Better the lender you know? Limited attention and lender familiarity in UK mortgage choices*

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June 4, 2020

Abstract

This paper studies the channels through which limited attention and brand familiarity affect consumer behaviour. Using unique combination of datasets on UK mortgage transactions, advertising, product data and pre-existing links between lenders and borrowers through other financial products, I develop a structural discrete choice model with limited attention to identify which characteristics of suppliers and products affect (a) the likelihood of the alternative being considered and (b) preferences for the alternatives that are considered.

I identify two distinct types of borrowers. Type 1, which has characteristics commonly associated with lower financial sophistication (e.g. lower income or worse credit history), tends to be less price-sensitive and more inattentive. It is much more likely to consider lenders with which they have a pre-existing checking account than 'unfamiliar' lenders. The wealthier and more educated Type 2 also displays inattention but a lesser extent and their consideration of alternatives is much less influenced by existing relationships with lenders. Both types show a strong preference for familiar lenders when choosing amongst the options they consider. They are willing to trade off nearly 5% of their post-tax annual income for taking out a mortgage with a lender with which they already have a checking account. In a counterfactual simulation I show that due to this strong 'brand loyalty', a hypothetical intervention to make borrowers aware of all available alternatives has only a surprisingly modest effect on market outcomes.

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*I am very grateful to Richard Blundell, Ian Preston, Aureo de Paula, Tarun Ramadorai, David Laibson, Abi Adams, Thomas Hoe, Claudia Robles-Garcia, Patrick Coen and Peter Andrews for their thoughts, comments and suggestions. I am also thankful to the seminar participants at the UK Financial Conduct Authority for their feedback and ideas. The code for this project partly draws on the *alogit* package for Stata by Jason Abaluck and Mauricio Caceres Bravo, and the *pylogit* Python package by Timothy Brathwaite, for which I am very grateful to their authors.

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1 Introduction

Price dispersion in the UK market for residential mortgages is considerable, and the vast majority of mortgage products are not exclusive to the lender's existing customers. Consequently, the returns to shopping around can be significant. Despite this, over 30% of UK customers with a personal current account and a mortgage, took out their mortgage with the lender that already provided their current account (FCA, 2018c). Moreover, among mortgage borrowers who did not use a broker, over a half chose a lender with whom they already had another financial product even though those 'familiar' lenders on average accounted for less than 20% of mortgage options the borrower could choose from (Iscenko, 2018).

The marketing literature has long been aware of the importance of brand loyalty in understanding consumer choices (Brown, 1953; Tucker, 1964; Oliver, 1999; Palmatier, Dant, Grewal, & Evans, 2006, and many others)[1]. There is also a more recent but growing body of empirical research in economics that documents brand inertia in health insurance (Handel, 2013; Heiss, McFadden, Winter, Wuppermann, & Zhou, 2016; Ho, Hogan, & Scott Morton, 2017), banking (Honka, Hortaçsu, & Vitorino, 2017), energy markets (Hortaçsu, Madanizadeh, & Puller, 2017) and many others. However, with the notable exception of Allen, Clark, and Houde (2019), the existing economic research has focused primarily on repeated choices of the same product rather than on cases where a relationship with the supplier exists in one market, but influences the consumer's choices in others, as is the case with mortgages and personal current accounts.

There is an important unanswered question as to the mechanism through which brand familiarity affects behaviour. One option from the literature on limited attention is that existing providers are chosen more often because consumers consider them by default, and only pay attention to other alternatives if the default option is sufficiently bad to warrant it (Heiss et al., 2016; Abaluck & Adams, 2017; Ho et al., 2017; Hortaçsu et al., 2017). An alternative possibility is habit formation, where using a provider increases the consumer's taste for their products through habit (Dubé, Hitsch, & Rossi, 2010) or reduced cognitive effort of operating a familiar environment (Murray & Häubl, 2007).

In this paper I explore these questions in the context of the UK mortgage market with a unique combination of transaction-level data, linked credit files and extensive datasets about firms' products, advertising and locations. I specifically investigate: (a) whether and how an existing current account relationship with a lender affects consumers' mortgage choices after controlling for other brand awareness factors, (b) the extent to which the attention and preference channels separately contribute to these effects, and (c) whether the effects are materially different depending on borrower demographics.

I develop a limited attention structural model based on the tradition of discrete choice models

[1] See also Bronnenberg, Dubé, and Gentzkow (2012) and Bronnenberg, Dubé, and Moorthy (2019) for comprehensive overviews of the literature.

with unobserved consideration sets. In this class of models, the probability of each alternative being considered is determined by the characteristics of the alternative in question, and the borrowers then make choices out of the resulting consideration sets according to their preferences (Swait & Ben-Akiva, 1987; Goeree, 2008; Van Nierop, Bronnenberg, Paap, Wedel, & Franses, 2010; Abaluck & Adams, 2017; Crawford, Griffith, & Iaria, 2019). I extend this alternative-specific consideration model by adding latent class model (Ben-Akiva et al., 1997; Greene & Hensher, 2003) elements, allowing for two types of borrowers that differ in their attention and preferences. Including factors associated with lender familiarity—existing banking relationships, proximity of branches, advertising—in both attention and preference parts of the model (alongside with the conventional product characteristics, where appropriate) gives me a unique opportunity to test what their effects are and which channel dominates.

This modelling approach allows me to distinguish two distinct types of borrowers. Type 1, which has demographic characteristics commonly associated with lower financial sophistication (lower income, worse credit history, lower education), is less price sensitive and somewhat prone to inattention. Borrowers in this type are also a lot less likely to consider lenders with whom they have no existing products (with consideration probability of 0.56) than familiar alternatives (with probability of 0.97). The average welfare gain that a Type 1 forgoes on average due to their limited attention is equivalent to reducing annual mortgage costs by 1.2% of their post-tax income. Although inattention is also present to some extent among Type 2 borrowers, who tend to be richer, more credit-worthy and more price-sensitive, their lapses in attention are much less linked to having an existing relationship with the lender, and around half as costly as for Type 1 (at 0.6% of their post-tax income). After controlling for existing relationships with lenders, other factors, such as advertising expenditure or branch presence near a borrower's home, have only a small effect on attention for both borrower types.

Both borrower types are similar, however, in exhibiting very strong preferences for lenders with whom they have an existing current account *among the options they consider*. The implied "own-lender" interest rate premium that borrowers are willing to trade off for going to their current account provider is equivalent to over 5% of post-tax annual income for both types.

I also simulate the effects of a hypothetical intervention that enforces full attention across all borrowers. I find that it has a fairly small effect on market shares and prices paid. Overall consumer surplus improves on average, by an equivalent of reducing interest rates by 17 basis points, but there are notable distributional differences.

The intervention improves welfare for most of the more inattentive Type 1 borrowers, whose average annual mortgage payments fall by £130 and average utility increases considerably. For Type 2 borrowers, however, the situation is less clear-cut. Most of them incur significantly higher borrowing costs after the intervention (an average increase of £200 per year) because of the positive demand shock to the best-priced mortgages on the market. The increased ability to find more suitable products on other preference dimensions (rate type, fees, location, etc) is just sufficient to compensate Type 2 for these price increases, leading to only a very small increase in average consumer surplus. Welfare declines in the new equilibrium for over a third of all borrowers (28% of Type 1 and 47% of Type 2). Overall, the benefits of making borrowers pay full attention (even if it were feasible) are surprisingly muted relative to the scale of the regulatory intervention it would require.

Related literature My work contributes to several broad strands of literature.

First, I contribute to the household finance literature on mortgage decisions. Due to their importance as the largest household financial liability, as well as data availability, mortgages have attracted a lot of research interest recently, especially in the area of price dispersion (Allen, Clark, & Houde, 2014; Iscenko, 2018; Bhutta, Fuster, & Hizmo, 2019), intermediation and advice (Woodward & Hall, 2012; Mysliwski & Rostom, 2018; Iscenko & Nieboer, 2018; Robles-Garcia, 2019; Foà, Gambacorta, Guiso, & Mistrulli, 2019), and, extensively, on promptness of remortgaging decisions (e.g. Campbell, 2006; Agarwal, Driscoll, & Laibson, 2013; Andersen, Campbell, Nielsen, & Ramadorai, 2019, , and others). Out of the recent literature in this field, my work is closest to Allen et al. (2019), who find that brand loyalty has a significant effect on lenders' market power in the Canadian mortgage market. Due to the central role of price negotiation for Canadian mortgages, and its absence in the UK price-posting mortgage market, however, Allen et al. (2019) and I model very different market structures. As a result, we provide complementary insights on the channels through which brand loyalty can affect consumer behaviour and equilibrium outcomes. Beyond mortgages but still within household finance, this paper fits in with the relatively new strand that applies methods from structural industrial organisation to study behaviour in retail financial markets (Handel, 2013; Heiss et al., 2016; Ho et al., 2017; Honka et al., 2017; Nelson, 2018; Benetton, 2019; Robles-Garcia, 2019). My findings about the differences in attention between the two borrower types, the types' demographic characteristics, and the distributional effects of interventions to help them also echo the recurring themes about the naive and sophisticated consumers in the behavioural industrial organisation literature (Gabaix & Laibson, 2006; Eliaz & Spiegler, 2006; Grubb, 2015; Armstrong, 2015, etc).

Second, this research is also part of the broader applied work on limited attention in consumer choice (e.g. Swait & Ben-Akiva, 1987; Goeree, 2008; Van Nierop et al., 2010; Crawford et al., 2019).[2] The model I develop is one of the first to exploit the recent identification results in Abaluck and Adams (2017), who show that attention and preference parameters in limited attention multinomial logit models are identified under significantly less strict restrictions than used in earlier papers. This allows me to avoid excluding advertising and other familiarity variables from the preference part of the model (unlike e.g. Goeree (2008) and Honka et al. (2017)) and to provide additional evidence

[2] A recent survey of this literature is available in Honka, Hortaçsu, and Wildenbeest (2019).

on the (small) effect advertising has on preference formation. More importantly, I am also able to explore and compare both potential channels through which lender familiarity affects behaviour in ways that are new to the literature.

I also find that accounting for the role of existing links with suppliers, especially in the preference channel, implies a much lower effectiveness of information remedies than has been suggested in earlier literature on limited attention, for instance the counterfactual simulations in Goeree (2008) or Hortaçsu et al. (2017). The results of my counterfactural simulation help bring recommendations from structural models closer to the recent evidence from randomised controlled trials of interventions to encourage switching in the UK energy (e.g. Tyers, Sweeney, & Moon, 2019) and financial (e.g. Adams, Hunt, Palmer, & Zaliauskas, 2019) sectors. This regulatory testing has often found that even very transparent, simple and timely provision of information about alternatives and gains from switching had very modest success in inducing consumers to switch providers, resulting in switching rate (percentage point) improvements in single digits.

The rest of the paper is structured as follows. Section 2 provides an overview of the data.[3] Section 3 outlines the theoretical model, followed by a more detailed discussion of the estimation approach and practicalities in Section 4. Section 5 describes the estimation results and predictions of the model. Section 6 discusses a policy counterfactual where full attention is enforced. Section 7 covers robustness checks for the main findings. Section 8 concludes. Additional tables and figures are provided in the Appendices.

