shocks should not be correlated with the funding shock.³⁹

I construct the dependent variables as follows. I track the minimum fee ($\{r_h, f_l\}$) and

³⁸In addition, my analysis focuses on analysis within homogeneous mortgage product categories, such as 70-75% LTV, where default risk is low. Within LTV band variation in default risk is explicitly not priced (as per the discrete pricing scheme commonly used), making the risk adjustment channel within LTV band in response to changes in CDS spreads likely to be small in the first place. And in most of the sample period from 2010, bank CDS spreads appear to be driven by banks' exposure to systemic factors such as the Euro Area sovereign debt crisis, that have limited links to the domestic mortgage market.

³⁹By construction, the lender-specific loan-to-deposit share is predetermined, and the aggregate funding shock is not driven by firm-specific decisions or should be exogenous to mortgage pricing decisions.

minimum rate ($\{r_l, f_h\}$) products for 2-year fixed rate, 70-75% LTV mortgages for first-time borrowers, per lender over time, and compute the average rate, fee and total cost (over one and two years) for each lender and quarter. I then merge these pricing statistics to lender-specific funding cost shocks to create a quarterly lender panel from 2009Q1 to 2016Q4. The main specification regresses changes in the outcome variables on changes in the funding cost shock ϕ , and γ_t and δ_j are time and lender fixed effects, respectively:

$$\Delta y_{jt} = \alpha + \beta \cdot \Delta \phi_{jt} + \gamma_t + \theta_j + \epsilon_{jt}, \quad (4)$$

where the outcomes are $y \in \{r, f, C_{1yr}, C_{2yr}\}$, for each price type and for the average across all products. The specification studies how lenders respond to firm-specific shocks to their competitive position, as aggregate shocks and lender-specific levels are absorbed in the fixed effects. While aggregate shocks such as changes in aggregate financial conditions are expected to be passed through, the pricing incentives with non-salient fees generate predictions as to how lenders respond to shocks that change their relative competitive position, in particular by matching prevailing interest rates while increasing fees when funding costs increase.

5.3. RESULTS

Pricing in response to funding cost shocks. Table 5 reports results for the main regression analysis. Column (1) to (4) show results for average interest rates, fees and total cost across products. In response to a one standard deviation change in the funding cost shock, interest rates remain unchanged, while fees and total cost (at the one year horizon) go up significantly, by around £40 and £50, respectively. This seems largely driven by pricing changes for the low rate, high fee product: while r_l (Column (5)) remains unchanged or if at all decreases a little, f_h (Column (6)) increases significantly by £110, which is also economically significant at around 15% of the average level of fees and a 0.5 standard deviation increase in fees. Total cost over one and two years increase by £102 and £94, respectively (Column (7) and (8)). This is in contrast to the high rate, low fee product: while total cost does seem to increase for a similar amount as the low rate, high fee product, albeit not significantly so, this seems driven by increases in r_h . The results suggest that lenders maintain the relative pricing of their low interest rate, but increase fees in response to a deterioration in their competitive position. The fact that the overall increase in fees is driven by the highest fee product is also intuitively consistent with the idea that competing for the lowest interest rate in the market is important - which can be partly achieved by increasing fees. I later also provide evidence that high-cost lenders appear more dependent on the high fee product type.

Pricing of low rate, high fee product by lender pricing type. Next I test if the dynamic pricing strategy is related to the heterogeneity in fee levels across lenders, i.e. if lenders who rely on high fees also adjust their fees more in response to a relative cost shock. I define lender pricing types based on how much prices are skewed towards the interest rate dimension via fees that are higher than the prevailing average, using terciles of the ranking difference in the total cost minus the interest rate ranking position. Lenders in the “low” category have a negative skew and hence relatively low fees (Columns (1) to (4)), “medium” lenders’ position in the total cost ranking is similar to that in the interest rate ranking (Columns (5) to (8)), and “high” lenders have a substantially better (i.e. lower) position in the interest rate ranking compared to the total cost ranking, i.e. have a high skew in their prices using high fees (Columns (9) to (12)). I find that the price adjustment in the low rate, high fee product seems indeed strongly driven by lenders with skewed price levels. While there is no significant adjustment in interest rates or fees in response to a relative funding cost shock for “low” skew types, fees respond marginally significantly for “medium” pricing types, and are strongly significant for lenders with highly skewed prices. The latter raise f_h by £201 (Column (10)) and total cost over two years by £144 (Column (12)) in response to a one standard deviation cost shock, while r_l remains relatively unchanged.

Robustness. The results are robust to using UK swap rates, different pricing statistics (e.g. median, minimum and maximum rates and fees of lender menus) and similar when omitting lender fixed effects. In addition, the analysis so far has focused on low risk mortgages for which the homogeneous product market and limited heterogeneity in unobserved borrower characteristics assumptions seem more valid. In contrast, I do not find cost pass-through via fees for riskier mortgages (reported in Table B.5 in the appendix). Average total costs across products increase substantially in response to a funding cost shock, by between £80 to £200, but this is almost entirely driven by increases in interest rates. This may suggest that pricing strategies differ across less risky and riskier LTV markets and may depend on the competitive structure and borrower population of a given LTV market. An intuitive explanation could be that if the adverse selection problem is much worse for high LTV loans, lenders may not want to attract borrowers based on a low interest rate with high fees.⁴⁰

Overall, I find evidence that lenders maintain their relative pricing of interest rates following

⁴⁰There is existing evidence that firms choose rent-extraction strategies differentially across borrower groups, for instance Nelson (2017) finds that US lenders target existing clients who have high credit scores but seem less likely to switch banks to increase credit card rates, while this strategy is not employed for low credit score borrowers where default risk is the main pricing factor.

a cost shock and increase fees for low risk mortgages, driven by changes in the pricing of the low interest rate, high fee product, and lenders who have high average levels of fees and hence more skewed prices relative to others.

6. INTERPRETATION AND DISCUSSION

6.1. THE ROLE OF FEES

There are two conventional views of the function of mortgage origination fees. On the one hand, they could compensate for a fixed cost component of originating a mortgage such as paper work and processing cost. That implies that they should not be related to higher frequency changes in marginal cost such as funding cost. Alternatively, fees could reflect a variable cost of originating larger mortgages. For instance in Denmark, consumers pay a percentage of the loan value in administration fees that depends only on loan characteristics,⁴¹ meaning that a given borrower does not have to compare fees for her cost minimization problem.

In the UK, while the interest rate-fee trade-offs imply optimal cut-offs for different loan values, the market is not clearly segmented or standardized by loan size and all product variants appear marketed as pooled, with an emphasis on the overall interest rate ranking. The evidence further suggests that fees serve as an active margin and additional degree of freedom when setting mortgage prices. This affects the direct comparability of total cost across mortgages: instead of comparing mortgage prices using a scalar, where the interest rate is a sufficient statistic for the total interest rate cost and can be compared using a general best-buy table, consumers face a price vector of interest rates and fees. In order to compare total cost across products, borrowers need to add fees to the loan-specific interest rate cost, which depends on the loan amount borrowed, and would require loan-amount-specific best-buy tables. This separation of pricing components (Grubb, 2015) and limiting of comparability across products (Carlin, 2009, Piccione and Spiegler, 2012) may decrease borrowers' total price sensitivity and make search more difficult. In addition, borrowers may be less able to find the cheapest product if both fees and interest rates vary, compared to if they were confronted with a composite (scalar) price measure. This is similar to findings by Ellison and Ellison (2009) in an online shopping environment for a homogeneous consumer electronic good, who document a range of case study practices to make search more difficult, including shrouding shipping cost and competing on additional quality dimensions. One interesting implication of their findings could be that without fees, the market would be extremely price-sensitive given the ease of price search

⁴¹E.g. collateral and period of interest rate fixation, see Danmarks Nationalbank, Statistics on Banking and Mortgage Lending, Interests, April 2018.

if there is a unique price ranking by interest rates. While this counterfactual is unobserved, I provide some supportive evidence by looking at the sample of borrowers who choose a zero fee product, who indeed generate less price dispersion in choice outcomes (Figure 8).⁴²

6.2. PRICING FEES IN A SPECIALIZATION EQUILIBRIUM

The empirical results point to lenders adjusting interest rates and fees separately in a way that may allow (some) lenders to extract rents from consumers who neglect fees.

The findings are consistent with a standard search framework that yields a specialization equilibrium, in which high-cost lenders are able to attract “uninformed”, that is less cost-sensitive consumers, but not informed consumers, who go to low-cost lenders, yielding a separating equilibrium or equilibrium price dispersion (Salop and Stiglitz, 1977, Varian, 1980, Galenianos and Gavazza, 2017). In the following, I discuss how this can be interpreted in the context of a differentiated product market model in line with the borrower-level discrete choice analysis. Suppose lender j maximizes profits

$$\Pi_j = (z_j - \kappa_j) \cdot s_j,$$

where z_j is a fee-inclusive price (“zero-fee interest”), κ_j is marginal cost and s_j is the market share based on borrower demand defined in Equation 2 (ignoring product types k and default risk for simplicity). The first-order condition pins down the standard optimal pricing rule for prices as the sum of marginal cost and mark-up:

$$\underbrace{z_j}_{\text{price}} = \underbrace{\kappa_j}_{\text{marginal cost}} + \underbrace{\frac{1}{\gamma^z(1-s_j)}}_{\text{mark-up}},$$

where γ^z is proportional to the total-cost elasticity from the demand estimation. It does not, however, pin down the optimal split of price components. If lenders are indifferent between interest and fee income, and if borrowers indeed exhibit lower demand elasticities with respect to fees than interest rates, then lenders would choose a corner solution and receive their entire income through fees, with 0% interest rates, which is highly counterfactual. Rather than fees being unconditionally non-salient, it seems intuitive of thinking of the fee elasticity as an (exponentially) increasing function of the level of fees, meaning that consumers become more attentive to fees, the higher they are. If different lenders are able to attract differentially cost-sensitive consumers (with γ_j^z), the marginal benefit of increasing the fee equals the marginal

⁴²This may point to trade-offs between the volatility of bank profits and improved consumer search for policy makers that are outside the scope of this paper.

cost at different levels of fees, generating fee heterogeneity.⁴³ In that sense, lenders with higher equilibrium fees are able to attract less cost-sensitive consumers, while lenders who do not skew their pricing are likely to attract more cost-sensitive consumers, generating a specialization pattern in line with the intuition from search models.

6.3. EVIDENCE FOR SPECIALIZATION EQUILIBRIUM

Heterogeneity in pricing across lenders. I provide further evidence for this type of specialization equilibrium by splitting lenders into terciles of the difference between their minimum total cost and interest rate ranking, as a measure of how much they skew their interest rate ranking using higher fees compared to other lenders. The results are shown in Table 7. The upper tercile of lenders have a positive difference of 6 on average, i.e. they have the $x + 6$ th-highest position in the total cost ranking, but only the x th highest interest rate ranking. As expected, they charge similar interest rates as their competitors, but higher fees, both for the high fee and low fee product. While they have similar size and funding structures as other lenders, they earn substantially lower returns on assets and equity and have higher funding costs. They also tend to have a higher branch density, measured as the number of households that have a branch nearby, and higher market share, suggesting that existing forms of market power based on branch networks (Drechsler et al., 2017) interact with those based on consumer mistakes and may make it easier for these lenders to acquire less cost-sensitive borrowers. Across lenders, fees do not seem to compensate directly for a greater branch density, however. Figure 7a and 7b show that there is a somewhat positive association between branch density and interest rates, but not fees, meaning that both the financial necessity and ability to attract less cost-sensitive borrowers seem to affect lenders' pricing decisions.

