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THE ROLE OF INTERMEDIARIES IN SELECTION MARKETS: EVIDENCE FORM MORTGAGE LENDING

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ABSTRACT

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The role of intermediaries in selection markets: Evidence from mortgage lending*

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Abstract

We study the role of brokers in selection markets. We find broker-clients in the Canadian mortgage market are observationally different from branch-clients. They finance larger loans with more leverage and longer amortization. We build and estimate a model of mortgage demand to disentangle three possible explanations for these riskier product choices: (i) selection on observables, (ii) unobserved borrower preferences for riskier loans, and (iii) a causal effect of brokers. Although we find that brokers influence product choices, the main reason borrowers choose high-leverage products is unobserved preferences. Borrowers prefer larger loans and brokers facilitate qualification for them.

1 Introduction

Intermediaries serve an important role in the economy by facilitating trade between firms and consumers. In decentralized markets, where search and negotiation are required for exchange, intermediaries can benefit consumers by effectively lowering their costs of searching for a firm with which to trade, including by identifying less well-known sellers (Rubinstein and Wolinsky (1987); Gavazza (2016); Biglaiser et al. (2020); Donna et al. (2021); Robles-Garcia (2020); and Salz (2022)).

At the same time, however, outsourcing search and negotiation creates an agency problem between the consumer and intermediary. For instance, (Egan 2019) describes how intermediaries distort households' investment decisions for convertible bonds. Similar concerns arise for other

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investment products (Bergstresser et al. (2008); Christoffersen et al. (2013); Chalmers and Reuter (2020); and Egan et al. (2022)), as well as insurance (Schneider (2012); Anagol et al. (2017)) and real estate (Jia-Barwick et al. (2017)). In the mortgage market a number of papers have documented conflicts of interest between borrowers and brokers (LaCour-Little (2009); Robles-Garcia (2020); and Guiso et al. (2022)).

In this paper we investigate the role of brokers in the Canadian mortgage market. Our starting point is the observation that consumers transacting through brokers choose different products than consumers transacting through bank branches. Broker-clients choose riskier mortgages (higher loan-to-value (LTV) ratios and longer amortization), but on average obtain lower interest rates than branch-clients. At the same time, the market appears to exhibit adverse selection into the broker channel. Consumers who use brokers tend to have lower income and credit scores relative to consumers who negotiate directly with a bank. The observable consumer characteristics, however, cannot fully explain the differences in product choices.

These observations suggest that brokers may influence borrower choices. For instance, they may affect the rate distribution that borrowers face, the set of financial institutions making offers, and they might steer borrowers towards riskier products. The latter is likely if their compensation is tied to loan size and amortization length.[1] We label these explanations for why borrowers transacting through brokers wind up with riskier products as the *causal effect of brokers*, and use the term *indirect rate effect* to refer to brokers negotiating better rates which indirectly affect product choices, and *direct broker influence* to refer to steering.

In credit markets there may be an additional reason that broker-clients end up with riskier loans: borrowers have heterogeneous preferences for mortgage products driven by unobserved consumer characteristics. For instance, borrowers with relatively few liquid assets prefer mortgages requiring a smaller down payment, while those with a relatively high propensity to move, or able to make accelerated payments over the life of the mortgage, are less concerned about future interest costs. From the lenders' perspective, however, these borrowers (with high prepayment risk and low liquidity) are less profitable.[2] As a result, generating quotes can be difficult for them, since suppliers in credit markets screen borrowers for profitability and often reject applicants (see Marquez (2002); Agarwal et al. (2020); and Argyle et al. (2022)). To the extent that consumers anticipate the cost of searching and negotiating, less profitable consumers are more likely to use a broker to help them with this more extensive search, thereby creating a correlation between the use of brokers and riskier choices. We label this explanation, *selection on unobservables.*

[1] A typical broker earns between 0.5% and 1.2% of the value of the mortgage at origination, and future compensation can include trailer fees, which are proportional to outstanding balances and reward brokers periodically for the duration that a borrower stays with the same lender. All compensation is paid by the lender.