2 Data

2.1 Datasets

Most of the research in this paper relies on the combination of the following datasets.

FCA Product Sales Data (PSD) This transaction-level dataset of all UK residential mortgage lending, collected by the UK Financial Conduct Authority, has been increasingly used in household finance and industrial organisation papers on the mortgage market in recent years (Benetton, 2019; Benetton, Bracke, Cocco, & Garbarino, 2019; Iscenko, 2018; Liu, 2019; Robles-Garcia, 2019). It contains extensive information about loan, collateral property, and borrower characteristics for each new mortgage in the UK.[4]

This paper covers mortgages issued for the purchase of a new property (no refinancing) during 18 months between January 2015 and July 2016. For comparability of alternatives and individuals, borrowers with niche products (interest-only or government-subsidised schemes) are excluded from the sample.

[3]For a more detailed discussion of the UK mortgage market structure more generally, see Iscenko (2018).

[4]More detail about the PSD and variables it includes is availabe in the PSD001 Data Reference Guide.

The focus of this paper on the impacts of borrowers' existing links with lenders (or other forms of familiarity) on behaviour requires another significant restriction on the applicable transactions. Around 70% of mortgage loans taken out during the relevant period use mortgage brokers for their search. However, there is strong evidence that decisions of brokers can be affected by factors, such as commission, that are not fully aligned with their customers' preferences (Woodward & Hall, 2012; Egan, 2019; Robles-Garcia, 2019). Because of the difficulty in disentangling borrowers' attention and preferences from those of their brokers in intermediated transactions, this paper only uses the 30% of mortgage loans that borrowers take out by approaching the lender directly.

Moneyfacts I merge the PSD with the daily commercial dataset of mortgage products on the market from Moneyfacts. This information enriches the dataset in two important ways: (a) it provides extensive additional information for each product (fees, any extra features, eligibility criteria, availability restrictions); and (b) it allows me to observe the potential choice sets for borrowers at any point in time without needing to infer it. In the UK mortgage market that is characterised by lenders posting menus of prices and eligibility criteria with no subsequent negotiation, Moneyfacts data about the price structure, features and criteria are a comprehensive and fixed characterisation of each mortgage product.

Credit bureau files Uniquely among the recent UK mortgage research (with the exception of Iscenko (2018) and Iscenko and Nieboer (2018)), I am able to incorporate borrowers' full credit bureau files for 6 years up to their mortgage application, obtained from one of the UK's top 3 credit reference agencies (called 'credit bureaus' in the US). These data cover over 90% of all mortgage transactions recorded in PSD. In addition to credit scores to gauge borrowers' riskiness, full credit files contain information about their personal current accounts (PCAs) and credit products at a given point in time, and about each borrower's location before moving to their mortgaged property. This information is essential for accurately identifying the existing relationships between borrowers and lenders, and the characteristics of their environment before the mortgage application which might shape attention to lenders (e.g. branch presence around the borrower's residence).

Other sources of data I draw on additional commercial datasets to obtain information about lenders' characteristics and their links with the borrowers.

Firstly, I use the quarterly bank branch location dataset from Experian GOAD. Combining this with borrowers' historical postcode data from the credit bureau makes it possible to explore each bank's branch presence around each individual borrower (e.g. the number of branches within 5 miles of where the borrower lives and the distance to the lender's closest branch).[5]

[5] All distances are calculated using the standard procedure of converting UK postcodes to latitude and longitude coordinates using the UK Office of National Statistics Postcode Directory and applying the Haversine distance formula.

Second, I obtain data on monthly advertising expenditure by each lender from the Ebiquity Portfolio. This portal contains data on total advertising expenditure by financial institutions, split by topic, media format and coarse region (e.g. North East England), where relevant. I restrict the expenditure to campaigns related to each lender's general banking and mortgages (as opposed to, for instance, an advertising campaign focused solely on a lender's credit card business).

Finally, as described in more detail in Iscenko (2018), I also use public and quasi-public data sources such as the UK 2011 Census to obtain postcode-level proxies for missing demographic characteristics (e.g. educational attainment and socio-demographic characteristics) and HM Land Registry to help identify newly built properties for assessing borrowers' eligibility for specific products.

2.2 Sample description

After the sample restrictions described above and exclusion of missing data[6], the final sample comprises 86,288 borrowers and 3,071,550 person-product observations.[7] The products in the sample come from 12 lenders which represent over 80% of total lending in the relevant period and include all major UK banks.

I randomly split the available observations into the sample used for estimating the demand-side model in section 4.1.1 (75% of borrowers) and a hold-out sample used to assess the model fit in section 4.1.3 (25% of the borrowers). Due to the relatively small number of observations for some of the mortgage products, the supply-side estimation as set out in 4.2 uses all available data. All reported results in section 5 are based on the predictions obtained by applying the estimated model to the full sample.

Table 1 summarises some of the key characteristics of the borrowers in the sample, and the options they face. The sample is approximately equally split between the first-time buyers (FTBs) (those taking out their first mortgage) and home movers borrowing to buy a new property. Despite the high proportion of FTBs, however, only just over 25% of the sample are in their 20s, reflecting the recent UK trend of households making their first property purchase later in life.

Credit scores tend to be high relative to the general UK population, which is not surprising within a sample of households which qualified for a mortgage. Both loan and collateral property values vary considerably in the sample, leading the loan-to-value (LTV) ratio to range from below 10% to 95% with an average of 66%. With lenders' mortgage product menus being very closely linked to borrower LTVs, this means that the different borrowers in the data will be facing very different choice sets. It is also clear from the product descriptive statistics in Panel C that there is substantial variation in costs that borrowers can incur across products.

[6] Iscenko (2018) discusses in more detail data attrition in the PSD due to the merge with Moneyfacts and credit bureau data in more detail and provides evidence that this does not result in any material sample selection bias.

[7] Section 4.1.1 describes the methodology for constructing these counterfactual choice sets.

Table 1: Sample descriptive statistics

	Mean	σ	$Q_{0.25}$	$Q_{0.5}$	$Q_{0.75}$
PANEL A: Borrower characteristics					
Age (years)	37.13	9.76	29	36	44
=1 if first-time buyer	0.44	0.50	0	0	1
Income (£1000)[a]	41.64	24.44	25.48	35.71	50.30
=1 if joint loan	0.60	0.49	0	1	1
Loan value (£1000)	167.40	112.06	90	137	210
Property value (£1000)	269.62	189.16	143	215	334
Credit score[b]	62.89	8.35	59.48	64.58	68.50
Loan-to-value ratio (LTV, %)	66.53	21.91	51.02	72.86	85.00
Lenders in choice set (N)	6.58	3.32	3	6	10
of which: with PCAs relationship (N)	1.08	0.93	0	1	2
with any existing product (N)	1.35	1.15	1	1	2
=1 if chose a lender with PCA	0.54	0.50	0	1	1
Observations (individuals)			86,288		
PANEL B: Lender features (relative to each borrower)					
Branches within 5 mi (N)	2.71	2.45	1.00	2.00	4.00
Regional advertising spend (£per cap pcm)[c]	2.39	1.59	1.03	2.15	3.45
Observations (lender-borrower pairs)			567,461		
PANEL C: Product features					
Initial interest rate (%)	2.64	0.79	1.99	2.53	3.14
Upfront fee (£)	562	548	0	295	999
Early repayment penalty (% of loan)	2.34	1.20	1.54	2.50	3.11
Fixed period length (years)	3.22	2.40	2.00	2.00	5.00
Observations (options)			3,071,550		

Note: (a) Income is the sum of post-tax household earnings for all individuals named on the mortgage loan. (b) Overall borrower credit score as reported to mortgage lenders by one of the three major credit bureaus in the UK, normalised to range from 0 to 100. (c) Average advertising expenditure by a lender in the broad region of the borrower's residence over 6 months up to mortgage application.

Several statistics in Panel A, when taken together, caution against overlooking familiarity and assuming all lenders are on 'equal footing' with regards to borrower attention. On average, each borrower has around six lenders to choose from and has an existing current account (or even any product) with just one of them. Yet, over a half of borrowers choose lenders with whom they already have a product.[8]

The distribution of the number of lenders with whom each borrower has PCAs is also important for making modelling decisions. As summarised in Abaluck and Adams (2017), in addition to the alternative-specific consideration (ASC) approach used in this paper, there is an option of modelling inattention using default-specific consideration (DSC). DSC has been used in the past to study cases in energy markets (Hortaçsu et al., 2017) or healthcare (Ho et al., 2017) where the existing provider has consumer's attention by default and other alternatives get considered only if the default option is sufficiently unsatisfactory. This might seem to be a natural framework for analysis of existing links in banking as well. Unfortunately, instead of there being one natural 'default' for everyone, over 25% of mortgage borrowers have a current account with more than one lender, and approximately the same number have no links with any of the represented lenders. In this context, it is difficult to apply the DSC approach meaningfully even with some modifications.

Panel B highlights additional variables on lender characteristics as they relate to each borrower, which both suggest that borrower attention may be important for mortgage choice and are more consistent with an ASC-type approach where multiple options might be vying for a borrower's attention. Due to the concentration of property purchases in urban areas, it very common for borrowers to have a branch of a potential lender within 5 miles of their residence. The availability of branches means (a) that access to lenders is unlikely to be a major issue but also (b) that most borrowers are likely to be exposed to different brands regularly. Furthermore, there appears to be a lot of variation in lenders' advertising expenditure, which given the existing findings on links between advertising and consideration (e.g Goeree, 2008; Terui, Ban, & Allenby, 2011; Honka et al., 2017) could mean that borrowers are prompted to consider lenders to a different extent.

3 Model

In this section I set out the basic model for borrower and lender decisions in the non-intermediated part of the UK mortgage market. As explained earlier, I focus on the subset of the market (approximately 30%) where borrowers choose their mortgage directly, without using the help of a broker to search for or apply for products. I assume that the choice of the direct as opposed to intermediated channel is determined exogenously.

[8] As clarified in more detail later, to count as having an existing relationship with a lender at the time of application, the borrower has to have opened their account at least 6 months before applying for a mortgage. This significantly exceeds the length of a typical UK housing transaction and thus minimises the risk that borrowers open a personal current account purely because they intend to apply for a mortgage with the same lender.

3.1 Demand

There are I borrowers (households), indexed by i, who are choosing a mortgage. In line with recent work on mortgage choice (Iscenko, 2018; Allen et al., 2019; Robles-Garcia, 2019) but in a simplification from Benetton (2019), I assume that the loan amount and property value (and hence the LTV ratio) are pre-determined by borrower's demographics, circumstances and financial position (e.g. savings for a deposit). The focus of the mortgage choice in the model is, therefore, a discrete choice a mortgage product from a choice set of products for which a borrower qualifies given their exogenous demographics, loan amount and LTV.

3.1.1 Attention

Let C_i be a set of mortgage choices available to borrower i. In modelling inattention, I largely follow the limited attention multinomial approach set out in Goeree (2008) and the alternative-specific consideration approach in Abaluck and Adams (2017), where attention to an available option $j \in C_i$ is a random event that occurs with some probability ϕ_{ij} that is a function of j's characteristics. In a departure from the standard setting, however, I do not let the probabilities of considering each *option* be entirely independent.