Dependence on zero-fee and high-fee products. Another way of showing variation in pricing across low and high-cost lenders is to look at their dependence on zero-fee compared to high-fee products. The true cost ranking across lenders should be fully and uniquely revealed (i.e. valid across the loan size distribution) when looking at the interest rate ranking across products without fees. So low cost lenders should have a relatively high market share in products without fees, while high-cost lenders may try to avoid products without fees, as they cannot improve their interest cost ranking by increasing fees. Hence high-cost lenders should also be relatively reliant on products with fees, in particular high fees. This seems to hold out in the

⁴³This is related but slightly different to the approach by Agarwal et al. (2014) for the US credit card market, who assume that non-salient fees are capped at an exogenous maximum level as their market setup does not require matching fee heterogeneity. An alternative way to preserve non-degenerate interest pricing as observed in the data is to allow for a fixed price frame r_l, r_h , as outlined in a previous version of this paper.

data. I measure within-lender market share as the share of products for a given lender in a given quarter that has zero or high fees, out of all products issued by that lender in that quarter (based on mortgage origination data from PSD). As a proxy of a lender’s cost-level, I compute the average total cost distance to the cost-minimizing product across all the products offered by a given lender in a given quarter⁴⁴ which I refer to as lender-time-specific excess cost. Figure 9a shows that there is indeed a negative relationship between the within-lender market share of zero fee products and lender-time-specific excess cost, while Figure 9b shows that there is a positive relationship for high-fee products.⁴⁵ This provides suggestive evidence that low-cost lenders are relatively more competitive in the zero-fee product market, and that high-cost lenders are relatively more reliant on high-fee products.⁴⁶

Excess cost dispersion in borrowing outcomes. In borrowing outcomes, I compute excess cost dispersion following Gurun et al. (2016), as the residual of a regression of total cost on borrower, product and regional characteristics. The excess cost residuals are plotted by fee categories in Figure 8. I find higher excess cost dispersion for products without fees, compared to products with fees, i.e. borrowers seem to come closer to the cost-minimizing benchmark in the class of products without fees than those with fees. It shows that borrowers with zero fee products indeed seem to have a narrower distribution and hence lower price dispersion, while the distributions for products with fees are more dispersed, and in particular high fees seem to come with a larger right tail of excess cost. This is further suggestive evidence that borrowers appear to underreact to fees and seem better at cost minimization if there is no fee involved.⁴⁷

6.4. DISCUSSION OF ALTERNATIVE CHANNELS AND ROBUSTNESS

This section considers additional alternative channels, most notably screening motives using fees which could be correlated with lender-specific cost shocks. I find limited evidence for lenders’ use of fees to screen for risk types.

Screening for borrower risk. First, the market setting makes it unlikely that lenders in the UK screen for prepayment risk using fees. In contrast to the US, lenders commonly set early

⁴⁴Based on the Moneyfacts product data and an average loan value of £150,000 as a reference value for comparison. As shown in Figure B.2 in the appendix, the cost ranking does not vary substantially across the loan size distribution, suggesting that some products are unambiguously more expensive than others.

⁴⁵This relationship is not mechanical, as there is an omitted category with medium fee products (0,1000].

⁴⁶Note that the proxy for high and low-cost lender is measured as time-varying, reflecting the idea that lenders’ position in the total cost ranking fluctuates over time.

⁴⁷Related work by Iscenko (2018) using a strictly dominated choice criterion finds that borrowers tend to take out mortgages that are strictly dominated in the interest rate dimension, which is a more narrow framework compared to the discrete choice model that allows borrowers to have lender- and borrower-lender-specific demand. The finding could be consistent with the evidence that preference factors, such as the branch network, appear more compensated in the interest rate dimension, while fees may still distort the subjective cost ranking within and across (interest-cost dominated) lenders.

repayment penalties, providing them with a more direct way to screen for prepayment risk than by using fees, also known as points (Stanton and Wallace, 1998) in the US. There is also limited variation in prepayment penalty terms for products within a given lender. Only 7 out of 27 lenders have any variation across products, and only around 10% of product observations offer different prepayment penalty terms within a given lender at the same point in time. I further confirm that prepayment penalty terms do not significantly alter the interest rate-fee trade-off pricing of a given lender in a regression framework, outlined below. This seeming lack of screening and pricing of heterogeneous repayment risk could be explained by the relatively short initial fixation periods of 2 to 5 years prevalent in the UK, at the end of which most borrowers refinance, as documented by Best et al. (2015).

Second, lenders could price in potential borrower selection on unobservable characteristics that affect default probabilities, for those who choose a relatively more expensive fee-interest rate alternative. For instance, Choi et al. (2009) show that demand for high-fee index funds seems to be primarily driven by mistakes due to financial illiteracy, which could be correlated with unobservable default risk. Lenders may also use products with fees to screen for liquidity risk which may be correlated with default, as highly liquidity-constrained borrowers may be unable to pay an upfront fee. But as seen in the main results, the cost pass-through occurs via fees only for low LTV products, indicating that the mechanism may play more of a role when default risk is low and selection on unobservables may play less of a role.

Complementary factors. Recent work has established advertising (Gurun et al., 2016, Hastings et al., 2017) and advice (Foà et al., 2015, Egan, 2018) as important factors behind dominated consumer choice. In my analysis, these factors are likely to reinforce the mechanism at hand. Interest rates are made salient in the way prices are framed and advertised in the market, while differences in fees are noted much less prominently or simplified as indicator variable in many price comparison tables. Brokers can steer borrowers towards more expensive mortgages due to incentive problems, as they may earn higher commission payments for such products. Lender pricing using high fees can be seen as a strategic complement to any of these channels, as the choice of high fee product could be promoted via advertising campaigns and commissions, and may affect consumers' choice and choice sets even when they process their mortgage through a broker.⁴⁸ There does not seem to be strong direct link between lender fees and broker commissions in the data, however, as the correlation in the loan sample is positive but small (3%),

⁴⁸In the UK, about half of borrowing is processed via brokers (Robles-Garcia, 2018). Changes to advisory requirements mandated in the FCA Mortgage Market Review in 2014 were found to have had a limited impact on cost (Iscenko and Nieboer, 2018), suggesting that the impact of brokers on chosen product cost may be relatively neutral.

pointing to a largely independent channel.

Screening for loan size. Lastly, a given lender’s pricing scheme does imply that borrowers with different loan sizes should choose different products, i.e. it should serve as a coarse way of screening for loan sizes. Based on offered prices and the loan value distribution over the sample period, only a relatively small sample of borrowers should consider products with fees at all, in particular high fees, compared to picking a product alternative with no or low fees. For the average borrower (borrowing at the average of the loan size distribution at a given point in time), the isocost curve with cost-minimizing fee-rate combinations tends to be steeper than the price terms that are on offer (as seen in Figure 3b), meaning that the cost-minimizing choice tends to be a product without fees or low fees. I can show that the interest rate cost reduction for the average borrower tends to be lower than the fee required to get the lower interest rate more formally in a product-level regression of interest rate cost on fees shown in Table B.6. If a borrower is indifferent between the low fee, high interest rate and the high fee, low interest rate product, the slope coefficient β on fees would be -1, i.e. a £1 paid in fees would yield a £1 interest rate cost reduction. The baseline correlation in column (1) with time and product (LTV) fixed effects is negative, but not significant. Column (2) and (3) saturate the regression further with lender and lender-time fixed effects, in order to measure the interest cost-fee trade-off within a given lender that is on offer at a given point in time. The coefficient is strongly negatively significant, but is only around -0.4. Columns (4) to (6) add additional product-level control variables including the early prepayment penalty, a cashback indicator as an example of measurable additional incentives and the length of the incentive description text. Only the incentive length shows up as positively significant within lender, tentatively suggesting that lenders provide a worse trade-off when the description of incentives is more extensive, consistent with obfuscation motives that make the product more complex (C  lerier and Vall  e, 2017). Lastly, column (7) introduces a square term for fees which is strongly positively significant, capturing the fact that the trade-off becomes worse for products with high fees, as expected.

7. CONCLUSION

This paper provides evidence for supply-driven fee dispersion in two steps: first, by showing that borrowers are less cost-sensitive towards products with high fees, in line with a market environment that emphasizes interest rates and leaves fees as a non-salient, but financially significant price component; and second, by showing that lenders internalize this demand-side friction and

maintain competitive interest rates, while increasing fees in response to lender-specific shocks to funding cost. The empirical strategy makes it less likely that fees compensate for (time-varying) variation in unobserved preferences or product characteristics. The paper further illustrates heterogeneity in lender pricing strategies: lenders who skew their prices towards low interest rates using higher-than-average fees indeed rely more on business from high fee products, and tend to have higher funding cost, lower return on equity and a bigger branch network, suggesting that the pricing strategy is related to both competitive pressure, as well as the ability to attract less cost-sensitive consumers.

To put these findings into a bigger perspective, they illustrate that incentives of financial intermediaries are important for household financial outcomes (Agarwal et al., 2017a), which could become a more prominent issue with the rise in data availability to single out consumers and their biases (Ru and Schoar, 2016). Pricing of non-salient cost components further relates to the changing nature of competition and market power in consumer goods and retail financial markets, away from physical branch networks (Drechsler et al., 2017) towards online-based distribution channels and hence an increasing importance of the information available to consumers, and what information consumers pay attention to, with potentially important macroeconomic consequences (Scharfstein and Sunderam, 2015, Agarwal et al., 2014). The work shows that competitive pressure may exacerbate firms' reliance on non-salient price components (Spiegler, 2006) and generate incentives for financial innovation (Heidhues et al., 2017).

Any policy responses⁴⁹ will have to assess the cost and benefits of decreasing price dispersion in the market, such as consumer cost savings through standardizing products against the risk of limiting (potentially welfare-increasing) product innovation, and indirect effects on demand and supply. Policies aimed at informing consumers may be beneficial to the extent that consumers for instance believe that fees are less dispersed than they are in reality, and hence correct beliefs about the marginal benefits of search or induce more efficient search.⁵⁰ The framing of cost may also affect the relative salience of cost components, in line with Bordalo et al. (2013).⁵¹ However, it also risks making certain features salient at the expense of others (Agarwal et al., 2014), e.g. by introducing a composite price, which firms have an incentive to deviate from.

Overall, these findings pose new questions relating to competition and consumer search in the presence of behavioral biases, and the importance of both supply and demand factors as well as their interaction effects, which seem fruitful topics for future work.

⁴⁹See Grubb (2015) for a review.

⁵⁰The effectiveness of such a policy may depend on what motivates consumers to search and what type of information would improve their search behavior (Alexandrov and Koulayev, 2018).

⁵¹For instance, (relative) differences in fees may be less salient than differences in interest rates, which may be reversed if interest rates were quoted in interest cost terms.