[2] When borrowers prepay, the lender loses out on the interest payments on the part of the principal that is prepaid, and therefore borrowers with high prepayment risk are less profitable. Borrowers with low levels of liquidity are also less profitable, but for different reasons. Individuals with low savings are less likely to be able to invest in high-margin investment products that banks try to cross-sell.

The objective of this paper is to separate the causal effect of brokers on mortgage-product choice from selection on unobservables. Determining whether brokers are simply helping borrowers generate quotes and qualify is crucial for policy makers. For instance, partial responsibility for the U.S. housing bubble and subsequent collapse during the Global Financial Crisis was attributed to the conduct of brokers (c.f. Berndt et al. (2010); Jiang et al. (2014)).[3] This led to a call for increased regulation. However, if brokers help with search, negotiation, and approval, then they are providing a valuable service, and stricter regulation could lead to worse outcomes for borrowers.

To assess these different explanations we take advantage of a comprehensive dataset containing detailed information on the universe of insured contracts from the Canada Mortgage and Housing Corporation (CMHC), which is the primary mortgage insurer in the country. The dataset comprises information about household/mortgage characteristics, including the rate and chosen lender, about demographic characteristics such as income and source of downpayment, and, most importantly, about which channel the borrower used to arrive at the chosen lender—own search or broker. We complement this dataset with data from Payments Canada and the Canadian Association of Accredited Mortgage Professionals, which provide information on the geographic locations of bank branches and brokers, respectively. Our focus is on the 2005 to 2007 period during which there were several macroprudential policy changes that affected the set of available mortgage products. These regulatory changes help to identify borrower preferences in Section 5.[4]

To separately identify selection on observables, selection on unobservables, and the causal effect of brokers, we develop and estimate a model of mortgage-product choice. In the model, consumers hold savings and carry non-mortgage debt and must make a discrete choice over mortgage products characterized by two features: amortization length and LTV. Consumers maximize indirect utility, given their preferences for expected consumption, lump-sum payments, and total interest costs. We allow for random coefficients on lump-sum payments and total interest costs to capture heterogeneity in consumer savings and prepayment risks.[5] The choice of LTV captures the trade-off between lump-sum payment and monthly consumption, while the amortization choice reflects a trade-off between total interest cost and monthly consumption. Mortgage qualification is incorporated through a total-debt-service (TDS) constraint. Lastly, we include channel-specific product fixed effects to capture the residual factors driving consumer choices after accounting for their tastes over observable mortgage characteristics.

[3] For an example of the popular press narrative see https://www.wsj.com/articles/SB117997159688112929.

[4] Macroprudential policies, whereby mortgage-lending guidelines are set by a regulator, have been more widely implemented since the Global Financial Crisis. These include restricting the maximum allowable LTV, payment-to-income (PTI) ratio, total-debt-service (TDS) ratio, loan-to-income (LTI) ratio, etc. For Canada, see (Allen, Grieder, Peterson, and Roberts 2020). For a broad review of macroprudential policies, see (Claessens 2015). We focus on the short period of loosening since there are many fewer potentially confounding factors than there were during and post-GFC.

[5] Borrower preferences for these features can also depend on other unobserved consumer characteristics: e.g., time preference, financial literacy, liquidity constraints, etc. For ease of exposition we focus on unobserved savings and prepayment risks.

Estimation proceeds in two steps. Our model of product choice takes as given the decision of whether or not to use a broker and the interest rate paid by the borrower, but unobserved heterogeneity in consumer savings and prepayment risks can endogenously affect mortgage rates, origination channel, and product choices. Therefore, we first use a control function approach, similar to (Adams, Einav, and Levin 2009), (Crawford, Pavani, and Schivardi 2018), and (Ioannidou, Pavanini, and Peng 2022), to take into account this selection issue.[6] Specifically, we construct control residuals from first-stage regressions of mortgage rates and broker usage using instrumental variables related to local bank and broker market structure. In the second step, we estimate the parameters in the product choice model via maximum likelihood using as input the control residuals generated in the first stage to control for the endogeneity in origination channel and mortgage rate. We maximize the joint likelihood of observing a particular product choice and the level of non-mortgage debt held by the borrower. The main parameters of interest are the random coefficients reflecting the heterogeneity in marginal disutility from lump-sum payments, the marginal disutility from total interest costs, and channel-specific product fixed effects.