In the context of mortgages, the nature of product listings in lenders' websites and marketing literature, mean that while looking up details of a specific product a borrower would be made aware of all of that lender's products for which they qualify.[9]Instead, for the sake of realism and computational tractability, I restrict the consideration decisions to be at the lender level. If a borrower i considers lender l, they consider every product j in the set of products l offers ($j \in J_l$) that is also in i's choice set ($j \in C_i$).

This approach means that the 'standard' alternative-specific consideration part of the model effectively occurs at lender rather than product level. Hence, the probability of lender l being considered by borrower i is given by:

$$\phi_{il}(\gamma) = \frac{e^{f(z_{il},\gamma)}}{1 + e^{f(z_{il},\gamma)}} \tag{1}$$

where γ are attention parameters and z_{il} is a vector of characteristics of lender l, including relational characteristics between l and i (e.g. the number of branches near i's home). I discuss the specific potential drivers of attention included in z_{il} in section 4.1.1.

Let $\bar{C_{ir}} \subseteq \bar{C}_i$ be a possible consideration set for i in a scenario r. As a shorthand, let $l \in \bar{C}_{ir}$ stand for the event when lender l is considered, leading to all of l's products being in i's consideration

[9]For instance, typically, the website would contain a short sequence of eligibility questions (first time buyer status, desired loan amount, desired property value) which lead to a full list of products available to borrowers who satisfy these criteria.

set $J_l \in \bar{C}_{ir}$. Then, the probability of any specific $\bar{C}_{ir}$ is:

$$\Phi_{ir}(\gamma) = \prod_{l \in \bar{C}_{ir}} \phi_{il}(\gamma) \prod_{s \notin \bar{C}_{ir}} (1 - \phi_{is}(\gamma)) \tag{2}$$

The total number of consideration sets is the $2^{n_{il}}$, where n_{il} is the total number of unique lenders in C_i.

3.1.2 Choice

Conditional on considering the subset of available alternatives $\bar{C}_{ir}$, a borrower's choice can be represented as the standard random utility model where borrower i's utility from a product j offered by lender l is given by:

$$V_{ijl} = x_{ijl}\beta + \chi_l + \xi_{jl} + \zeta_{ij} \tag{3}$$

where x_{ijl} are the characteristic of mortgage j as experienced by i (e.g. expected monthly interest payment), β is a vector of taste parameters, χ_l is a lender-level fixed effect (such as service quality and other unobservables that do not vary between products from the same lender), ξ_{jl} is an unobservable market-wide shifter of demand for j (discussed in more detail in section 4.1.2 on identification), and ζ_{ij} a random shock to i's taste for j.

The probability that i chooses j out of the consideration set $\bar{C}_{ir}$ is then:

$$s_{ijlr} = Pr([V_{ijl} > V_{iks} \quad \forall k \in \bar{C}_{ir}]) \tag{4}$$

3.1.3 Borrower heterogeneity

I allow the parameters that determine attention and choice to be affected by demographic characteristics of the borrower, using the latent class approach (Ben-Akiva & Bierlaire, 1999; Greene & Hensher, 2003). To keep the model tractable and interpretable, I allow for two borrower types, each with its own set of parameters, (β_1, γ_1) and (β_2, γ_2), respectively. Any given borrower's type is a stochastic function of their demographic characteristics. Borrower i belongs to type t with probability σ_{it}. Naturally, with only two types $\sigma_{i2} = (1 - \sigma_{i1})$.

After accounting for demographic variation, the unconditional probability of observing borrower i choosing j from lender l is:

$$P_{ijl} = \sum_{t=1,2} \sigma_{it} \sum_{\bar{C}_{ir} \subseteq \bar{C}_i} \Phi_{ir}(\gamma_t)\ s_{ijlr}(\beta_t) \tag{5}$$

3.2 Supply

Although the primary focus of this paper is on borrower behaviour, I develop a simple model of supply-side behaviour to analyse a policy counterfactual in section 6.

3.2.1 Lender mortgage pricing

There are N_L lenders who compete to sell mortgages to households by setting prices in a one-shot, noncooperative Nash equilibrium setting. Each lender l has a set of mortgage products J_l that cover a range of product characteristics and eligibility criteria. Lenders maximise expected profits by setting interest rates for each of these products. As before, there are no discrete markets in the standard sense: because different lenders specify eligibility criteria differently, mortgage choice sets vary between borrowers, as explained in section 4.1.1.

Lenders are assumed to have correct expectations about the pool of potential borrowers and sets of products for which those borrowers qualify. There is no default risk.

Given the demand probabilities defined in (5), lender l's expected profit of offering product j is:

$$\Pi_{jl} = \sum_{i \in I_j} P_{ijl} t_j (r_j - mc_j) \tag{6}$$

where I_j is the set of all borrowers i such that $j \in C_i$, t_j is the length of the initial deal period for product j, r_j is the interest rate for the product, and mc_j is the marginal cost of selling j. Additional elements of product pricing (fees or exit charges) are implicitly assumed to be exogenous, and enter lenders' profits through mc_j. Similar to earlier work (e.g. Robles-Garcia, 2019), I assume households switch to a new mortgage product at the end of the teaser period, and that the loan amount is exogenous (normalised at one).[10] For each borrower that qualifies for product j, the change in the interest rate affects the probability of choosing the product but not the value of the loan.

The lender chooses the interest rates for all products in J_l to solve the following total profit maximisation problem:

$$\max_{\{r_j\} j \in J_l} \Pi_l = \sum_{j \in J_l} \sum_{i \in I_j} P_{ijl} [t_j (r_j - mc_j)] \tag{7}$$

The first-order conditions of (7) can be rearranged to give a sequence of profit-maximising interest rates:

$$r_j^* = mc_j - \sum_{i \in I_j} \left(\frac{\partial P_{ijl}}{\partial r_j} \right)^{-1} \left[P_{ijl} + \sum_{k \neq j \in J_l} \frac{\partial P_{ikl}}{\partial r_j} \frac{t_k}{t_j} (r_k - mc_k) \right] \tag{8}$$

[10] The switching assumption is based on a high rate of prompt remortgaging in the UK market. A recent Financial Conduct Authority (2018a) report on the mortgage market shows that 77% of borrowers switch to a new mortgage product within 6 months of their teaser rate expiring.

where the first term captures the marginal cost, the second is the mark-up and the third term reflects the effects of the r_j on the profits from l's other products.

4 Estimation

Having set out the theoretical framework in general terms, in this section I describe the practical detail of estimating it with the available data. I first go through the variable specification for each part of the demand model, and explain why the parameters are identified in this setting. I conclude the demand sub-section by discussing the performance of the estimated baseline model. I then cover these topics for the supply model as well.

4.1 Demand

4.1.1 Specification

Choice sets Financial products, including mortgages, typically have strict and multidimensional eligibility criteria which make it invalid to assume that each borrower can access the whole market or even a standardised segment of the market. Instead, I construct borrower-specific counterfactual choice sets C_i using the observed choice data and the extensive information on product listing times and eligibility criteria for each product available from Moneyfacts.

Using the latter, I can identify products that (a) were on the market at the time the borrower made their choice, (b) were available for at least a month to allow for date measurement error) and (c) for which the borrower satisfied all the eligibility criteria. The explicit criteria I consider are: geographic, borrower type (e.g. first-time buyer only), existing customer exclusivity, as well as minimum and maximum limits on age, income, loan-to-value (LTV) ratio, loan-to-income (LTI) ratio, property value and loan amounts.

Then, for further robustness, I use the observed transaction data to calculate additional 'implicit' eligibility criteria: the minimum credit score, maximum LTV, and maximum LTI across the borrowers accepted for each product. I then exclude from the counterfactual choice sets any product for which the borrower does not meet these implicit criteria.[11]

Consideration sets I further restrict the probability of i paying attention to product j which was set out in (1) by assuming that $f(z_{il})$ is linear in z:

$$\phi_{il}(\gamma_t) = \frac{e^{z_{il}\gamma_t}}{1 + e^{z_{il}\gamma_t}} \tag{9}$$

[11] This approach is identical in terms of data and methodology to the first stage of identifying dominated products – defining the 'available choice sets' – in Iscenko (2018).

where γ is a vector of parameters to be estimated.

The potential drivers of attention in z_{il} aim to capture factors that might affect the salience of a particular lender in the borrower's without the borrower deliberately looking for information. One such factor is advertising intensity, which I include in the model as the average advertising expenditure by lender l in i's broad geographical region (e.g. North-East England) per capita in the six months before the application. Another factor is the visibility of the lender's brand in the surrounding area, captured by the number of l's bank branches within 5 mile radius of the borrower's postcode. Furthermore, larger lenders are likely to be more visible in other ways, such as featuring in news coverage more or being recently chosen by the borrower's friends and family. I control for this by including in z_{il} lender's size as measured by their mortgage lending volume in 2014 (i.e. before the estimation sample starts).

For investigating a more direct form of familiarity, I include an indicator for the borrower having an existing relationship (a personal current account (PCA)) with the lender[12] and the number of years the borrower had continuously had an account with this lender prior to application.[13]

Utility I further assume that the individual taste shock ζ_{ij} in the utility function (3) follows the type 1 extreme value distribution. This means that the probability of i choosing j out of a consideration set $\bar{C}_{ir}$ in equation (4) can be expressed as:

$$s_{ijlr}(\beta_t) = \frac{e^{x_{ijl}\beta_t + \chi_l}}{\sum_{k \in \bar{C}_{ir}} e^{x_{iks}\beta_t + \chi_s}} \tag{10}$$

The initial interest rate (r_j), appears in x_{ijl} both on its own and interacted with the teaser period length. The interaction is necessary to account for the fact that a borrower can be reasonably expected to give a greater weight to an interest rate that will apply for a longer period. For the same reason, I include the interaction of the reversion (post-teaser) interest rate with the teaser period length as well as the reversion rate on its own.

Other product and lender characteristics in x_{ijl} are: upfront fees, cashback, early repayment penalty, fixed effects for the length of the fixed-rate period, offer of free property valuation (a commonly offered incentive), whether the mortgage offers payment holiday and underpayment options. I also calculate several features that are unique to each borrower-product/lender pair: the distance from the borrower's address at application to the lender's nearest branch, and how far the borrower's LTV and credit score are from the minimum eligibility criteria for the product. These last two variables control for potential preference for products where the borrower has more 'headroom' over minimum standards and thus may perceive a lower risk of rejection.

[12]To avoid the reverse causality affecting results (borrowers opening an account with a lender with which they want to get a mortgage), I require the PCA to be at least 6 months old at the time of mortgage application. The results in the paper are not materially affected by requiring that the account is at least a year old instead.

[13]The results in this paper are also robust to a more complex ways of measuring existing relationships, as shown in section 7.

I also allow all of the drivers of attention for the lender l, z_{il} other than lender size[14], to also influence product preferences by appearing in x_{ijl} as it appears plausible that e.g. a borrower might have a preference for having multiple branches nearby in addition to finding the lender more salient due to their presence.