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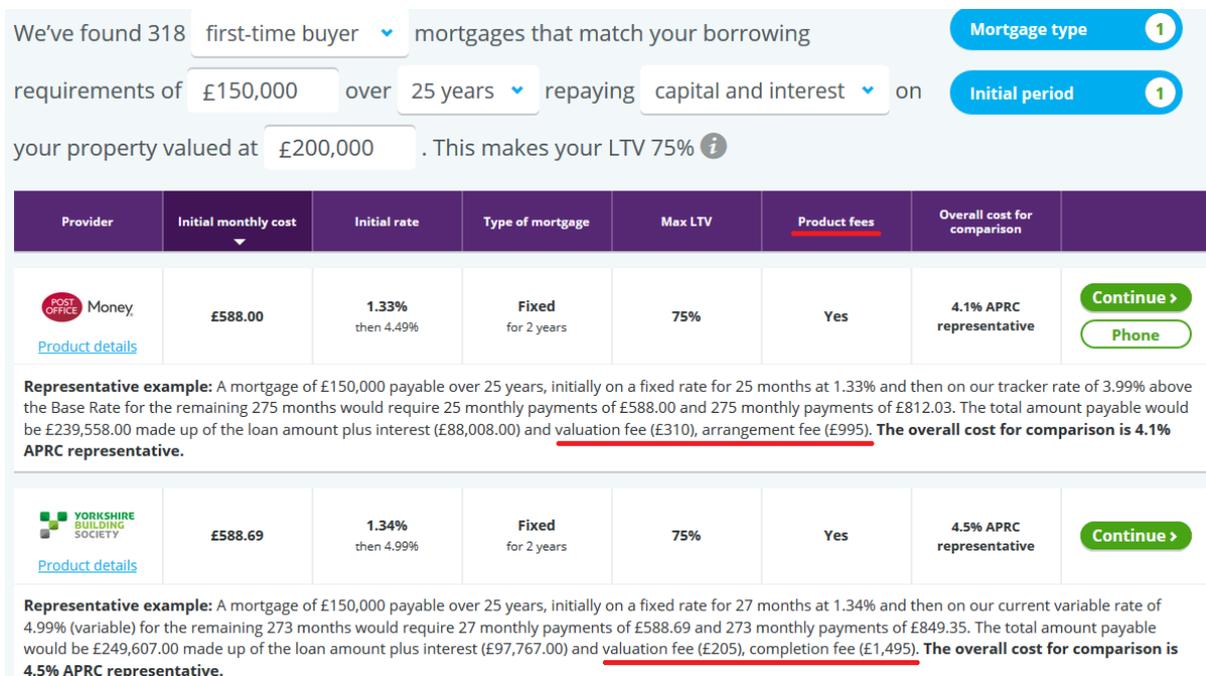
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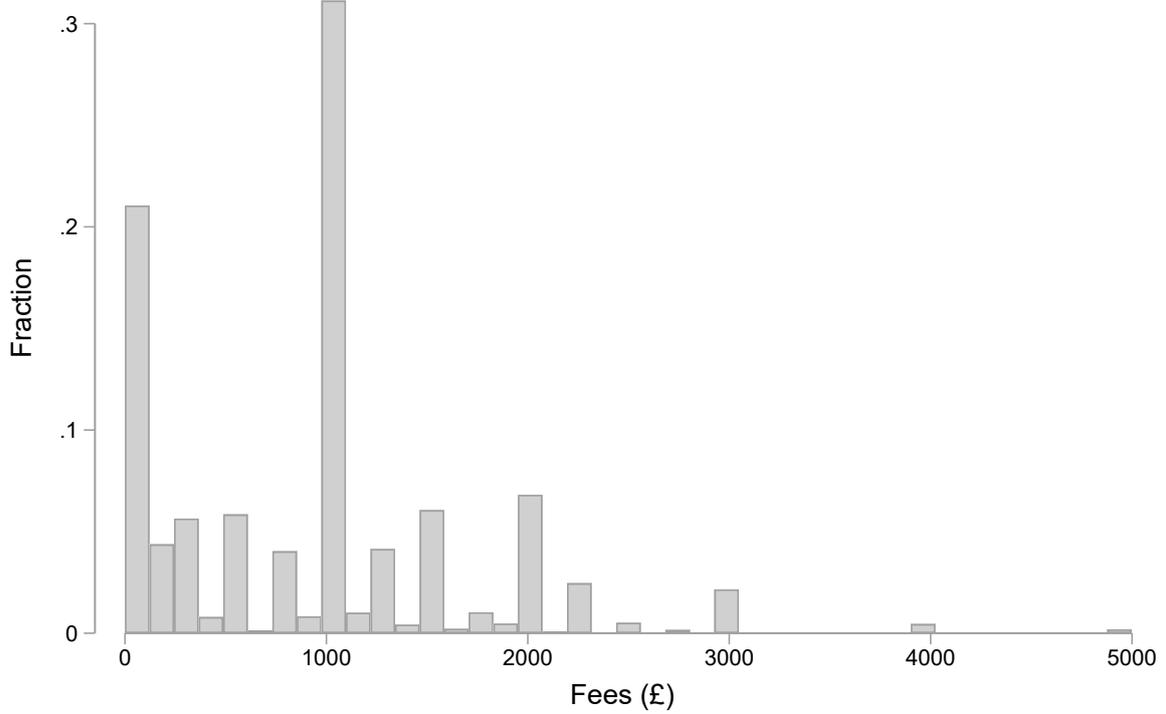
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FIGURE 1: EXAMPLE PRICE TABLE FROM MONEYSUPERMARKET.COM



Notes: This figure shows a typical price table for mortgage products, based on the search result for a 2-year fixed rate mortgage product, with maximum 75% LTV, for first-time buyers and a loan size of £150,000, from MoneySupermarket.com. The default ranking is by interest rates, with a fee indicator and the value of fees in the footnotes.

FIGURE 2: DISTRIBUTION OF FEES



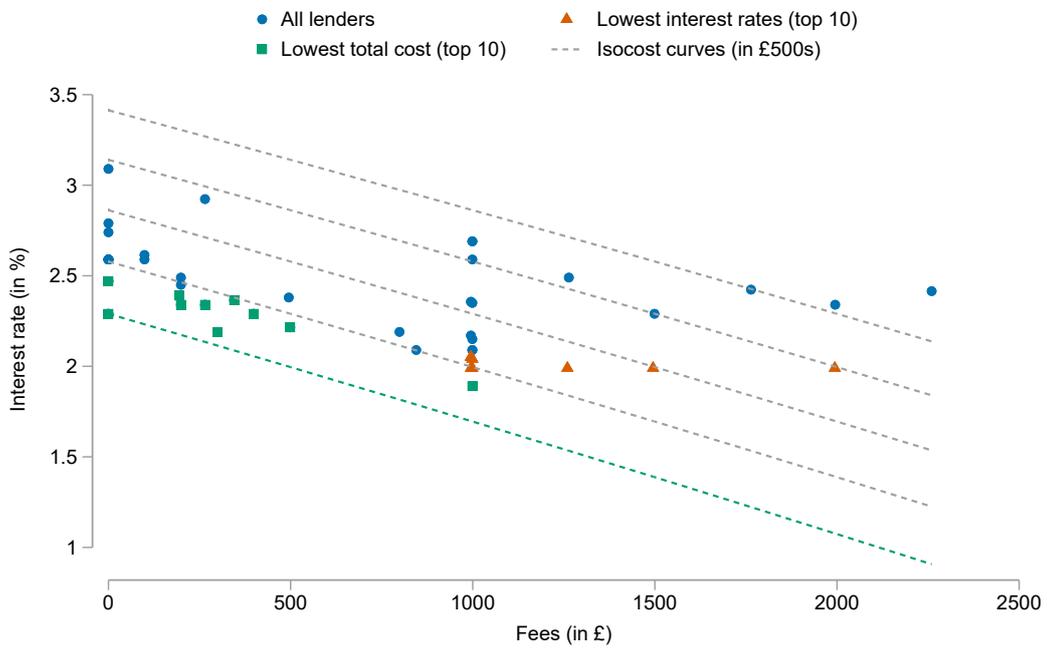
Notes: This figure shows a histogram of fees, based on all products on offer for 2yr fixed rate, 70-75% LTV products over the sample period between January 2009 and December 2016.

FIGURE 3: EXAMPLE OF PRODUCTS ON OFFER

(A) INTEREST RATE RANKING (W/O FEES)

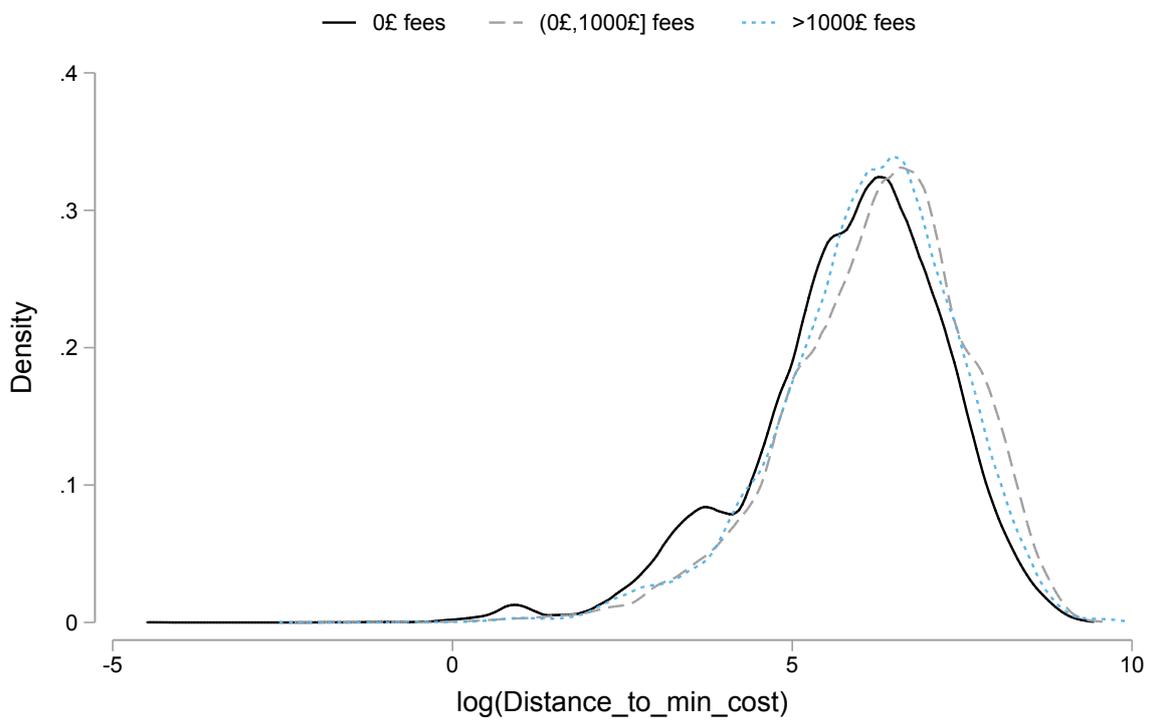


(B) INTEREST RATES, FEES AND TOTAL COST CURVES



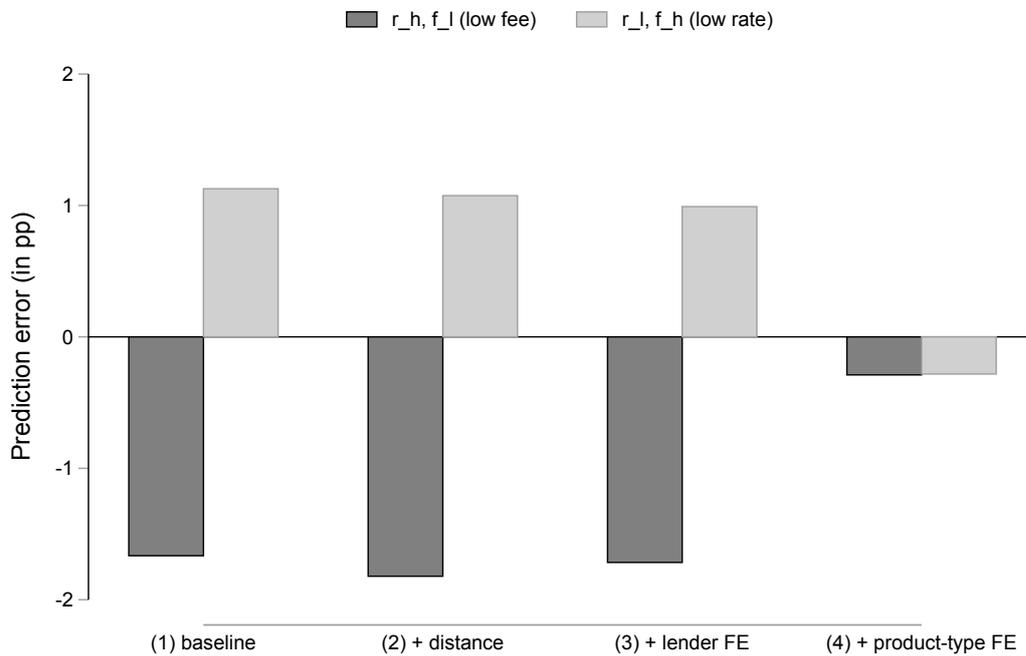
Notes: Figure 3a shows the set of 2yr 70-75% LTV products on offer in February 2014 as a pure interest rate ranking, when ignoring fees. Figure 3b shows the same set of products in interest rate-fee space, together with isocost-curves based on the total cost of a given product over two years and the average loan size in that month, amortized over 25 years.