Given the model estimates, we test the null hypothesis that the product fixed effects are not different across channels, and we reject the null. We interpret this result as implying that brokers directly influence borrowers' mortgage product choices: holding everything fixed, the same broker-client might choose a different product if they were to use a bank branch to originate their mortgage. Having established the direct influence of brokers on borrower choice, we next quantify its importance in explaining the differences in product choices across channels relative to the other explanations: (1) indirect rate effect of brokers, (2) selection on unobservables, and (3) selection on observables. For this, we turn to counterfactual analysis in which we gradually shut down different mechanisms influencing product choices.

Setting the product fixed effects equal across channels simulates the elimination of direct broker influence, holding fixed the rate distribution. In this scenario, broker-clients are 5.99 p.p. *less* likely to choose a long amortization product. In contrast, they are 0.45 p.p. *more* likely to choose a low down payment product. This suggests that brokers, on average, directly influence their clients choices towards longer amortization but not higher LTV. Brokers, however, also generate lower rates for their clients, which may indirectly affect product choices. To quantify this indirect rate effect, we consider a counterfactual where the broker-clients face rates set by bank branches. We predict that, on average, they would pay 23 bps more at a branch. The higher rates lead 2 p.p. of broker-clients to switch away from higher-LTV products, while having a relatively small impact on amortization choice.

Next, we set the control function variables in the random coefficients to mimic those of branch borrowers, effectively pushing broker-clients' unobserved savings and prepayment risks closer to-

[6] In Appendix B we propose a model based off of (Allen, Clark, and Houde 2019) that rationalizes the control variables constructed to deal with endogeneity of origination-channel choice and the corresponding rates. See (Wooldridge 2015) for a discussion of control functions and how they relate to IV estimation.

wards those of branch-clients. Doing so allows us to quantify the importance of selection on unobservables, which we find explains about one-quarter of the difference in the share of longer-amortization products and all of the differences in the share of high-LTV products.

Overall, we find that, holding observable characteristics fixed, a significant fraction (30.75%) of broker-clients choose a different and, on average, costlier product than they would if they instead used a branch. However, less than half of this is due to the direct influence of brokers. We find that 13.6% of broker-clients make different choices once this influence is eliminated. In particular, brokers play an important role in amortization choice. Focusing on the affected borrowers, we find that eliminating broker influence would, on average, shorten their amortization length by 4.55 years, lower the outstanding balance by $5,579 after five years of origination, and reduce the interest cost expenses over the entire amortization period by $34,196.

In contrast, the main reason broker-clients are more likely to select high-LTV products is selection on unobservables. Our findings suggest that, if there were no selection on unobservables, 16.88% of broker-clients would choose different products, on average lowering their loan amount by $7,171, amortization length by 3.25 years, and total interest cost by $44,931. These clients, however, are not steered to risky products, but prefer them. They choose to use a broker to generate quotes and qualify for larger loans, consistent with behavior described in (Agarwal, Grigsby, Hortacsu, Matvos, Seru, and Yao 2020). Estimating a model without controlling for selection on unobservables would overstate the effect of direct broker influence, making it the dominant explanation for both high-LTV and high-amortization choices.

Our findings have important policy implications. In a number of jurisdictions, including in Canada, regulations have been put in place affecting intermediary incentives. Our findings suggest that, although some movement towards costlier products is the result of broker influence, most is not, and so regulating broker activity could in fact harm consumers. That being said, our evidence on the direct broker influence, especially as it relates to amortization, implies that borrowers might benefit from increased transparency. For example, brokers (and banks) should be required to quantify the trade-off between the increased flexibility of longer-term mortgages, with the extra interest costs, including additional mortgage insurance fees. Specifically, borrowers should be made aware that even though longer amortization allows for lower monthly payments, they accumulate more interest, and one way to reduce these costs is to make accelerated payments, when possible. In Canada, several provincial regulators have introduced policies aimed at increasing transparency. For example, Alberta and Ontario have regulation requiring that brokers disclose information on compensation, and British Columbia requires brokers to disclose any direct or indirect conflict of interest.[7]

[7]See Section 21 of Ontario Regulation 188/08 (https://www.ontario.ca/laws/regulation/080188/v3), Section 65 of the Alberta Real Estate Act Rules (https://www.reca.ca/wp-content/uploads/2022/08/Rules-2022-08-19.pdf), and Section 17.3 of the British Columbia Mortgage Broker Act (https://www.bclaws.gov.bc.ca/civix/document/id/complete/statreg/96313_01).