Borrower types To complete the latent class model of borrower heterogeneity, I assume that the probability of a borrower i belonging to type 1, σ_{i1} has the following form:

$$\sigma_{i1}(\delta) = \frac{e^{d_i \delta}}{1 + e^{d_i \delta}} \tag{11}$$

where d_i is a vector of i's demographic characteristics and δ is a vector of parameters to be estimated. Borrower's characteristics that are allowed to affect the borrower type are: credit score, age, income, LTV ratio for the loan, as well as indicators for whether they are a first-time buyer, are applying for a joint mortgage or are self-employed. I do not observe borrower's education directly, but I include the percentage of population in low-skilled occupations in their postcode as proxy for educational attainment.

Likelihood Combining equations (9) and (10) in this section with the probability of observing i choosing a product j as specified in (5) gives the following observed demand probability:

$$P_{ijl}(\beta, \gamma, \delta) = \sum_{t=1,2} \sigma_{it} \sum_{\bar{C}_{ir} \subseteq \bar{C}_i} \prod_{l \in \bar{C}_{ir}} \frac{e^{z_{il}\gamma_t}}{1 + e^{z_{il}\gamma_t}} \prod_{s \notin \bar{C}_{ir}} (1 - \frac{e^{z_{is}\gamma_t}}{1 + e^{z_{is}\gamma_t}}) \frac{e^{x_{ijl}\beta_t + \chi_l}}{\sum_{k \in \bar{C}_{ir}} e^{x_{iks}\beta_t + \chi_s}} \tag{12}$$

where σ_{it} is as defined in (11).

The corresponding empirical log-likelihood function for any observed set of choices for a set of individuals I is:

$$LL(\beta, \gamma, \delta) = \sum_{i \in I} \log \left(\sum_{j \in C_i} y_{ij} P_{ijl}(\beta, \gamma, \delta) \right) \tag{13}$$

where y_{ij} is an indicator variable that takes the value of 1 if i chose j and 0 otherwise.

Given the likelihood function in (13), I estimate the taste, attention and demographic parameters with exact maximum likelihood.[15]

[14] Unlike other attention variables, size only varies across lenders and has no within variation, meaning that it is fully absorbed by lender fixed effects.

[15] I verify that the solution is a global maximum using the basin-hopping global search algorithm (Wales & Doye, 1997; Jones, Oliphant, Peterson, et al., 2001–) with gradient-based BFGS optimisation in the inner local loops.

4.1.2 Identification

This section provides an informal discussion of how the estimation procedure described above allows me to separately identify the attention, utility and borrower latent class parameters.

Latent class parameters To the extent that the utility and attention parameters are identified (as will be shown later), the latent class element of the model just mixes between two fully identified alternative-specific consideration models for each type. All demographic variables that affect the type probability σ_{it} are excluded from the attention and utility specifications. One identification concern could be that some of the demographics (e.g. income, age), which affect borrower type, can also influence which products borrowers qualify for and thus contribute to the variation in choice sets across borrowers that helps to identify parameters in other parts of the model. This should not be a problem in practice for the following reasons: (a) I do not solely rely on choice set variation to identify other parameters, (b) the latent class specification also includes borrower education (% of low-skilled workers in borrower's postcode) which is not part of mortgage product eligibility criteria, and (c) some of the important drivers of choice set variation (e.g. timing of the mortgage choice) are excluded from the latent class specification.

Attention parameters Abaluck and Adams (2017) show that attention and preference parameters are separately identified in the class of limited attention models that includes the approach I describe in section 4.1.1. The identification comes from the asymmetries in cross-derivatives of choice probabilities (i.e. restrictions from economic theory) even when exactly the same variables appear in the probability of attention, ϕ_{il}, and indirect utility, V_{ijl}. An important identifying exclusion restriction in their setting is that the probability of paying attention to the alternative j depends solely on characteristics of j and not any other alternatives. As can be seen in (9) above, the model I estimate satisfies this restriction and exclude characteristics of rival options from the probability of considering each lender.

To achieve a more realistic description of borrower choice, I also impose additional exclusion restrictions beyond the minimum required in Abaluck and Adams (2017). I assume that the detailed product characteristics — interest rate, fees, eligibility status, etc — affect borrowers' preferences but not their probability of attention. This granular product information is not fully covered by the headline advertising or branch shop fronts, and requires effort (i.e. attention) to find out, which makes it implausible that it would influence borrower's attention.

Utility parameters There are two recurring identification concerns in standard demand estimation: (a) market shares and (b) potentially endogenous product characteristics (e.g. price). I address these in turn.

With respect to (a), Abaluck and Adams (2017) prove that full consideration market shares are identified in limited attention discrete choice models under the assumptions described above. Without additional concerns about endogeneity of product characteristics, this is sufficient to identify the parameters in the utility function.

In my setting, identification is further strengthened by two sources of exogenous variation choice probabilities within the same 'market'. First, as described in Berry and Haile (2016), there is standard micro-data variation due to changes in characteristics that are specific to each borrower-lender combination (e.g. distance to the nearest branch). Second, my data on eligibility criteria and exact product availability dates allow me to create borrower-specific choice sets. As borrower characteristics (e.g. the desired loan amount) change, new products get incrementally added to and removed from their choice sets, leading to further variation in the individual choice probabilities.[16]

The concern regarding (b) endogenous characteristics, is that the unobserved product-level demand shifter ξ_{jl} in the utility function (equation (3)) may be correlated with the price (interest rate). I use a different approach to this problem from the standard instrument-based solutions originating from Berry, Levinsohn, and Pakes (1995).[17]

The reasons for adopting a different approach are twofold. First, in contract with most settings in which the BLP price instruments are used, mortgage prices are multi-dimensional — characterised by a combination of multiple interest rates, fees and penalties. Choosing to use instruments for some of these dimensions (e.g. the main interest rate) but not others can therefore be somewhat arbitrary. Second, mortgages, like many other financial products, are fundamentally different from cars or other consumer goods in that they are essentially just a detailed description of cash transfers between different time periods and states of the world. Conditional on a comprehensive specification of the financial attributes and, importantly, the lender, a mortgage product does not have meaningful intrinsic utility or quality. As a result, the interpretation and importance of the *product-specific* unobservable fixed effect ξ_{jl} for mortgages are different from many traditional IO settings.

In light of these considerations, I deal with the potential endogeneity of product characteristics with an approach that is standard in the literature on another financial market — US health insurance (see, e.g., Abaluck & Gruber, 2011; Ho et al., 2017). I rely on using my comprehensive dataset of the objective mortgage product characteristics (costs, time profile of interest rate changes, additional incentives, eligibility) to explicitly control in x_{ijl} for all observable information about products that a borrower might reasonably have access to when they make a decision. There can be differences between lenders in their service quality and speed, perceived or real risk of rejection, or even just the positive sentiment about the brand, but those are captured by lender fixed effects

[16] My sample of c86,000 borrowers contains 63,859 unique choice sets, which all involve different combinations of 2,592 products.

[17] Berry and Haile (2016) provide a recent summary of the approaches in the BLP tradition, by summarising the identification concerns in the original (and more general) settings, showing that the use of choice-level data does not in itself identify endogenous prices, and discussing the potential sources of price instruments.

χ_l.[18] Given the extensive available data and the 'formal' nature of individual mortgage products, I then assume that $\mathbb{E}\left[\xi_{jl} \mid x_{ijl}, \chi_l\right] = 0$.

4.1.3 Performance

In-sample fit The full details of the estimated baseline demand-side model are reported in Table 8 in the Appendix. The model has an in-sample McFadden R^2 of 0.326. I test the baseline model against the null hypothesis that the attention and preference parameters are the same across both borrower types using the maximised likelihood from a model with one borrower type (model (1) in Table 10).[19] The likelihood ratio test strongly rejects this null hypothesis with the LR test statistic of 12,358 and p-value of 0.000.

I further test and reject the null hypothesis that there is no limited attention by comparing the homogeneous limited attention model above to the simple conditional logit as defined in (10) (LR test statistic of 10,137 and p-value of 0.000).

Out-of-sample performance I use the estimated parameters to make predictions for the hold-out sample of 21,572 borrowers that were not used in the estimation. The model fits the key moments of the out of sample data well. As shown in Figure 1, the predicted joint market shares for the largest four, middle four and the smallest four lenders are very close to those observed in the data. On the level of individual firms, the predicted market shares are within 2 percentage points of the observed ones for all but two lenders in the hold-out sample.[20] The model predicts whether or not each specific borrower chooses a specific lender with 88.4% accuracy.

The fit is also good with respect to other dimensions of the choices. Table 2 compares the average characteristics of predicted choices[21] to the average product characteristics of chosen and not chosen observations. For all product characteristics, the averages across predicted choices match the actual chosen products well and are distinct from options that were not chosen.

[18] In motivating his use of price instruments, Benetton (2019) gives an example of the identification challenge posed if a lender lowers screening standards while raising its interest rate. This is a legitimate concern that I address in two ways: one by enforcing the product's screening criteria at choice set construction stage (so as to not overstate potential demand for cheaper products) and also by including controls for borrower's 'headroom' relative to the product's minimum standards in the utility model. There could conceivably be more idiosyncratic lending criteria (e.g. different willingness to lend on flats in public housing blocks) that could vary with price. Those standards, however, are typically part of lender's overall policy and do not vary between products. As such, they are taken care of by lender fixed effects in the utility specification. (See the UK Finance Mortgage Lenders' Handbook for conveyancers, compiled by the UK mortgage lenders' trade association from individual firms, for additional evidence that the legal processes and minimum standards are set within a lender and do not vary across products.)

[19] Although the two models may not appear to be nested, one can obtain the standard limited attention multinomial logit model from my latent class version in equation (12) by restricting $\beta_1 = \beta_2$ and $\gamma_1 = \gamma_2$ (39 degrees of freedom). Then the demographic factors no longer affect the likelihood.

[20] I am unable to disclose lenders' individual market shares for comparisons due to confidentiality restrictions on the use of PSD.

[21] These are calculated as probability-weighted averages of the variable of interest across all products in each borrower's choice set, with the predicted $\mathrm{P(Choice)}_{ij}$ as a weight. The results are not materially different if the product with the highest $\mathrm{P(Choice)}_{ij}$ for each borrower is treated as their predicted choice.