FIGURE 4: WITHIN-BANK PRICE DISPERSION



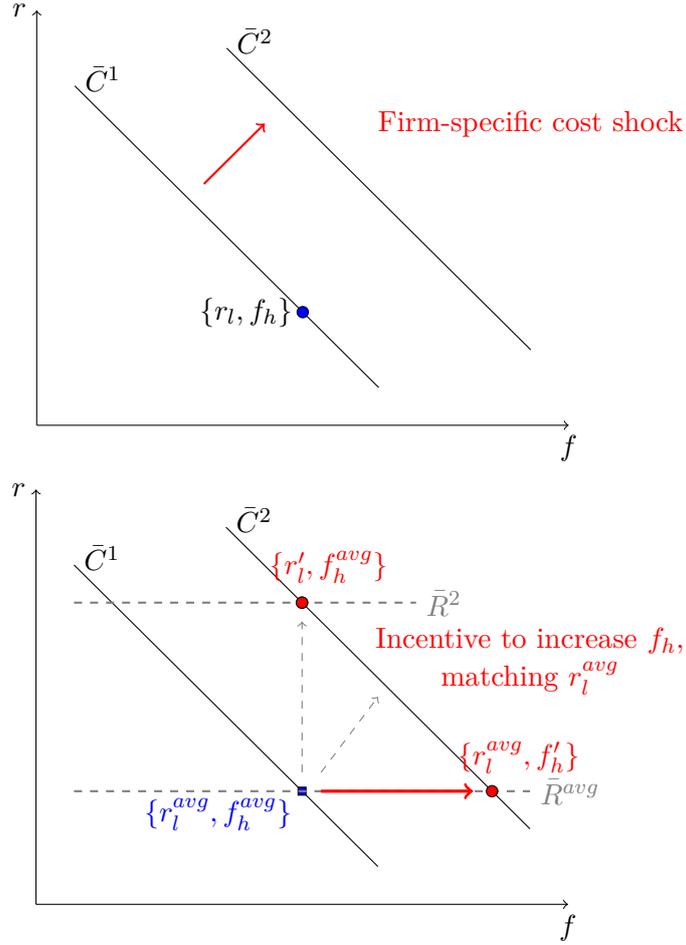
Notes: This figure shows the distribution of the log distance of the cost of the chosen product type (no fees, medium and high fees), compared to the cheapest product alternative available, for a given lender at a given point in time. It hence captures price dispersion “within” a given lender, which would be a degenerative distribution centered at 0 if borrowers always chose the cost-minimizing product for a given lender and point in time. The figure is based on realised 2-year fixed rate, low LTV loan outcomes from 2015 to 2016.

FIGURE 5: LOGIT MODEL PREDICTION ERROR (BY PRODUCT TYPE)



Notes: This figure shows the average logit model prediction error (e_k), defined as the difference between the realized and predicted market shares (where $e_{jk} \equiv s_{jk} - \hat{s}_{jk}$), across all lenders, by product type k ($\{r_h, f_l\}$ or $\{r_l, f_h\}$), for four model specifications as estimated in Table 4. Models (1) to (4) correspond to column (1) to (4) in Table 4, respectively. It shows that borrower-lender specific variables such as distance to nearest branch (2) and lender-specific fixed effects cannot explain the systematic prediction errors for low fee-type products ($\{r_h, f_l\}$), compared to low rate but high fee-type products ($\{r_l, f_h\}$). The average difference in prediction errors only disappears once explicitly controlling for product-type fixed effects (4).

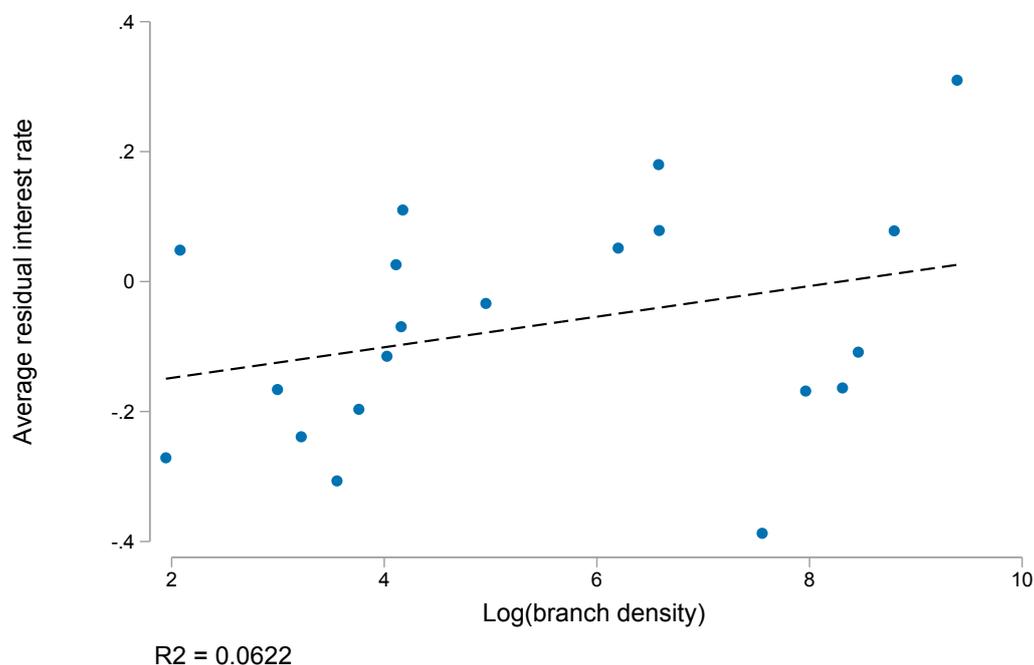
FIGURE 6: ILLUSTRATION OF PRICING WITH NON-SALIENT FEES



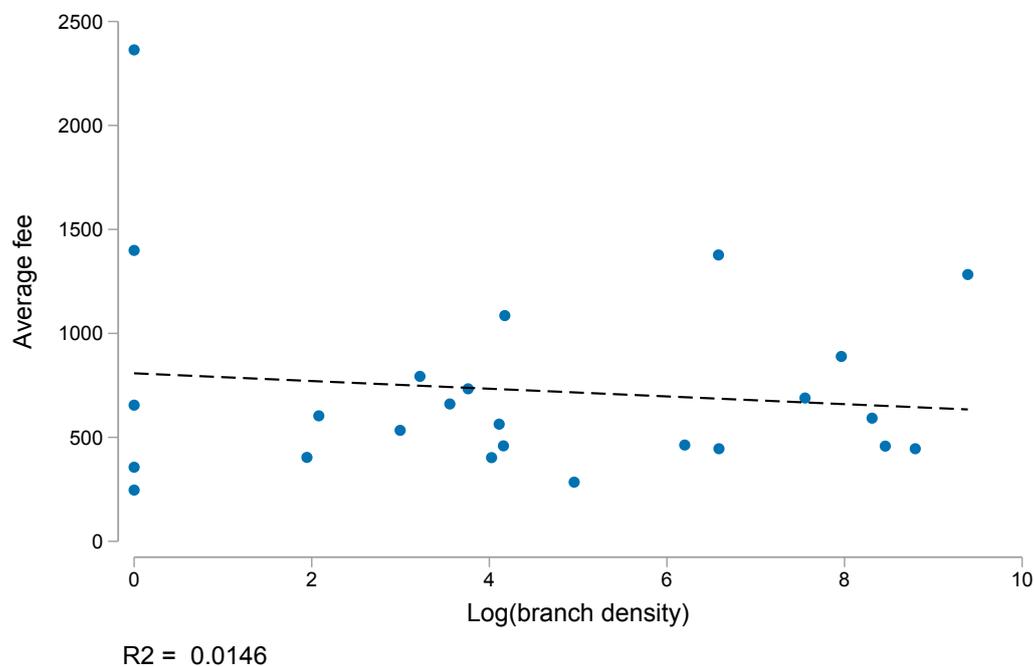
Notes: This figure illustrates the pricing incentives of a lender following a firm-specific shock to funding cost, from isocost level \bar{C}^1 to \bar{C}^2 , where $\bar{C}^2 > \bar{C}^1$. The now cost-dominated product (relative to prevailing average interest rates and fees $\{r_l^{avg}, f_h^{avg}\}$) is repriced to dominate in the non-salient price dimension, fees (f_h'), while maintaining a competitive interest rate (r_l^{avg}), if consumers neglect fees. Non-salient fees can be interpreted as consumers narrowly considering “iso-interest-cost” curves \bar{R} , where $\bar{R}^2 > \bar{R}^1$, which are flat across the fee dimension, compared to when consumers consider total cost.

FIGURE 7: AVERAGE INTEREST RATES AND FEES AND BRANCH DENSITY

(A) INTEREST RATES

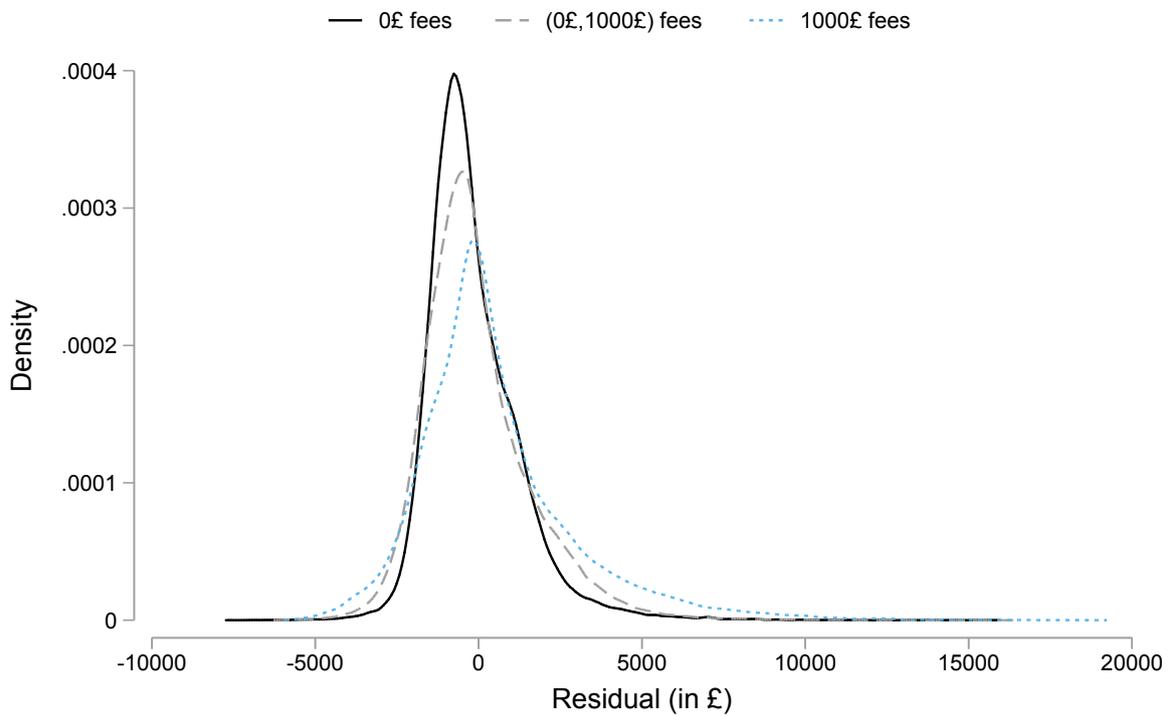


(B) FEES



Notes: This figure shows a scatter plot of the average residual interest rate (with monthly average levels partialled out) and fee across the full sample period from 2009 to 2016, respectively, and log branch density. Branch density is measured as the number of borrowers for whom a given lender operates the closest nearby branch (yielding similar distributions when using up to second, third etc. closest branches). It suggests that higher branch density is partially compensated via higher interest rates, but less so higher fees, where the relationship is flatter.