Literature Review: In addition to (LaCour-Little 2009), (Robles-Garcia 2020), and (Guiso, Pozzi, Tsoy, Gambacorta, and Mistrulli 2022) mentioned above, (Hall and Woodward 2012), (Allen, Clark, and Houde 2014b), (Jiang, Nelson, and Vytlacil 2014), and (Myśliwski and Rostom 2022) study the role of brokers in mortgage markets. However, none focus on the role of brokers in helping borrowers generate quotes and qualify for a loan. The role of intermediaries in other financial markets has been studied—for example, (Bar-Isaac and Gavazza 2015) in the Manhattan rental market and (Egan 2019) in the market for financial advisors. There is also a growing literature structurally examining the impact of intermediaries on outcomes (c.f., (Gavazza 2016), (Salz 2022), (Biglaiser, Li, Murry, and Zhou 2020), (Donna, Pereira, Pires, and Trindade 2021), and (Grunewald, Lanning, Low, and Salz 2021)).

We are also related to a series of papers on financial advice, namely (Foerster, Linnainmaa, Melzer, and Previtero 2017), (Egan, Matvos, and Seru 2019), (Charoenwong, Kwan, and Umar 2019), (Foà, Gambacorta, Guiso, and Mistrulli 2019), and (Bhattacharya, Illanes, and Padi 2021), and to a large and growing literature using structural methods to study credit markets.[8] (Allen, Clark, and Houde 2014a), (Allen, Clark, and Houde 2019), and (Allen and Li 2023) focus on the mortgage-search and negotiation process in order to explain the observed dispersion in transaction rates. (Benetton 2021) and (Benetton, Gavazza, and Surico 2019) study the UK market. Considerable attention has been paid to the US mortgage market (c.f. Alexandrov and Koulayev (2017); Aguirregabiria et al. (2020); and Buchak et al. (2020)). (Clark, Houde, and Kastl 2021) provide a review of this research, as well as related work on other credit products, such as sub-prime auto loans (Adams et al. (2009)), auto insurance (Honka (2014); Braido and Ledo (2018)), and small business lending (Crawford et al. (2018)).

The rest of the paper is organized as follows. Section 2 describes the Canadian mortgage market, including the presence of mortgage brokers. Section 3 introduces our datasets and presents a descriptive analysis of the data. Section 4 presents the model. Section 5 discusses the estimation strategy. Sections 6 and 7 describe the empirical results. Section 8 concludes.

[8] Related to financial advice, researchers have also studied the role of advertising in mortgage markets. For example, (Gurun, Matvos, and Seru 2016) find that sub-prime lenders that advertise more within a region sell more expensive mortgages; (Grundl and Kim 2019) document heterogeneous effects of advertising on borrowers' decisions to refinance.

2 The Canadian mortgage market and the role of intermediaries

2.1 Mortgage products, insurance, and qualification

In Canada, a typical newly-originated mortgage fixes the interest rate for 5 years but amortizes over a much longer period. That is, every five years, borrowers have to renew their outstanding balance and renegotiate for a new rate. In our sample, 78% of first-time buyers obtain 5-year fixed rate mortgages (FRM); the remaining contracts are either shorter-term FRMs or variable rate. The prevalence of short-term mortgages stems from both the Interest Act and bank funding structure. For mortgages with loan term longer than 5 years, the Interest Act allows a borrower to fully prepay at any time after 5 years. In addition, a major advantage of 5-year mortgages is access to cheaper funding. The Canadian mortgage-backed-securities market is backed by the federal government, and these contracts are for 5 years. Retail deposits, which is the largest source of funding, is also 5 years or less. As a result, Canadian lenders rarely offer mortgage products over 5 years. Finally, note that lenders impose significant penalties for 'excess' prepayment or refinancing before the end of the term.[9]