Figure 1: Out-of-sample performance: Lender market share prediction accuracy

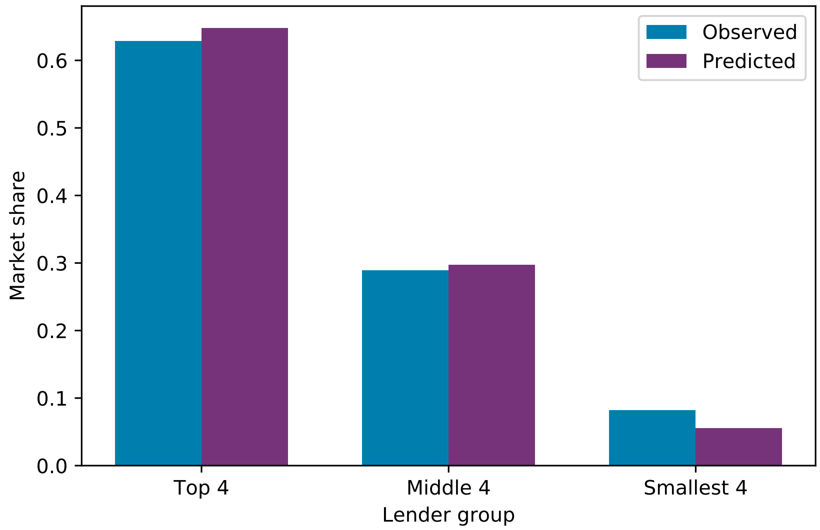


Table 2: Out-of-sample performance: mean product characteristics

	Predicted choices	True: chosen	True: not chosen
Initial interest rate, %	2.74	2.73	2.64
Reversion interest rate, %	4.03	4.02	3.96
Upfront fee, £	530.87	539.24	563.11
=1 if 2-year fixed rate	0.43	0.43	0.36
Teaser period, years	3.29	3.34	3.45
=1 if existing relationship with bank	0.51	0.54	0.17
N current accounts held	0.80	0.88	0.25
Distance to closest branch, mi	1.87	1.86	2.31
N of branches within 5mi radius	3.23	3.27	2.71
Observations (options)		21,572	748,637

4.2 Supply

As explained in section 3.2.1, I focus on the lender's setting of initial interest rate. To the extent that any other product characteristics (including fees and the reversion rate) affect pricing, they do so by changing the marginal cost of the product.

I recover mc_j from equation (8) by using the estimated demand parameters and information about product, lender and borrower characteristics.

Identification In section 4.1.2 above, I argue that the demand side of the model is identified and so generates valid price-elasticities as inputs into the pricing equation. Subject to demand-side identification, in my simple Nash-in-prices setting with constant marginal costs, marginal costs obtained from the first-order conditions are identified without the need for further instruments (Berry & Haile, 2016). In essence, my supply side is identified through (admittedly, very substantial) theoretical restrictions.

Given the purpose that marginal costs serve in the simulations, I do not need to identify how they vary with specific contributing factors such as product characteristics, lenders' funding costs or capital regulations.

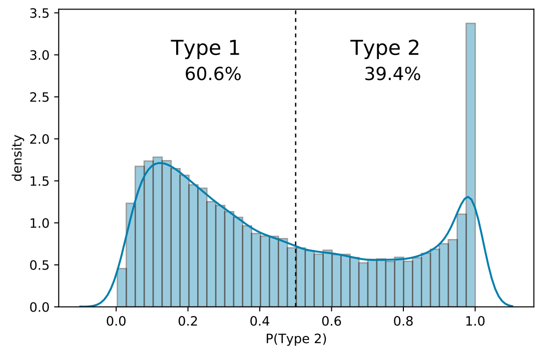
5 Results

In this section I report the results and predictions of the estimated model. First, I outline the results of the demographic heterogeneity part of the model, describing the two borrower types, their distribution and characteristics. In the following subsection, I discuss the extent of the limited attention predicted by the model and how it varies between the two borrower types. I conclude the overview of the results by elaborating on the role of bank familiarity in borrowers' attention and preferences, including the implied premiums that the two types are prepared to pay for choosing a familiar alternative.

In discussing the results, I use the following shorthand terms to refer to the key outputs of the demand-side model:

- **P(Attention)**$_{il}$: probability that borrower i considers the lender l as defined in (9).
- **P(Preference)**$_{ij}$: probability that i prefers the alternative j to all others in their *full choice set*. This is equivalent to the overall probability of choice in the standard multinomial logit setting (equation (10)).
- **P(Choice)**$_{ij}$: the overall probability of observing i choosing alternative j in practice. It is the P_{ijl} as defined in (12) above.

Figure 2: Distribution of predicted probabilities of Type 2, (σ_{i2})



5.1 Demographic variation

The model identifies two distinct groups of borrowers. As shown in Figure 2, the distribution of the probability that a borrower i belongs to type 2 is bimodal, with a clear mass at 1 and another concentration of borrowers around 0.1. If one uses P(Type 2) = 0.5 as a cut-off between the types, the majority (60.6%) of borrowers fall into type 1 and 39.4% are allocated to type 2. There is, however, a sizeable group of borrowers (around 15%) who have roughly equal chances of being either type as their P(Type 2) is between 0.4 and 0.6.

The parameter estimates from the borrower type probability model (reported as average marginal effects in P(Type 2) in Table 3a) paint a coherent picture of the two groups. The probability of belonging to type 2 increases strongly with household income and credit score. This probability gets lower, however, for borrowers who are older, more leveraged (as measured by the LTV ratio), self-employed or for those who live in areas with more unskilled or low-skilled workers. The negative effect of a joint application on the probability of belonging to type 2 is likely to be due to the fact that the net income in that case would be for the household as a whole, and the incomes of the two individual applicants are likely to be lower. Figure 7 contains bivariate plots to illustrate how the predicted probability of being in type 2 changes across the distributions of borrower's income, loan amount and (postcode-level) education.

The factors that make the borrower more likely to be in Type 1 are remarkably similar to the demographic characteristics that are shown to be associated with the increased likelihood of dominated mortgage choices and larger avoidable costs in Iscenko (2018). In fact, the two groups - the poorer, less educated, more leveraged and the richer, more educated and better at managing credit - recur regularly in the literature as the unsophisticated and sophisticated consumers, respectively (e.g. Lusardi, Mitchell, & Curto, 2014).

There are notable differences in the estimated preference parameters between the two borrower

Table 3: Estimated marginal effects on borrower type and on product demand across types, in pp

(a) Demographic effects on P(Type2)

	Δ P(Type 2)
Credit score	0.308
Age (years)	-0.514
Net income (£1000)	1.719
Loan-to-value (LTV, %)	-0.136
=1 if first-time buyer	10.568
=1 if joint mortgage	-16.157
=1 if self-employed	-9.672
Postcode: % low-skilled	-0.284

(b) Differences in effects on demand between types

	Δ P(Choice)	
	Type 1	Type 2
Initial interest rate (%)	-2.57	-3.00
Reversion interest rate (%)	-0.91	-1.26
=1 if 2-year fixed rate	2.06	3.12
=1 if 5-year fixed rate	-1.55	3.64
Distance to closest branch (mi)	-0.19	-0.18
Headroom to max LTV (pp)	2.10	1.17

types. As can be seen from the selected average marginal effects on the $\mathrm{P(Choice)}_{ij}$ in Table 3b [22], Type 2 borrowers tend to be more price-sensitive with respect to both interest rates, show a stronger preference for fixed interest rate mortgages and are less concerned about how close they are to the maximum LTV standards of the mortgage. In contrast, Type 1 borrowers appear to put a much larger weight on not being close to the maximum LTV for the product, potentially due to greater concerns about the application being rejected. Although Type 1 prefers a 2-year fixed rate to an adjustable rate mortgage, they in fact put a negative value on longer-term fixed rates relative to the rate varying throughout the contract. Both types appear to have broadly equal (and relatively small) preference parameters for the distance to the lender's nearest branch, suggesting it is not a major consideration for borrowers, at least as far as preferences are concerned.

In addition to preferences in product characteristics, the two estimated types also differ in their degree of inattention and the extent to which lender familiarity plays a part in their attention and choices. The next section explores those differences in more detail.

5.2 Limited attention

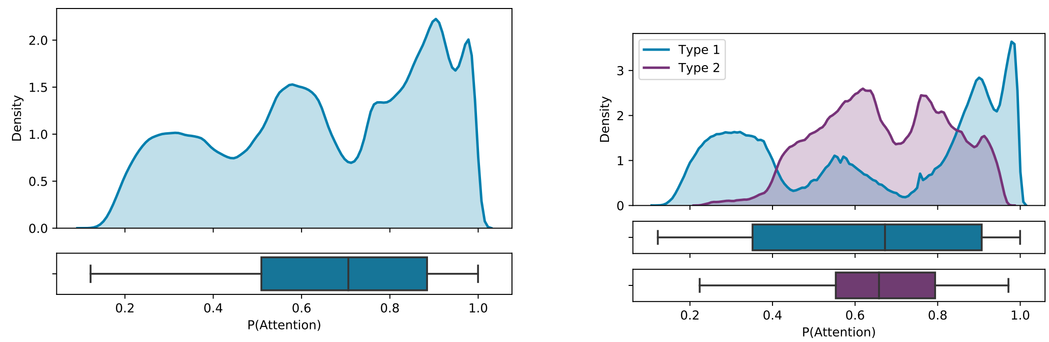
The estimated model suggests that there is non-negligible inattention. The average predicted $\mathrm{P(Attention)}_{il}$ across all borrower-lender pairs is 0.65. As can be seen from the whole distribution in Figure 3a, there is a lot of variation in the predicted probabilities, with some lenders having almost no chance of being considered by some borrowers.

[22] For interest rate variables, the table reports the total marginal effect (both from standalone interest rate terms and their interaction with the teaser length). For instance, for type 1 the marginal effect of the initial rate on borrower i's choice of product j is:

$$\frac{\partial P_{ijl1}}{\partial r_j} = (\beta_1^{\text{ir}} + \beta_1^{\text{ir x tlength}} t_j) \sum_{\bar{C}_{ir} \subseteq \bar{C}_i} \Phi_{ir}(\gamma_1)\ s_{ijlr}(\beta_1)(1 - s_{ijlr}(\beta_1))$$

where t_j is the length of the teaser period for product j. The reported parameters are simple averages of these individual and product-specific partial derivatives. All parameters used to calculate the reported marginal effects are significant at 1% confidence level.

Figure 3: Distribution of the predicted $\mathrm{P(Attention)}_{il}$



(a) Overall

(b) Split by borrower type

Figure 3b compares the distributions for the two borrower types. Inattention appears to manifest differently in Type 1 and Type 2. The latter display a moderate degree of inattention fairly consistently. Over three quarters of predicted values of $\mathrm{P(Attention)}_{il}$ for this type lie between 0.5 and 0.9, meaning that they are more likely than not to consider most of the available lenders but often also have a small chance of not paying attention. In contrast, borrowers allocated to Type 1 have a highly bimodal distribution: they either consider a lender nearly with certainty or they are very unlikely to consider to them. As I explore in more detail in the section on familiarity, existing relationships between the lender and the borrower play a critical role in determining which side of the distribution the lender occupies. Type 1 borrowers are also more likely to consider only one lender, with probability of 0.143 compared to 0.118 for Type 2.[23]

The estimated parameters and fitted probabilities allow me to approximate the expected cost of inattention with a simulation. First, I use 1000 sets of Gumbel distribution draws for each taste shock to generate a realisation of borrower utilities from each product as defined earlier in equation (3). Second, I obtain 1000 sets of uniform distribution draws and compare them with the predicted $\mathrm{P(Attention)}_{il}$ to simulate which products get considered. For each of the 1000 scenarios, I calculate the difference between the maximum utility across all products available to borrower i and the maximum utility within their simulated consideration set. Naturally, if the 'best' product in that simulation is considered, the difference is 0. For each borrower, the expected cost of inattention is the average difference across the all scenarios. I then use estimated utility parameters and borrower demographics to convert the forgone utility into equivalent changes in the interest rate and annual borrower income which are reported in Table 4.