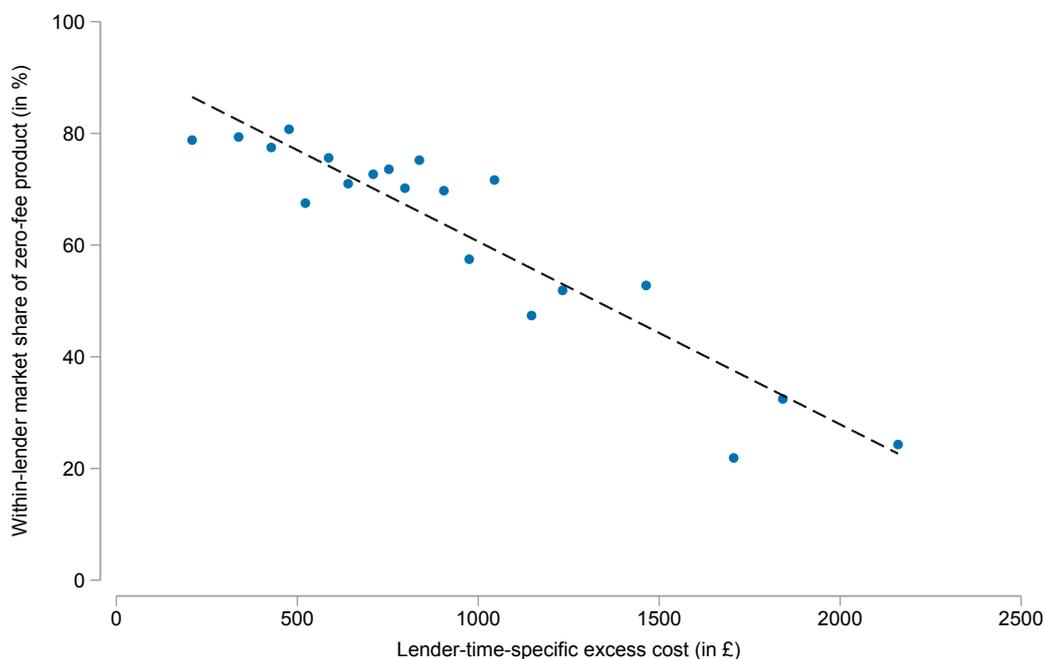
FIGURE 8: EXCESS COST DISPERSION BY FEE CATEGORY



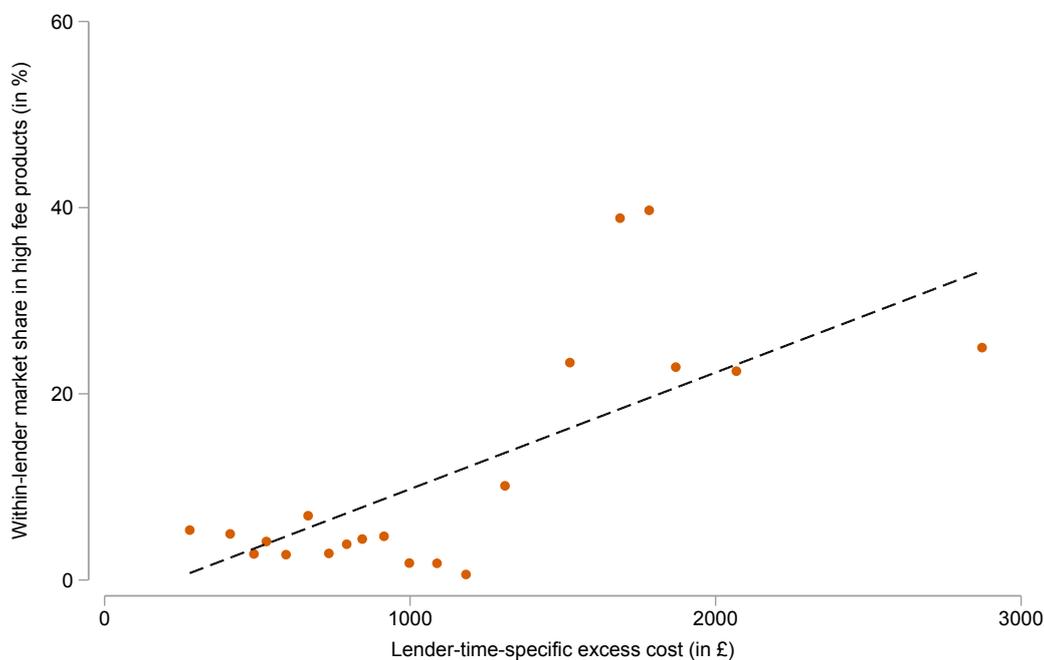
Notes: This figure shows the densities of excess cost by fee categories (low, medium and high fees). Excess cost is measured as the residual e_{ijt} from a regression of loan-level realized total cost on LTV band, year-month and region fixed effects, using loan-level data from 2015-2016: $C_{ijt} = \alpha + \beta X_{it} + \gamma_t + \theta_j + \epsilon_{ijt}$. It measures the dispersion in cost paid when partialling out other observable characteristics, which seems to be larger, with a bigger right tail for high fee products ($>£1000$).

FIGURE 9: RELATIVE MARKET SHARES BY LENDER EXCESS COST LEVEL

(A) RELATIVE MARKET SHARE IN ZERO-FEE PRODUCT



(B) RELATIVE MARKET SHARE IN HIGH-FEE PRODUCT



Notes: Figure 9a shows a binned scatter plot of within-lender market share (share of products in a given fee category out of all products issued by the lender in a given quarter) in the zero-fee product by lender-time-specific excess cost, measured as the difference between a given lenders' average total cost of mortgages on offer and the cost-minimizing product in a given quarter. Figure 9a shows the equivalent binned scatter plot for high-fee products where high fees are defined as fees > £1000.

TABLE 2: DESCRIPTIVE STATISTICS

<i>Panel 1: Summary of Moneyfacts variables (monthly)</i>					
Variable	Observations	Mean	Std. Dev.	Min	Max
Interest rate (in %)	26451	3.36	1.24	0.99	7.89
Max LTV, first-time buyer	26451	77.43	10.04	60.00	95.00
No additional product fees (indicator)	26451	0.21	0.40	0.00	1.00
Arrangement fees (in £)	9423	1009.34	449.48	99.00	3995.00
Booking fees (in £)	10987	465.78	520.76	95.00	4999.00
Completion fees (in £)	7286	506.93	362.09	50.00	2400.00
Reservation fees (in £)	735	563.97	298.93	99.00	999.00
Fees (sum of fee components)	26451	708.43	611.46	0.00	4999.00
<i>Panel 2: Lender characteristics (annual)</i>					
Variable name	Observations	Mean	Std. Dev.	Min	Max
log(total assets)	212	17.78	2.07	12.39	21.71
Return on assets (in %)	212	-0.07	1.47	-10.57	4.91
Return on equity (in %)	212	0.10	15.95	-74.39	39.96
Loan to deposit-ratio	212	1.06	0.30	0.28	2.59
Net interest margin (in %)	212	1.41	0.71	0.30	4.57
<i>Panel 3: Lender panel variables (quarterly)</i>					
Variable name	Observations	Mean	Std. Dev.	Min	Max
<i>Levels</i>					
Wholesale funding shock	696	9.51	9.49	0.29	70.94
Avg. interest (\bar{r})	696	3.04	0.92	1.42	5.92
Avg. fees (\bar{f})	696	689.91	385.35	0.00	3665.67
Avg. total cost over 1yr (\bar{C}_{1yr})	696	8351.79	979.46	6480.50	11298.91
Avg. total cost over 2yr (\bar{C}_{2yr})	696	16013.67	1849.75	12865.75	21948.01
<i>Changes</i>					
Wholesale funding shock	671	0.00	1.00	-2.78	3.50
Avg. interest (\bar{r})	671	-0.08	0.26	-1.12	1.27
Avg. fees (\bar{f})	671	4.28	205.87	-800.00	2666.67
Avg. total cost over 1yr (\bar{C}_{1yr})	671	-69.74	313.22	-1365.31	2772.89
Avg. total cost over 2yr (\bar{C}_{2yr})	671	-143.75	535.36	-2533.13	3429.85

Panel 1 reflects the main dataset that contains offers for first-time buyers and 2-year fixed rate contracts only. Data on lender characteristics and funding data (Panel 2 and 3) are obtained from SNL Financial and Bloomberg. Variables in Panel 3 are built from Moneyfacts, lender characteristics and funding data.

TABLE 3: PROPORTION OF COST-DOMINATED PRODUCTS BY FEE CATEGORY (IN %)

Excess cost	Fees					Total
	zero fees	(0,500]	(500,1000]	(1000,1500]	>1500	
<=500	4.6	5.4	4.3	0.1	0.0	14.5
(500,1000]	4.4	5.4	10.0	1.3	0.0	21.1
(1000,2000]	6.6	6.3	13.4	5.5	2.7	34.5
(2000,4000]	2.8	5.1	8.0	4.1	2.8	22.9
>4000	0.7	1.8	2.7	1.2	0.6	7.1
total	19.1	23.9	38.5	12.3	6.2	

Notes: This table shows the proportion of all products (in %) between January 2009 and December 2016 split by excess cost, computed as the total cost less the lowest cost product available in a given month, and fee categories. Total cost is computed for a 2-year fixed rate mortgage over two years, at 70-75% LTV for first-time buyers, for a loan size of £150,000, amortized over 25 years.

TABLE 4: LOGIT MODEL ESTIMATION RESULTS

Dep. Var.: <i>chosen</i>	Main sample					Non-bunching sample				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Total cost (in £,000)	-0.202*** (0.009)	-0.131*** (0.010)	-0.187*** (0.013)	-0.259*** (0.010)	-0.322*** (0.017)	-0.191*** (0.011)	-0.110*** (0.011)	-0.225*** (0.015)	-0.208*** (0.011)	-0.339*** (0.021)
Distance to nearest branch (in km)		-0.022*** (0.001)					-0.027*** (0.001)			
$I_{[r_i, f_i]}$				0.562*** (0.014)					0.135*** (0.015)	
Lender FE			✓		✓			✓		✓
Borrower-specific controls										
Observations	450297	450297	450297	450297	450297	347147	347147	347147	347147	347147
Cases	23067	23067	23067	23067	23067	17767	17767	17769	17767	17768

Notes: This table displays estimates of equation 2 for two samples and five specifications each. The main sample contains borrowers with 2yr fixed rate, 70-75% LTV products and is restricted to standard characteristics (age 25 to 45, loan-to-income ratio ≤ 4.5 , and amortization period of ≤ 30 years). The non-bunching sample contains only borrowers whose original LTV is below 75 and who are hence not reliant on fees to borrow within the 75% LTV band, in order to avoid higher interest rates (which jump discretely at 5-10% LTV bands). Column (1) shows the baseline specification using only total cost as explanatory variable for the random-utility model and is estimated as an alternative-specific conditional logit, using the main sample. Columns (2) to (5) estimate alternative specifications. Column (2) includes the borrower-lender-specific distance to the closest branch (in km) and hence differs across lenders within the choice options of the same borrower. Column (3) includes lender fixed effects. Column (4) includes an indicator-variable for $k = 2$ (product type $\{r_h, f_i\}$) which is equivalent to a product-type fixed effect. Column (5) is a specification with borrower-specific controls, income and age. Columns (6) to (10) correspond to Columns (1) to (5) for the baseline model, using the non-bunching sample. Standard errors are shown in parentheses, coefficients are denoted with *** for $p < 0.01$, ** for $p < 0.05$, * $p < 0.1$.

TABLE 5: CHANGES IN PRICING AND TOTAL COST

Dep. Var:	$\Delta \bar{r}$	$\Delta \bar{f}$	$\Delta \bar{C}_{1yr}$	$\Delta \bar{C}_{2yr}$	Δr_l	Δf_h	$\Delta C_{1yr}^{r_l, f_h}$	$\Delta C_{2yr}^{r_l, f_h}$	Δr_h	Δf_l	$\Delta C_{1yr}^{r_h, f_l}$	$\Delta C_{2yr}^{r_h, f_l}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\Delta \phi$ (std.)	0.00 (0.03)	41.35** (19.52)	48.74* (24.94)	56.12 (52.87)	-0.01 (0.03)	109.97** (44.79)	102.08** (40.63)	94.20* (50.70)	0.04 (0.04)	0.04 (0.04)	45.06 (37.31)	92.05 (73.70)
Year-Quarter FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Lender FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	671	671	671	671	671	671	671	671	671	671	671	671
R^2	0.498	0.097	0.451	0.518	0.513	0.071	0.388	0.519	0.443	0.443	0.413	0.477

Notes: This table reports results from 12 different regressions of changes in average interest rates, fees and total cost (over one and two years) on changes in funding shock ϕ (columns (1)-(4)), and the equivalent for $\{r_l, f_h\}$ -products (columns (5)-(8)), and $\{r_h, f_l\}$ products (columns (9)-(12)); based on lender-level panel data between 2009 Q1 and 2016 Q4, at quarterly frequency. Prices are for 2-year fixed rates and 70-75% LTV product offers only. All regressions absorb time (year-quarter) and lender fixed effects. Standard errors are reported in parentheses and clustered at the lender level. */**/***/ denote $p < 0.1$, $p < 0.05$ and $p < 0.01$, respectively.