[23] These probabilities are calculated across 1000 simulated consideration sets for each borrower. In each simulation s, borrower i is deemed to consider a lender l if the predicted $\mathrm{P(Attention)}_{il}$ exceeds the simulation-specific independent random draw from the uniform distribution for this borrower-lender pair (R_{ils}).

Table 4: Summary inattention measures, split by type

	Mean among:	
	Type 1	Type 2
P(Attention)$_{il}$	0.641	0.669
P(Consider 1 lender)$_i$	0.143	0.118
$\mathbb{E}$[Utility forgone from missing best] :		
Initial interest rate equivalent (pp)	-0.306	-0.177
Income change equivalent (%)	1.224	0.731

Individuals in Type 1 typically forgo larger utility improvements due not considering better products. Their average expected costs are equivalent to forgoing a 0.31 percentage point fall in interest rate, which in turn means around a 1.2% reduction in annual household income. For Type 2, the expected costs of inattention are considerably lower, equivalent to a 0.18 percentage point change in the initial interest rate or 0.73% of annual post-tax household income.

5.3 The role of familiarity

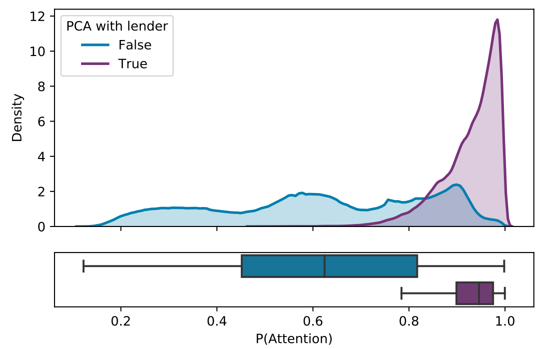
This section explores in more detail the powerful effect that a borrower's existing link with the lender though current product holdings ('lender familiarity') has on their attention towards that lender and the likelihood of choosing their products conditional on paying attention. As explained in the specification section (4.1.1), in the baseline model, a 'familiar' lender is one with which the borrower has an existing personal current account (PCA). This section's results about the importance of lender familiarity for attention and choice are robust to more complex specifications, for instance, those that take account of the number of existing PCA and non-PCA products with the lender.

5.3.1 Familiarity and attention

Having lender's familiarity has a large positive effect on their likelihood of being considered, shifting the whole distribution of the probabilities towards 1, as can be seen in Figure 4. Almost 9 out of 10 borrower-lender pairs that are linked by an existing PCA have P(Attention) of 0.8 or higher, whereas it gets above 0.8 for only 27% of pairs without an existing link.

Both types of borrowers are affected by familiarity when they decide whether to consider a particular lender. Its importance is, however, a lot more pronounced for Type 1. Those borrowers almost certainly consider lenders with which they have a relationship (mean P(Attention) of 0.97) and are much less likely to consider unfamiliar lenders (mean P(Attention) of 0.56). For Type 2, the mean likelihoods of considering familiar and unfamiliar lenders are less dramatically but still

Figure 4: Distribution of $\mathrm{P(Attention)}_{il}$, by familiarity



significantly different, at 0.88 and 0.63 respectively.

The differences in attention towards familiar and unfamiliar lenders summarised in Figure 5a for both types arise through several channels. First, there is the direct impact of the existing PCA relationship on attention. Even controlling for other drivers of attention in the model, the mere fact of the borrower i having a PCA with the lender l increases $\mathrm{P(Attention)}_{il}$ by 24.7 percentage points for Type 1 and 21.2 percentage points for Type 2. This effect is further amplified by the length of this existing banking relationship. For Type 1, every additional year[24] of having the PCA with l increases the probability of considering them by 51.8 percentage points. In contrast, the length of the banking relationship does not have a statistically or economically significant effect on attention for Type 2 borrowers.

Second, there are additional characteristics of the each borrower-lender pair (also summarised in Table 5), which influence attention and are positively correlated with the likelihood that the borrower has an existing current account. These characteristics further contribute to the dramatic differences between familiar and unfamiliar lenders in Figures 4 and 5a. Both types of borrowers are somewhat more likely to consider lenders with more branches near their address, although attention is a lot more responsive to this for Type 1 borrowers (marginal effect of 1.45 percentage points per additional branch compared to 0.49 for Type 2). Lender's higher mortgage lending volumes in the past are also positively but weakly associated with greater attention for both borrower types. Curiously, lenders' advertising expenditure has the expected weakly positive marginal effect on $\mathrm{P(Attention)}_{il}$ for Type 1, but appears to be negatively associated with attention for Type 2 borrowers. Given that a £1 per capita per month change in advertising expenditure is a large change (approx. 65% of 1 standard deviation), the estimated effect on attention is not very economically significant even for Type 2. Advertising campaigns that anticipate and seek to counter (partially) slumping demand could be a possible explanation for the negative association with attention.

[24] Beyond the initial six months required for the PCA with the lender to count as an existing relationship.

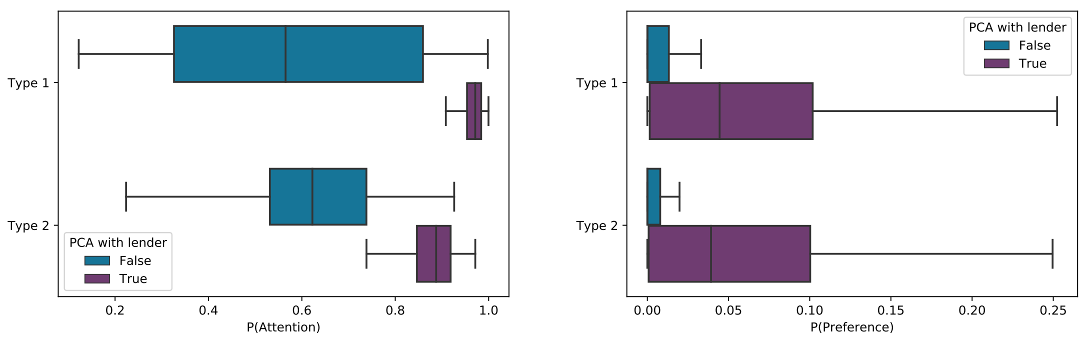
Table 5: Average marginal effects on P(Attention), by type

	Δ P(Attention)[a] Type 1	Type 2	Corr with has PCA
=1 if has PCA with lender	24.70	21.24	1
Length of lender relationship (years)	51.84	0.17[b]	0.74
Branches within 5 mi (N)	1.45	0.49	0.11
Regional advertising spend (£per cap pcm)	1.97	-4.64	0.05
Lender size: lending volume in 2014 (£m)	0.63	0.19	0.13

[a] Marginal effects reported in percentage points for interpretability. All underlying parameters are significant at 1% level unless stated otherwise.
[b] Only significant at 5% level.

Figure 5: Distributions of predicted probabilities, by lender familiarity and type

(a) P(Attention) (b) P(Preference)



5.3.2 Familiarity and preferences

Lender familiarity affects choice through borrower preferences as well. As shown in Figure 5b, an existing relationship with a lender is associated with around 4.5 percentage point increase in median probability of the product offering the highest utility out of the whole choice set ($\text{P(Preference)}_{il}$) for both consumer types. Curiously, none of the other familiarity and attention factors described in the preceding section − length of the relationship, branches, lender size or advertising − have economically significant effects on preferences.

Preferences for familiarity also translate into a higher probability of observing choices of products from familiar lenders, even when holding the attention channel constant. Table 6 reports the estimated marginal effects of lender familiarity on P(Choice)_{ij} through the preference channel. In this case, Type 2 borrowers are more sensitive to lender familiarity than Type 1. The average marginal preference effect of an existing PCA with the lender is to increase the probability of the lender's products being chosen by 4.34 percentage points for Type 2 and 3.33 percentage points for

Table 6: Marginal effects and willingness to pay for familiar banks, split by type

	Mean among:	
	Type 1	Type 2
Δ P(Preference)$_{il}$	3.44	4.55
Δ P(Choice)$_{il}$	3.33	4.34
Own-bank utility premium		
Initial interest rate change (pp)	-1.27	-1.41
Income change equivalent (%)	5.05	5.70

Type 1. Both are extremely large effects, more than doubling P(Choice)$_{ij}$ from its sample average of 0.028.

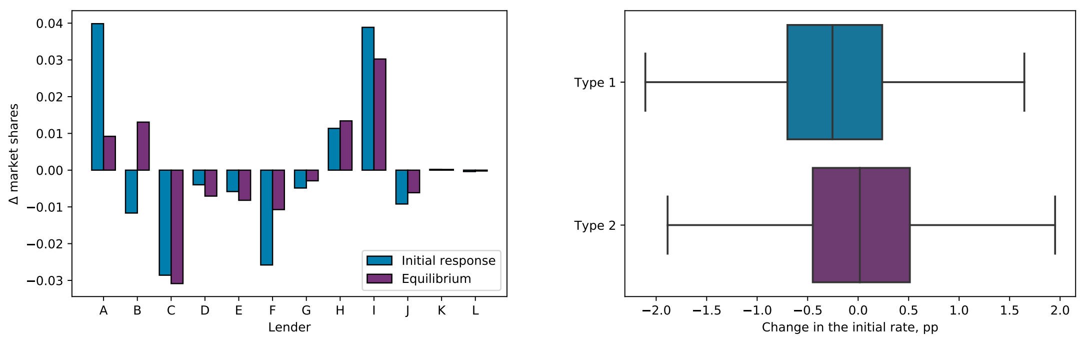
Table 6 also shows the implied own-bank premiums that would be required to compensate the borrower for taking out an otherwise identical product from an unfamiliar lender without reducing their utility. The premium is equivalent to reducing the mortgage interest rate by 1.27 and 1.41 percentage points, respectively, for Type 1 and Type 2 borrowers. These interest rate changes are equivalent to reducing the annual mortgage payments as a percentage of income by 5 percentage points for Type 1 and 5.7 percentage points for Type 2 per year.

It is clear that borrowers being more likely to think about their own current account providers first is not the cause of the own-bank premium because it is separated by the model into a distinct attention channel. Other possible drivers of the premium include: (a) risk aversion with respect to some lender characteristics such as lending standards or service quality which are perceived to be more uncertain in unfamiliar lenders, (b) greater (perceived or real) effort costs of applying to a new provider for a mortgage, or (c) greater ongoing effort of managing accounts across multiple financial institution. In either case, the effects are clearly substantial and are not attenuated among otherwise apparently more sophisticated borrowers (Type 2).