TABLE 6: CHANGES IN PRICING AND TOTAL COST, BY LENDER PRICING TYPE

Dep. Var:	Low			Medium			High					
	Δr_l	Δf_h	$\Delta C_{1yr}^{r_l, f_h}$	Δr_l	Δf_h	$\Delta C_{1yr}^{r_l, f_h}$	Δr_l	Δf_h	$\Delta C_{1yr}^{r_l, f_h}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)			
$\Delta\phi$ (std.)	0.01 (0.02)	13.16 (9.02)	17.66 (24.16)	22.16 (48.35)	-0.06 (0.08)	116.93* (49.46)	66.56 (46.33)	16.19 (113.06)	-0.03 (0.03)	201.66*** (46.97)	173.22*** (42.32)	144.77** (59.38)
Year-Quarter FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Lender FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	190	190	190	190	234	234	234	234	217	217	217	217
R^2	0.477	0.196	0.426	0.484	0.631	0.119	0.522	0.645	0.577	0.212	0.424	0.559

Notes: This table reports results from 12 different regressions of pricing characteristics for the low rate, high fee product-type only, for different lender pricing types. Lender pricing types are defined using the tercile of ranking difference (total cost minus interest rate ranking position), as a measure of how much prices are skewed towards the interest rate dimension, using fees that are higher than the prevailing average. Lenders in the “low” category have a negative skew and hence relatively low fees (columns (1)-(4)), “medium” lenders’ position in the total cost ranking is similar to that in the interest rate ranking (columns (5)-(8)), and “high” lenders have a substantially better (i.e. lower) position in the interest rate ranking compared to the total cost ranking, i.e. have a high skew in their prices using high fees (columns (9)-(12)). Regressions are based on lender-level panel data between 2009 Q1 and 2016 Q4, at quarterly frequency. Prices are for 2-year fixed rates and 70-75% LTV product offers only. All regressions absorb time (year-quarter) and lender fixed effects. Standard errors are reported in parentheses and clustered at the lender level. */**/*** denote $p < 0.1$, $p < 0.05$ and $p < 0.01$, respectively.

TABLE 7: LENDER CHARACTERISTICS BY PRICING TYPE

Pricing type	Low	Medium	High
<i>Lender characteristics</i>			
Number of lenders	9	9	8
Δ ranking	-7.6	-0.3	5.7
log(assets)	16.6	18.5	17.9
ROA (in %)	0.5	0.3	-0.1
ROE (in %)	8.1	2.8	2.0
Net interest margin (in %)	1.4	1.7	1.5
Loan/dep	1.0	1.0	1.1
Funding cost shock	1.8	2.2	2.3
Lender FE (norm.)	1.1	2.9	3.8
Branch density	715.9	1826.5	2724.2
Market share	0.028	0.030	0.075
<i>Pricing</i>			
Low rate (r_l)	1.92	1.76	1.76
High fee (f_h)	733.33	1083.76	1243.99
High rate (r_h)	2.18	2.30	2.16
Low fee (f_l)	151.43	61.26	373.94
Excess cost	833.06	858.27	1699.96
Within-lender pay dist.	366.40	519.86	631.17
<i>Borrower characteristics</i>			
LTI	3.28	3.53	3.63
LTV	72.35	72.34	72.63
Income (in £)	52900	48707	50021
Age	32.21	32.21	31.39
Loan amount (in £)	170411	166076	172911

Notes: This table displays average lender, pricing and borrower characteristics across “low”, “medium” and “high” pricing types, defined using the tercile of ranking difference (total cost minus interest rate ranking position), as a measure of how much prices are skewed towards the interest rate dimension, using fees that are higher than the prevailing average. There are 9 low, 9 medium and 8 high-type lenders. Δ ranking captures the average ranking difference, which is negative for low types (position in total cost ranking is lower than interest rate ranking), around 0 for medium types, and positive for high types (position in total cost ranking is high than interest rate ranking, i.e. is more expensive in total cost terms, indicating high fees). Branch density is computed as the number of borrowers for whom a given lender operates the closest nearby branch (yielding similar distributions when using up to second, third etc. closest branches). Excess cost is computed as the difference between a given product and the minimum cost product in a given month. Within-lender pay distance is the difference between the offer taken by a particular borrower in a given quarter for a given lender, compared to the cheapest alternative by that lender at the same point in time. All values are averaged across lenders by pricing type.

ONLINE APPENDIX FOR “NON-SALIENT FEES IN THE MORTGAGE MARKET”

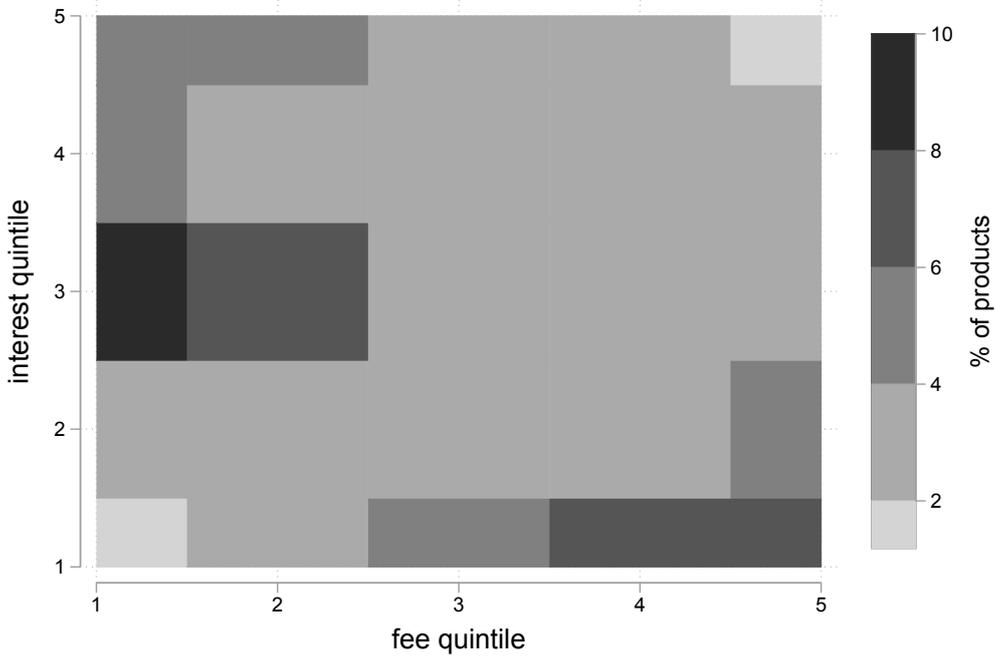
A. FURTHER DATA DESCRIPTION

MoneyFacts product-level data. The full Moneyfacts dataset from 2009 to 2016 contains 364,750 observations. Duplicates and mortgages with non-standard eligibility criteria such as shared ownership or buy to let mortgages are dropped, in order to come close to the homogeneous product benchmark as possible and to avoid additional product characteristics that affect a very small share of products. I further restrict my sample to fixed-rate mortgages (approximately 70% of the sample), available to first time buyers, with a 2-year fixation period (70% and 40% of the remaining sample, respectively). For the lender-level analysis, I only keep mortgage offers by the 27 largest lenders which make up about half of the observations. The resulting main Moneyfacts sample contains 26,451 unique mortgage offers, with approximately 280 observations on average each month. Some product characteristics, in particular fees and prepayment penalties, are extracted via a keyword search of raw text variables in the Moneyfacts data, as shown in Table B.1, with the extracted values marked in blue. “Arrangement Fee Notes” is a text variable that records different arrangement fee components and all fee components are added up, where composite fees serve as the main fee variable. There are four different arrangement fee components in the data, “Arrangement”, “Booking”, “Completion” and “Reservation”. However, they mostly reflect differences in naming convention across lenders where no lender has more than two different fee components, and they are all considered as part of the arrangement fees required at loan issuance. “Incentive Notes” captures additional incentives and rebates. An example for an additional incentive is a cash rebate of e.g. £100, but the incentive does not seem to affect the interest rate-fee trade-off, i.e. does not seem to be *priced* in terms of differential fees or interest rates and so should not affect the analysis within a given lender, which I confirm more formally in a regression setup. One potential explanation is that these products were offered as part of a temporary marketing campaign. “Prepayment penalty” specifies the terms of the early repayment penalty. I compute a £ cost for the product-level regressions for an average loan size and repayment structure. Prepayment penalties rarely vary within a given lender and are identical for most lenders across products. They do not seem to significantly affect the interest rate-fee trade-off in the regression analysis.