The fact that a non-price characteristic plays a significant role in borrower preferences also means that borrowers are not very price-elastic. The mean own-price demand elasticity in the sample is -3.64, suggesting that a 10% increase in interest rates would, on average, reduce demand by a third. Price elasticity varies a lot, however, across borrowers and products, with standard deviation of 1.73. This is not surprising given the amount of heterogeneity permitted by my demand model and the presence (or absence) of existing links with lenders for different borrowers. The implied marginal cost of an average loan is 1.33 percentage points (i.e. £133 on a £10,000 loan), but, again, with substantial variation across lenders and products. These estimated average marginal costs are broadly consistent with the size of the variable costs in the recent regulatory report on UK lenders (FCA, 2018b). Table 9 in the appendix provides a breakdown of demand elasticities and marginal

Figure 6: Impacts of the counterfactual simulation with full attention

(a) Changes in market shares (b) Distributions of interest rate changes



costs by lender size, loan-to-value band and interest rate type.[25]

6 Counterfactual simulation: forced full attention

The extent of inattention documented in section 5.2 raises a question about the scope for an intervention to improve borrower welfare. To explore this I simulate the market effects of a hypothetical extreme policy where each borrower is made to pay attention to the whole choice set available to them (e.g. by making it mandatory to use a comprehensive comparison tool before taking out a mortgage). In practice, an intervention like this would likely also involve considerable search and time costs for borrowers arising from the larger number of options they would have to consider. It would also involve additional implementation costs. I abstract from these factors in the current setting to consider the upper bound on the benefits borrowers might experience from the change. I simulate this change by turning off the attention channel (setting $\mathrm{P(Attention)}_{il} = 1$ for all i and l and letting consumer demand and lender pricing adjust to a new equilibrium.

In running this simulation, I assume that lenders' marginal costs, set of offered products, and characteristics of the existing products (other than the initial rate) are not affected by the intervention. There is no new entry or exit, and no changes to advertising or the branch network. Borrowers' preferences and existing PCA relationships with lenders remain the same.

Figure 6a, shows the initial and equilibrium effects on the market shares of individual lenders. Even under full attention, the market shares of most lenders appear little changed, with a small number of exceptions.The proportion of borrowers choosing familiar lender does, however, decline somewhat from 54% to 49%.

[25] Fixed costs such as IT, branch network, etc, tend to be very large in banking and can exceed costs that scale more directly with lending volume, such as funding costs (FCA, 2018b). As a result, the traditional mark-ups over marginal cost do not have a very meaningful interpretation in this context and are not reported.

Table 7: Summary of average changes under full attention relative to the baseline

	Mean among:		
	Type 1	Type 2	All
Price effects:			
Δ interest rate (pp)	-0.092	0.033	-0.043
Δ annual payment (£)	-129.975	197.036	-1.214
Expected utility change:			
Equivalent Δ interest rate (pp)	-0.258	-0.023	-0.165
Equivalent Δ annual payment (£)	-289.523	-33.095	-188.554

The effect on the equilibrium interest rates is more pronounced. Interest rates offered by lenders decline by 23 basis points on average across all mortgage products. The falls in the interest rates incurred by borrowers on their *chosen* products is a lot smaller, averaging just 4.3 basis points (because they were largely choosing better priced products to begin with).

The new policy affects the two types of borrowers very differently. As shown in Figure 6b, the consequences for Type 1 borrowers is broadly favourable: interest rates on their equilibrium mortgage choices fall for almost two thirds of this group with decline of 9.2 basis points on average. The mean cost saving is £130 per year. On the other hand, the interest rates increase for more than a half of the Type 2 borrowers. Consequently, this group has larger mortgage payments on average in the new equilibrium, on average paying 3.6 basis points (or just under £200) more in interest. Even though there are more Type 1 borrowers, the larger loan sizes in Type 2 mean that the changes in pound mortgage costs across the population as a whole broadly net out and remain constant on average.

The mechanism for rise in prices for Type 2 appears to be as follows. Some of the cheapest lenders prior to intervention are significantly more popular with Type 2 borrowers (both in terms existing PCAs and resulting mortgage choices), but not very likely to be considered by many borrowers, especially Type 1. As a result, those lenders enjoy a relatively larger positive demand shock from increased attention, allowing them to raise interest rates closer to market average while still gaining market share and retaining demand from their existing Type 2 PCA customers.

Considering all products could lead borrowers to discover options that were better for them on terms other than price and thus increase overall utility despite the very modest interest rate improvements. Comparing 1000 simulated counterfactual choices for each borrower under the new equilibrium and the original baseline suggests that the beneficial effects of full attention do, indeed, exceed the changes in prices alone.[26] The average expected utility increase for a Type 1 borrower

[26] The simulation follows a similar process to the one described in section 5.2 for calculating costs of limited attention. As before I generate 1000 independent random draws of the utility taste shocks, $\zeta_i j$ from the Gumbel distribution and uniform distribution draws to simulate which product get considered by each borrower under lim-

is equivalent to a 26 basis point reduction in their initial interest rate, more than double the actual observed interest rate change for this group. This interest rate change is equal to a reduction of annual mortgage payments by £289.

On average, being able to discover products with better non-price characteristics under full attention improves utility for Type 2 just enough to compensate them for the rise in prices. The average change in consumer surplus for this group is equivalent to a decrease in mortgage costs by 2.3 basis points or £33 per year. Overall, the change to the full attention equilibrium results in average expected welfare gains equivalent to the interest rate being reduced by 16.5 basis points (or by 6.3% from the baseline average rate).

Importantly, the intervention is far from universally beneficial, even after accounting for consumer surplus from better matching on non-price characteristics. In fact, welfare declines in the new equilibrium for more than a third of the population (28% of Type 1 and 47% of Type 2 borrowers).

This simulation exercise highlights that even if an intervention to enforce full attention to alternatives without subjecting borrowers to search costs were feasible, it could still entail welfare losses for a significant number of borrowers. Even on average, the predicted improvements in welfare are perhaps less dramatic than would be expected of an intervention of this scale.

Most notably, the market structure and shares are barely affected by the mandated full attention, in important part because of the large role that existing links between borrower and lender play in shaping preferences – both for more and less 'sophisticated' types of borrowers. This means that if the policy motivation is concern about the concentration in the market, making consumers aware of alternatives, however clearly, is unlikely to be effective insofar as many of those borrowers have pre-existing links to incumbents.

The simulation results also show that in the context where existing links matter, even a costless hypothetical intervention to increase attention creates welfare transfers between consumer groups. The previously more inattentive borrowers benefit, on average, from the increased price competition among the more expensive lenders. But many of the more sophisticated borrowers, who searched more for the cheaper lenders (or were lucky to have an existing relationship with them) before the intervention, can lose out after full attention is enforced across the market, especially when price elasticity is low due to strong preferences for other factors (like lender familiarity). Given the demographic characteristics of the two types, the transfer is largely from the better-off consumers to the poorer ones, but there are also winners and losers within each type.

In practice, of course, there is also likely to be an additional (e.g. cognitive or time) cost of the enforced full attention even if search is simplified. Revealed preference would suggest that this cost is likely to be higher for those who are more inattentive ex ante, which could considerably reduce

ited. For each draw and each borrower I calculate their maximised utility (a) under limited attention and the original product characteristics, conditional on the simulated consideration sets, and (b) under the new full attention equilibrium, with new equilibrium interest rates and other product characteristics. Each borrower's expected utility change from the new policy is the average difference between (b) and (a) across 1000 simulations.

their welfare gains from the intervention as well.

7 Robustness

I explore several alternative specifications and data sub-samples to confirm the robustness of the results in this paper. For the sake of interpretability, ease of comparison between the different models, and computational efficiency, I estimate the standard (single borrower type) alternative-specific consideration models under these different approaches. Table 10 shows the results of the alternative models alongside the single-type version of the baseline specification in this paper (1).

Alternative specifications of familiarity I check that the estimated parameters, and especially the strength of the effects of lender familiarity, are robust to different specifications using two alternative models. In the first (model (2) in Table 10), I keep the indicator for the existing link through personal current accounts as is, and include an additional indicator for the borrower having other credit products with the lender, such as credit cards, personal loans, mortgages, etc. In the second alternative (model (3)), instead of the binary indicators for the existence of the link with a lender, I instead control for the number of personal current accounts and the number of other credit products the borrower has with each lender. As can be seen from the regression results in Table 10, these more sophisticated measures of the existing relationships between borrowers and lenders do not add much to the fit of the model or materially change the parameters on other product characteristics. Controlling for other products reduces the estimated effect of the link through current accounts slightly, but it still remains the main channel through which existing relationships affect attention and preferences.

First-time buyers only There could be a concern that borrowers who are not new to the housing market, and are taking out a mortgage to move from their existing property could have prior information about lenders through their previous mortgage loans. Those borrowers may have learnt about the lenders through their earlier (now refinanced) mortgage loans, but kept an open current account from that period. I can observe their 'vestigial' current accounts, but not the history of mortgage relationships that finished over 6 years ago. Thus I could misinterpret the effects of relevant learning from previously held mortgage products as more general preference for brand or lender familiarity acquired through current account links. To see the extent to which the results could be distorted by past experiences by 'home movers', I estimate the model baseline model specification in a sub-sample of first-time buyers: households who have not owned a property (and hence not had a mortgage) before. Model (4) in Table 10 shows the results of this exercise.

The estimated parameters for first-time buyers are qualitatively (and often quantitatively) similar to those in the full sample for nearly all of the variables. The only notable exception is the distaste that first-time buyers have for fixing interest rates for more than two years, which is not found in the full sample. The likely reason for the differences is that there are penalties for moving house before the fixed rate period expires, first-time buyers are more likely to be buying a property to get on the housing ladder but with the expectation of having to move soon. These households tend to be younger than the sample as a whole (mean age of 31.8 vs 37.1), and thus are more likely to have their housing size and location needs change in the near future due to a job change or having (more) children.

The findings on lender familiarity reported in the paper are robust to using the first-time buyer sub-sample. They show an even stronger preference for lenders with whom they had an existing current account. Their estimated tendency to consider 'familiar' lenders more than 'unfamiliar' ones is also only marginally smaller.

8 Conclusion

This paper applies a novel combination of the latent class and limited attention multinomial logit models to explore the drivers of inattention and product preferences in the UK mortgage market. I identify two groups of borrowers, who broadly have characteristics associated with greater and lesser financial sophistication described in earlier research (in e.g. Lusardi et al., 2014). I find that borrowers who belong to the 'demographically' less sophisticated type tend to be more inattentive and are relatively more likely to focus their attention on 'familiar' lenders, with whom they already have a relationship through a personal current account.

I also find, however, that even after accounting for limited attention, mortgage borrowers exhibit a strong preference for products from 'familiar' lenders. Both types of consumers, effectively trade off borrowing cost savings of up to 5% of post-tax income for going to a lender with whom they have an existing relationship. This behaviour has implications for policy. As I show in the counterfactual scenario, even a hypothetical intervention that achieves full attention among borrowers without subjecting them to increased search cost, has an ambiguous effect in a setting with very loyal borrowers. Lenders' market shares change little, and improvement in prices is not dramatic. On average, prices paid and consumer surplus improve due to the previously less attentive consumers finding better deals. However, there is a significant minority (including nearly a half of the more 'sophisticated' type) whose welfare is reduced in the new equilibrium even before any search costs are taken into account. In the context of substantial and strong existing links to providers (often through other products), just making borrowers aware of alternatives has only a limited effect on their choices.