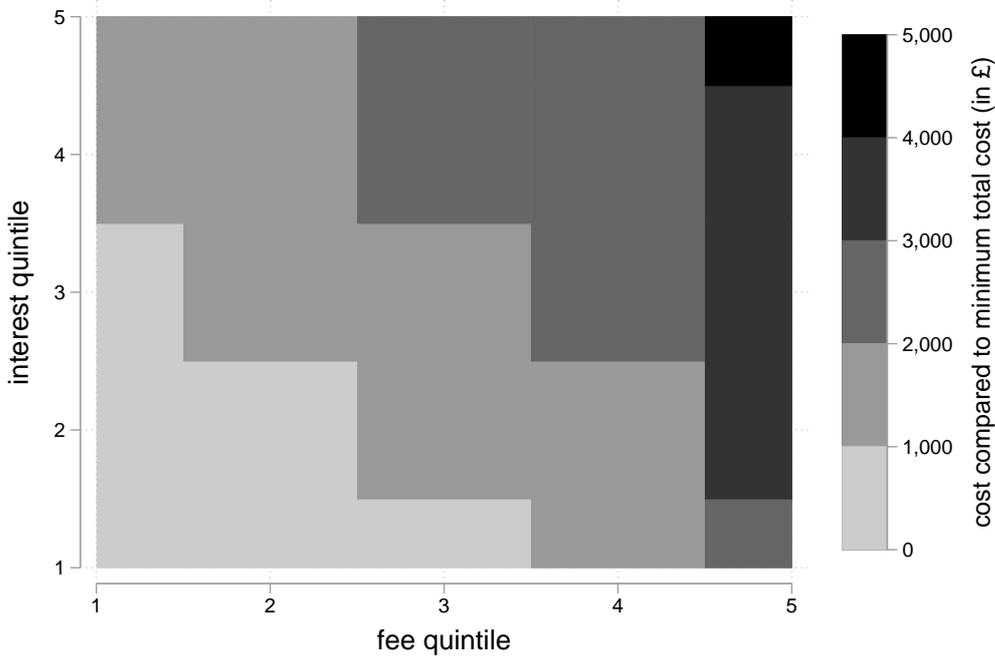
B. ADDITIONAL FIGURES AND TABLES

FIGURE B.1: PRODUCTS BY INTEREST AND FEE QUINTILE

(A) SHARE OF PRODUCTS BY INTEREST AND FEE QUINTILE

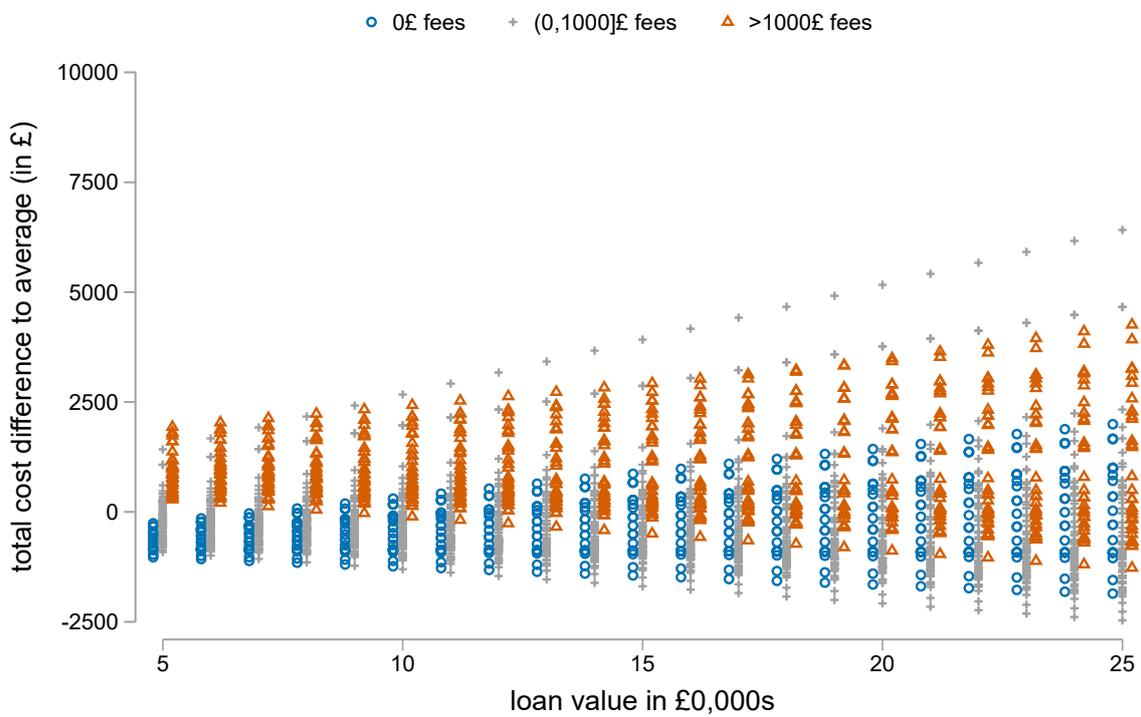


(B) COST DIFFERENTIAL FOR AVERAGE PRODUCT IN INTEREST AND FEE QUINTILE



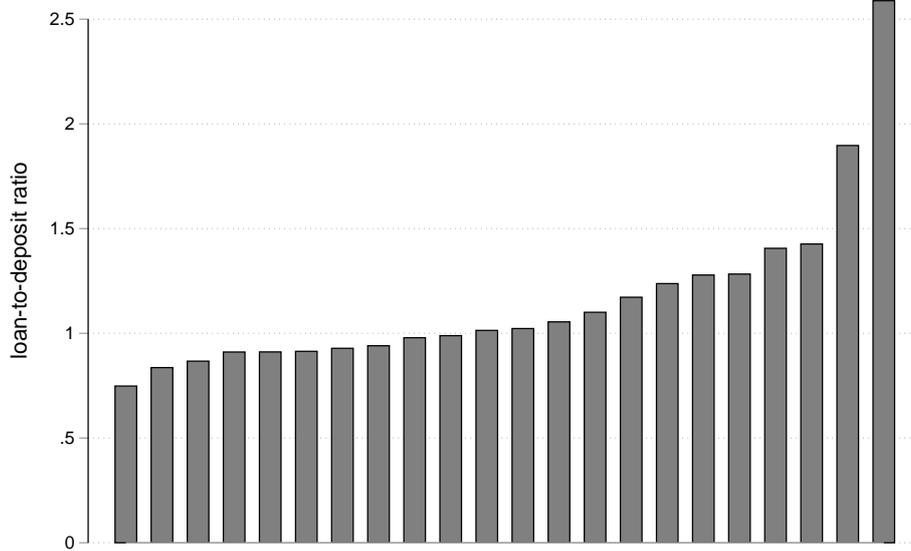
Notes: Figure B.1a shows the frequency of products by its position in the rate and fee distribution in a given month, based on 75% LTV 2-year fixed rate products from January 2009 to December 2016. For instance, the lower left corner represents products in the lowest interest and fee quintile and make up around 2% of total products. Figure B.1b shows the average (across products in a given interest and fee quintile) cost differential in £, measured as the difference between total cost and the minimum total cost product in a given month, based on a 75% LTV 2-year fixed rate product over two years, for a loan size of £150,000 amortized over 25 years.

FIGURE B.2: TOTAL COST DISPERSION BY FEE CATEGORY



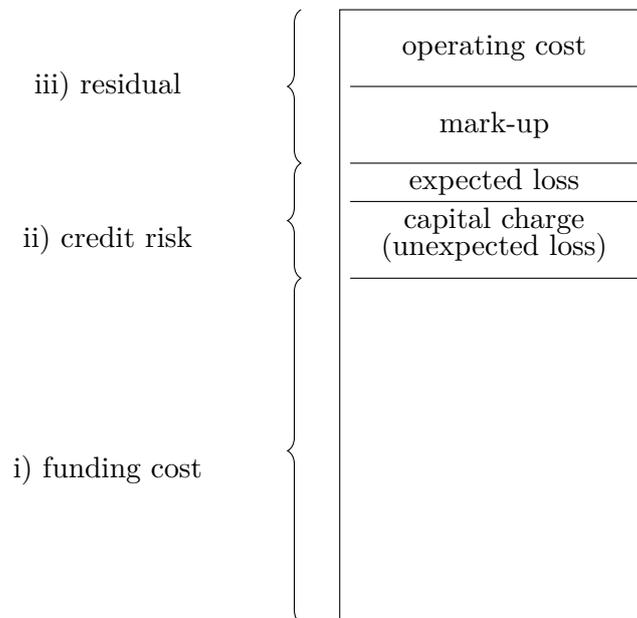
Notes: This figure shows the total cost dispersion relative to the average product, by loan value and fee category, for the set of 2yr, 70-75% LTV products on offer in February 2014 (corresponding to Figure 3a and 3b).

FIGURE B.3: LOAN-TO-DEPOSIT RATIO (2008)



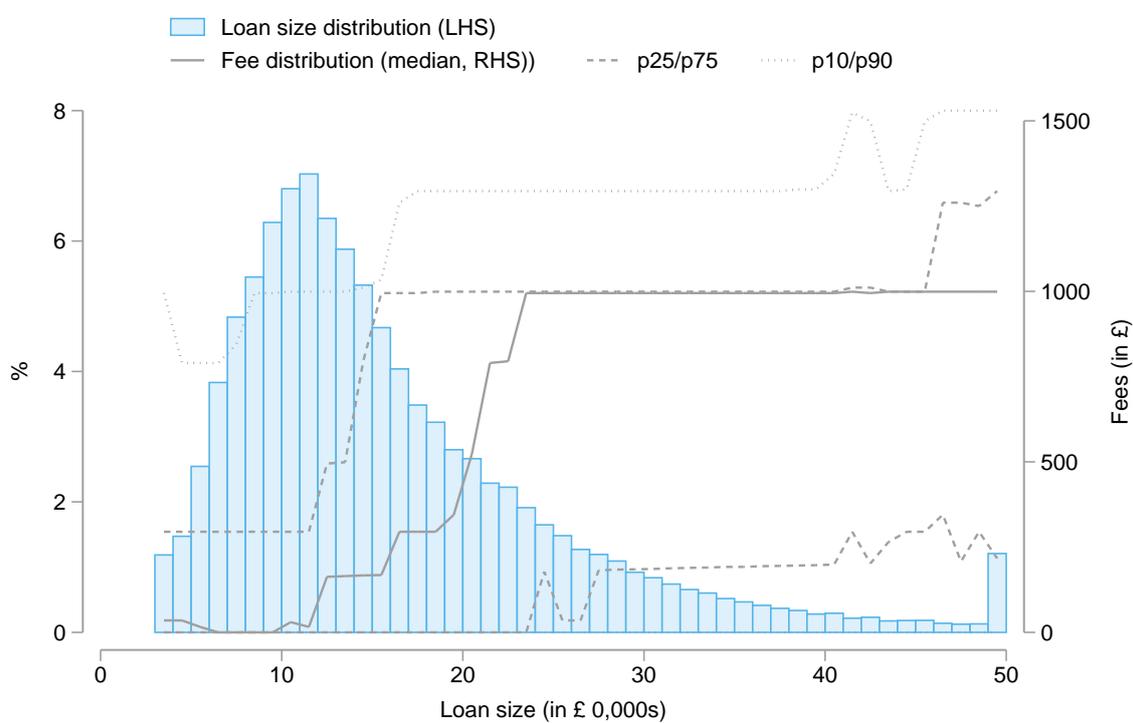
Notes: This figure shows loan-to-deposit ratios in 2008 across lenders.

FIGURE B.4: ILLUSTRATION OF MORTGAGE PRICE COMPONENTS



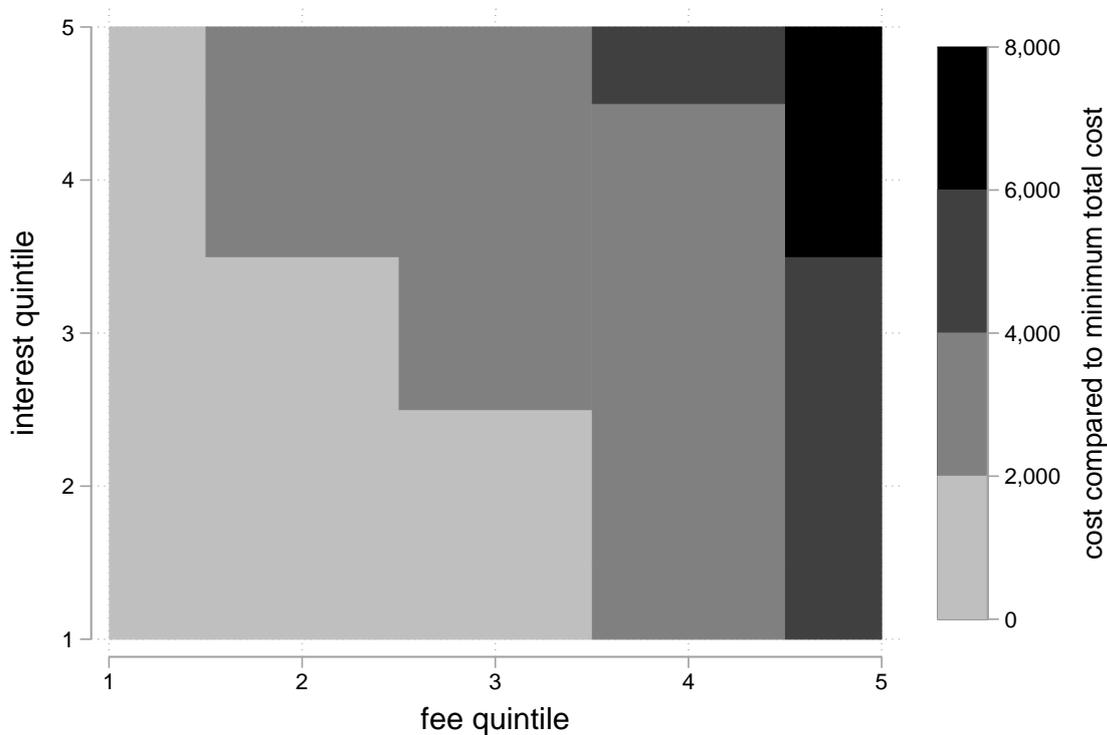
Notes: Adapted from [Button et al. \(2010\)](#). The proportions are stylized, but similar to what they estimate for the period between 2010 and 2012.

FIGURE B.5: LOAN VALUE HISTOGRAM AND FEE DISTRIBUTION



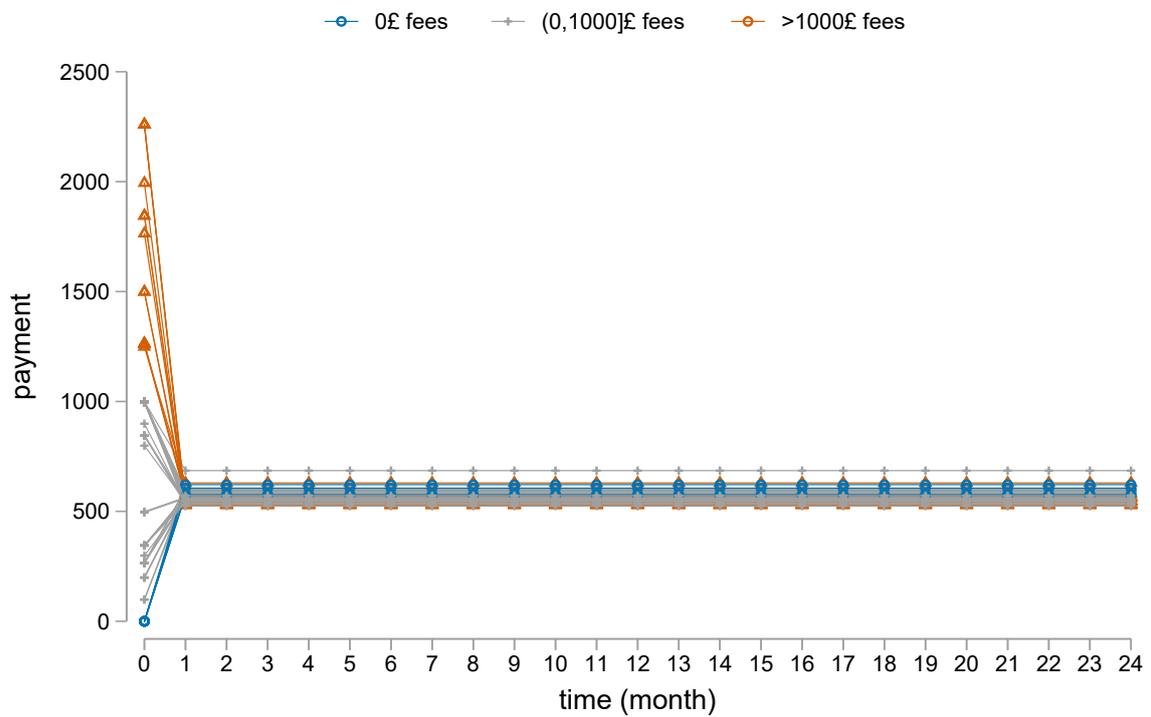
Notes: This figure shows the realised loan size and fee distribution (based on mortgages originated between 2015-2016).

FIGURE B.6: COST DIFFERENTIAL FOR AVERAGE PRODUCT IN INTEREST AND FEE QUINTILE (HIGH LOAN VALUE)



Notes: This figure shows the average (across products in a given interest and fee quintile) cost differential in £, measured as the difference between total cost and the minimum total cost product in a given month, based on a 75% LTV 2-year fixed rate product over two years, for a loan size of £250,000 amortized over 25 years.

FIGURE B.7: MORTGAGE PAYMENT PROFILE OVER TIME



Notes: This figure shows the payment profile for a borrower who takes out a 2yr fixed rate mortgage at 75% LTV for an average loan size, for the range of 2yr 75% LTV products in February 2014 (corresponding to Figure 3a and 3b).

TABLE B.1: EXAMPLE OF MONEYFACTS DATA STRUCTURE

Variable	75% LTV, low fee	75%, high fee
Collected date	30/04/2013	30/04/2013
Lender	Halifax	Halifax
Initial Period (in months)	27	27
Max LTV % FTB	75	75
Initial Rate	3.39	2.69
Arrangement Fee Notes	Completion GBP295	Arrangement GBP995, Completion GBP295
Incentive	GBP150 rebate. No Higher Lending Charge (HLC).	GBP150 rebate. No Higher Lending Charge (HLC).
Prepayment penalty	to 31/8/15: 3/2% Mortgage Advance	to 31/8/15: 3/2% Mortgage Advance
	90% LTV, low fee	90% LTV, high fee
Collected date	30/04/2013	30/04/2013
Lender	Halifax	Halifax
Initial Period (in months)	28	28
Max LTV % FTB	90	90
Initial Rate	5.59	4.99
Arrangement Fee Notes	Completion GBP295	Arrangement GBP995, Completion GBP295
Incentive	No Higher Lending Charge (HLC).	No Higher Lending Charge (HLC).
Prepayment penalty	to 31/8/15: 3/2% Mortgage Advance	to 31/8/15: 3/2% Mortgage Advance

Notes: This table shows four illustrative mortgage offers by the same lender at the same point in time. It shows the data structure and provides examples of the text variables “Initial Text”, “Arrangement Fee Notes”, “Incentives”, and “Redemption Penalty”. The main variables extracted via keyword search are interest rates, fee components and total fee amount (in blue).

TABLE B.2: PROPORTION OF COST-DOMINATED PRODUCTS BY FEE CATEGORY (IN %) (HIGH LOAN VALUE)

Excess cost	Fees					Total
	zero fees	(0,500]	(500,1000]	(1000,1500]	>1500	
<=500	0.9	2.2	3.6	0.4	0.0	7.3
(500,1000]	2.6	3.5	6.1	0.8	0.2	13.2
(1000,2000]	5.8	6.0	11.9	3.4	2.0	29.0
(2000,4000]	7.2	7.1	10.5	4.9	2.6	32.3
>4000	2.7	5.1	6.4	2.7	1.3	18.2
total	19.1	23.9	38.5	12.3	6.2	

Notes: This table shows the proportion of all products (in %) between January 2009 and December 2016 split by excess cost compared to the lowest cost product available in a given month, and fee categories. The cost are computed for a 2-year fixed rate mortgage over two years, at 75% LTV for first-time buyers, for a loan size of £250,000, which corresponds to about the 90th percentile of the loan size distribution, amortized over 25 years.

TABLE B.3: DESCRIPTIVE STATISTICS FOR DISCRETE CHOICE ANALYSIS

Variable	Observations	Mean	Std. Dev.	Min	Max
Interest	23067	2.19	0.59	1.44	5.29
Fees	23067	691	582	0	2250
Loan value	23067	171689	93186	38000	499999
Income	23067	52779	29154	15184	158420
Age	23067	32.95	5.49	25.00	45.00
LTI	23067	3.34	0.77	1.25	4.50
LTV (adjusted)	23067	72.43	2.96	65.00	75.00
Bunching indicator	23067	0.23	0.42	0.00	1.00
Distance to nearest branch (km)	23067	2.56	2.67	0.05	74.70
Amortization period (term)	23067	26	4	12	30

Notes: This table displays descriptive statistics for the main sample of borrowers underlying the discrete choice analysis, based on 2-year fixed rate borrowers at 75% LTV, with standardised characteristics (age 25 to 45, LTI \leq 4.5, amortization period \leq 30 years), between 2015 and 2016. The bunching indicator is 1 for borrowers who are able to bunch at the 75% LTV band using fees. The distance to the nearest branch (of a given lender) is computed using the borrower's location and a 2016 snapshot of all UK bank branch locations.

TABLE B.4: BALANCE TESTS FOR FUNDING SHOCK ϕ

	Lagged levels			Changes		
	2009	2012	2016	2009	2012	2016
log(assets)	6.03 (6.98)	0.36 (1.80)	0.55 (0.98)	-0.52 (0.39)	-0.03 (0.06)	-0.09 (0.16)
return on assets	-10.85 (10.06)	-9.51*** (1.55)	1.96 (1.77)	-0.16 (0.14)	-0.01 (0.02)	0.01 (0.02)
net interest margin	-2.04 (7.77)	1.71 (3.93)	-2.71* (1.42)	-0.30 (0.47)	-0.01 (0.12)	0.08 (0.09)
leverage	0.48 (0.50)	0.19 (0.19)	-0.17 (0.10)	-0.01 (0.01)	0.00 (0.00)	-0.00 (0.00)
big 6 lenders (indicator)	-21.40 (29.06)	11.08 (8.21)	2.33 (3.58)	0.11 (0.32)	0.06 (0.05)	-0.01 (0.03)
Observations	16	22	27	16	22	22
R^2	0.443	0.726	0.393	0.160	0.236	0.084

Notes: */**/** denote $p < 0.1$, $p < 0.05$ and $p < 0.01$, respectively. This table reports results from 6 different regressions, based on cross-sectional regressions of funding shock ϕ_j on lender characteristics for the years 2009, 2012 and 2016 separately, in lagged levels and changes. The table is based on Table 3 in [Goldsmith-Pinkham et al. \(2017\)](#). Standard errors are clustered at lender level.

TABLE B.5: CHANGES IN PRICE COMPONENTS AND TOTAL COST (HIGH LTV)

Dep. Var:	$\Delta \bar{r}$	$\Delta \bar{f}$	$\Delta \bar{C}_{1yr}$	$\Delta \bar{C}_{2yr}$	Δr_l	Δf_h	$\Delta C_{1yr}^{r_l, f_h}$	$\Delta C_{2yr}^{r_l, f_h}$	Δr_h	Δf_l	$\Delta C_{1yr}^{r_h, f_l}$	$\Delta C_{2yr}^{r_h, f_l}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\Delta \phi$ (std.)	0.09*** (0.02)	-10.41 (11.54)	84.13*** (20.73)	178.66*** (38.33)	0.10*** (0.02)	11.82 (28.07)	82.17*** (26.74)	166.89*** (42.98)	0.08*** (0.02)	-25.09* (12.81)	85.86*** (18.66)	202.16*** (38.85)
Year-Quarter FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Lender FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	515	515	515	515	515	515	515	515	515	515	515	515
R^2	0.271	0.083	0.255	0.274	0.246	0.100	0.233	0.258	0.247	0.085	0.236	0.262

Notes: This table reports results from 12 different regressions of changes in average interest rates, fees and total cost (over one and two years) on changes in funding shock ϕ (column (1)-(4)), and the equivalent for $\{r_l, f_h\}$ -products (columns (5)-(8)), and $\{r_h, f_l\}$ products (columns (9)-(12)), based on lender-level panel data between 2009 Q1 and 2016 Q4, at quarterly frequency. Prices are for 2-year fixed rates and 90-95% LTV product offers only. All regressions absorb time (year-quarter) and lender fixed effects. Standard errors are reported in parentheses and clustered at the lender level. */**/** denote $p < 0.1$, $p < 0.05$ and $p < 0.01$, respectively.

TABLE B.6: FEE-RATE TRADE-OFF

Dep. var: interest cost	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Fees	-0.2022 (0.1255)	-0.4742*** (0.1115)	-0.4371*** (0.1198)	-0.2419** (0.1049)	-0.4567*** (0.1015)	-0.3878*** (0.1033)	-0.9848*** (0.1427)
Early prepayment penalty				-0.0251 (0.0365)	0.0612 (0.0890)	0.0618 (0.2523)	0.0440 (0.2577)
Cashback indicator				-0.0141 (0.2867)	-0.1015 (0.1862)	-0.1152 (0.1382)	-0.1144 (0.1087)
Incentive (length)				-1.4142 (1.1843)	1.0558 (0.6393)	2.5928*** (0.8425)	1.5745** (0.6952)
Fees ²							0.0003*** (0.0001)
Year-Month FE	✓	✓	✓	✓	✓	✓	✓
LTV FE	✓	✓	✓	✓	✓	✓	✓
LTV × Year-Month FE	✓	✓	✓	✓	✓	✓	✓
Lender FE	✓	✓	✓	✓	✓	✓	✓
Lender × Year-Month FE						✓	✓
Observations	26450	26450	26450	26450	26450	26450	26450
Adj. R ²	0.838	0.896	0.919	0.840	0.896	0.920	0.925

Notes: This table reports results from 7 different regressions of interest cost, calibrated to the average loan size in a given month, on fees, based on product-level panel data for the full sample, at monthly frequency. The early prepayment penalty is computed for the average loan size. The cashback indicator is 1 if a product provides additional cash incentives (such as a £100 rebate). The incentive length is measured as the text length of the description of additional incentives. Standard errors are clustered at lender level. */**/** denote $p < 0.1$, $p < 0.05$ and $p < 0.01$, respectively.