More generally, given the extent to which past choices of a personal current account provider shape borrowers' preferences and decisions about other products, it is important for policymakers and researchers to consider the 'portfolio' of consumers' product holdings rather than focus on individual markets. Likewise, when suppliers operate across a wide range of product lines, as is often the case in the finance and technology sectors, adopting a cross-market perspective could be necessary to understand their competitive behaviour and market outcomes.

The work in this paper could be extended in multiple ways. First, it could be insightful to consider the behaviour of brokers in intermediated transactions in the context of limited attention and preferences for familiar alternatives. Looking at both the direct and intermediated channels would also allow more comprehensive policy counterfactuals to be explored. Second, like all limited attention work in the alternative-specific consideration tradition (as defined by Abaluck and Adams (2017)), I have to implicitly assume that attention is not rival. For instance, having a lender's branch near the borrower's home has the same effect on attention regardless of how many other competitors have branches nearby. Search costs are also difficult to measure and conceptualise in this setting as each alternative is independent. To the extent identification permits, it may be instructive to revisit the topics in this paper using a model that combines sequential search with characteristics-based inattention.

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A Extra materials

Figure 7: Distribution of predicted type by demographic characteristics

(a) Income vs loan amount

(b) Income vs education

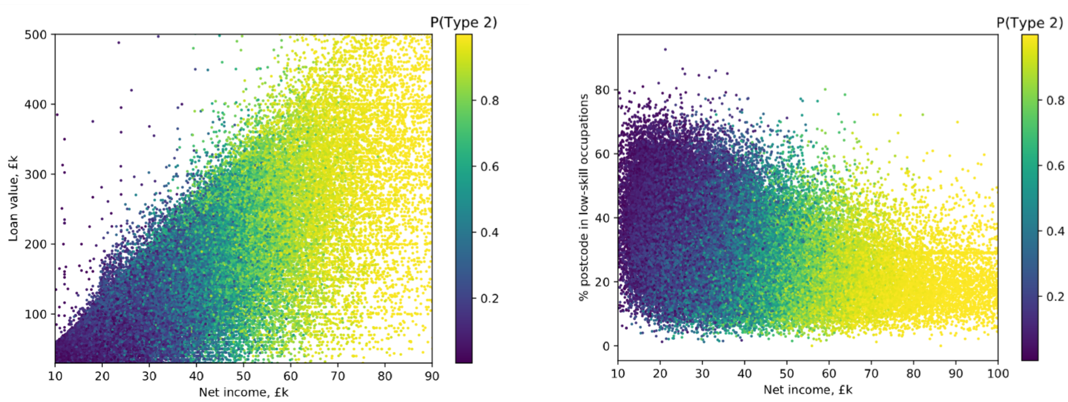

Table 8: Estimated parameters from the baseline model: Full

	Type 1		Type 2	
	parameter	p value	parameter	p value
Preference parameters (β)				
Initial interest rate (%)	-0.7353	0.0000	-0.9739	0.0000
Reversion interest rate (%)	-1.5250	0.0000	-1.3602	0.0000
Initial rate X teaser period length	-0.1505	0.0000	-0.1615	0.0000
Reversion rate X teaser period length	0.3142	0.0000	0.2146	0.0000
Upfront fee (£)	-0.0012	0.0000	0.0005	0.0000
Cashback amount (£)	0.0008	0.0000	0.0012	0.0000
=1 if free property valuation	-0.2173	0.0000	0.0929	0.0104
=1 if 2-year fixed rate	0.9859	0.0000	1.5438	0.0000
=1 if 3/4-year fixed rate	0.5666	0.0000	1.0443	0.0000
=1 if 5-year fixed rate	-0.7440	0.0000	1.8045	0.0000
=1 if 10-year fixed rate	-3.8914	0.0000	1.3662	0.0006
=1 if has payment holiday option	0.4340	0.7057	-2.1733	0.0586
=1 if has underpayment option	0.9902	0.3892	1.1925	0.2998
Early repayment penalty (% of loan)	0.1918	0.0000	-0.3439	0.0000
Distance to closest branch (mi)	-0.0924	0.0000	-0.0904	0.0000
Headroom to max LTV (pp)	1.0062	0.0000	0.5776	0.0000
Headroom to min credit score	0.0098	0.0000	0.0199	0.0000
Branches within 5 mi (N)	0.0326	0.0000	0.0285	0.0909
Regional advertising spend (£per cap pcm)	-0.0211	0.0418	0.3810	0.0000
=1 if has PCA with lender	1.5951	0.0000	2.1499	0.0000
Length of lender relationship (years)	0.0252	0.0000	0.0983	0.0000
Lender FEs	Yes		Yes	
Attention parameters (γ)				
Intercept	-2.0467	0.0000	0.7997	0.0000
Lender size: lending volume in 2014	0.0564	0.0000	0.0093	0.0000
Branches within 5 mi (N)	0.1289	0.0000	0.0245	0.0002
Regional advertising spend (£per cap pcm)	0.1758	0.0000	-0.2324	0.0000
=1 if has PCA with lender	2.2008	0.0033	1.0647	0.0000
Length of lender relationship (years)	4.6188	0.0000	0.0083	0.0444
Demographic parameters for P(Type 2) (δ)				
Intercept	-3.1991	0.0000		
Credit score	0.0211	0.0000		
Age (years)	-0.0353	0.0000		
Net income (£1000)	0.1180	0.0000		
Loan-to-value (LTV, %)	-0.0093	0.0000		
Postcode: % in low-skill occupations	-0.0195	0.0000		
=1 if first-time buyer	0.7254	0.0000		
=1 if joint mortgage	-1.1090	0.0000		
=1 if self-employed	-0.6639	0.0000		
N (individuals)	64,716			
N (observations)	2,301,341			
Fitted log-likelihood	-149,268			
McFadden's adjusted R^2	0.3265			

Table 9: Estimated marginal costs and demand elasticities

	Demand elasticity[a]		Marginal cost[b]	
	Mean	σ	Mean	σ
All	-3.641	1.730	1.327	1.165
Lender size:[c]				
Larger 6	-3.625	1.739	1.291	1.195
Smaller 6	-3.674	1.712	1.400	1.101
Max LTV band:[d]				
(0, 50]	-1.952	1.863	1.144	1.046
(50, 70]	-2.533	1.849	1.219	1.156
(70, 85]	3.259	1.800	1.358	1.240
(85, 100]	-4.630	1.843	1.890	1.124
Fixed rate:				
Yes	-3.808	1.741	1.475	1.158
No	-2.240	0.693	0.715	1.018

Mean and standard deviation across products that satisfy the given condition. (a) Elasticity for each product j is an unweighted average of own-price elasticities for j across all borrowers who have it in their choice set. Borrower-product level elasticities use the individual marginal effects of the interest rate on P(Choice) described in footnote 22. (b) Marginal cost is obtained using the approach described in section 4.2. (c) Lender size ranking is based on total mortgage lending volume. (d) Bands are based on the maximum loan-to-value ration accepted for each product.

Table 10: Alternative specifications in a single type model

	Full sample			FTB only[a]
	(1) Baseline	(2)	(3)	(4)
Preference parameters (β)				
Initial interest rate (%)	-0.8383^{***}	-0.841^{***}	-0.8332^{***}	-0.8423^{***}
Reversion interest rate, (%)	-1.5328^{***}	-1.5335^{***}	-1.5285^{***}	-2.1994^{***}
Upfront fee (£)	-0.0004^{***}	-0.0004^{***}	-0.0004^{***}	-0.0006^{***}
Cashback amount (£)	0.0009^{***}	0.0009^{***}	0.0009^{***}	0.0009^{***}
=1 if free property valuation	-0.3118^{***}	-0.3119^{***}	-0.3103^{***}	-0.5089^{***}
=1 if 2-year fixed rate	1.1115^{***}	1.1113^{***}	1.1100^{***}	0.9363^{***}
=1 if 3-year fixed rate	0.6187^{***}	0.6183^{***}	0.6139^{***}	-0.3113^{***}
=1 if 5-year fixed rate	0.1188	0.1184	0.1169	-2.296^{***}
=1 if 10-year fixed rate	-2.0717^{***}	-2.0737^{***}	-2.0737^{***}	-8.3731^{***}
Initial rate X teaser period length	-0.1445^{***}	-0.1444^{***}	-0.1444^{***}	-0.1233^{***}
Reversion rate X teaser period length	0.2737^{***}	0.2738^{***}	0.2733^{***}	0.4248^{***}
=1 if has payment holiday option	−0.3983	−0.3086	−0.3015	−0.2014
=1 if has underpayment option	0.5152	0.4260	0.4013	1.1420
Early repayment penalty (% of loan)	-0.0655^{***}	-0.0654^{***}	-0.0651^{***}	0.1315^{***}
Distance to closest branch (mi)	-0.1048^{***}	-0.104^{***}	-0.1042^{***}	-0.1422^{***}
Headroom to max LTV (pp)	0.7204^{***}	0.7155^{***}	0.7352^{***}	0.4609^{***}
Headroom to min credit score	0.0146^{***}	0.0146^{***}	0.0147^{***}	0.0179^{***}
Branches within 5 mi (N)	0.0458^{***}	0.0463^{***}	0.0415^{***}	0.0803^{***}
Regional advertising spend (£per cap pcm)	0.1324^{***}	0.1310^{***}	0.1281^{***}	0.0790^{***}
Length of lender relationship (years)	0.0443^{***}	0.0334^{***}	0.0504^{***}	0.0195^{***}
=1 if has PCA with lender[b]	1.6661^{***}	1.5865^{***}		2.225^{***}
=1 if has other products with lender[c]		0.6785^{***}		
Number of PCAs with lender[b]			0.6752^{***}	
Number of other products with lender[c]			0.3705^{***}	
Attention parameters (γ)				
intercept	0.6109^{***}	0.6169^{***}	0.6176^{***}	1.0031^{***}
Lender size: lending volume in 2014	0.0302^{***}	0.0301^{***}	0.0293^{***}	0.0287^{***}
Branches within 5 mi (N)	0.0451^{***}	0.0451^{***}	0.0512^{***}	0.0175^{*}
Regional advertising spend (£per cap pcm)	-0.1213^{***}	-0.1201^{***}	-0.1192^{***}	-0.0743^{***}
Length of lender relationship (years)	0.0406^{***}	0.0336^{***}	0.045^{***}	0.0196^{***}
=1 if has PCA with lender[b]	1.4670^{***}	1.4390^{***}		1.3036^{***}
=1 if has other products with lender[c]		0.2897^{***}		
Number of PCAs with lender[b]			1.0688^{***}	
Number of other products with lender[c]			0.3042^{***}	
Lender FEs	Yes	Yes	Yes	Yes
N (individuals)		64,716		28,260
McFadden's adjusted R^2	0.2988	0.3004	0.2975	0.2899

(a) Model estimated in the sub-sample of first-time home buyers only, with no prior home or mortgage ownership. (b) Measure of the relationship with the lender through personal current accounts (PCA) opened over 6 months before to the mortgage application date. (c) 'Other products' include credit cards, personal loans, and mortgages and exclude lines of credit directly linked to current accounts (e.g. overdraft facility)

$^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$.