The Canadian mortgage market consists of two sectors—conventional, which have a low LTV ratio and, hence, are uninsured, and high-ratio, which are high LTV and require insurance (for the full amortization period of the mortgage). During our sample period—2005 to 2007—roughly 80% of first time home buyers required mortgage insurance. The primary insurer is Canada Mortgage Housing Corporation (CMHC), a Crown corporation with an explicit guarantee from the federal government. A private firm, Genworth Financial also provided mortgage insurance and had a 90% government guarantee. The market share of CMHC during our sample period averages 70%.

The government sets the rules for mortgage-insurance qualification. These rules include a maximum LTV and debt-service ratio, a minimum credit score, as well as a maximum amortization. Importantly, some of these rules changed during our sample period to facilitate home ownership. For example, prior to 2006 the maximum allowable amortization was 25 years. In 2006 the federal government sequentially expanded the insurance to mortgages with longer maturities. The maximum amortization period was increased to 30 years in March, then to 35 years in June, reaching its peak of 40 years in December 2006. Near the time of the last change, the maximum LTV was increased from 95% to 100%, thus allowing for zero down-payment loans. Insurance premiums are the same across insurers, and depend on LTV and amortization. Importantly, there is a change in the premium schedule during our sample period.[10] The relaxation of macroprudential policies,

[9]Borrowers are normally allowed to make an annual prepayment up to 20% of the loan amount without incurring penalties. In practice, CMHC reports an average annualized prepayment rate of only 1% in the Canadian mortgage-backed securities market. This masks heterogeneity across borrowers—survey evidence (https://www.canadianmortgagetrends.com/2010/11/caamps-mortgage-market-report-2010/) highlights that about 20% of Canadians made some type of prepayment in 2009.

[10]For mortgages with a 25-year amortization, the insurance premium is 1% for 80% LTV, 1.75% for 85% LTV, 2% for 90% LTV, 3.25% for 95% LTV (reduced to 2.75% after April 2005), and 3.1% for 100% LTV (when it was

together with the change in premium schedule, creates exogenous variation in borrower choice sets. The qualification rules were tightened starting in October 2008 in response to the U.S. house-price correction.

Finally, in addition to the mortgage-insurance qualification criteria, lenders also screen borrowers for profitability. Borrowers are unprofitable if they are likely to prepay their mortgage (prepayment risk) or have few liquid assets. The former case has been well documented—lenders lose out on the interest payments related to the part of the principal that is prepaid. MBS investors also lose out from the premature return on principal, which drives up the cost of funding, and so borrowers with high prepayment risk are less profitable. Borrowers with low levels of liquidity are also less profitable because the opportunity to cross-sell high-margin investment products is diminished. For example, Canada has some of the highest mutual fund fees in the world, c.f. (Ruckman 2003) and (Khorana, Servaes, and Tufano 2008), and these are sold by the same banks that originate mortgages. In contrast, because mortgage brokers only deal in mortgages, cross-selling is rare.

2.2 Market structure

The Canadian mortgage market is dominated by six national banks (Bank of Montreal, Bank of Nova Scotia, Banque Nationale, Canadian Imperial Bank of Commerce, Royal Bank Financial Group, and TD Bank Financial Group), a regional cooperative network (Desjardins, operating in Quebec), and a provincially owned deposit-taking institution (Alberta's ATB Financial). Collectively, they control 90% of banking industry assets. A number of smaller banks (ING, HSBC, Laurentian, etc.) and credit unions also serve the market. Mortgage originators also service the loan—they do not sell the service rights to a third party, which is common in the U.S.

In the last twenty years a new set of players has emerged—Mortgage Finance Companies (MFCs). MFCs are non-depository monoline institutions that mostly administer mortgages through brokers and fund their lending through securitization or sales to third parties. By 2010, MFCs controlled about 10% of the mortgage market. (Coletti, Gosselin, and MacDonald 2016) point out that the rise of the MFCs can be linked to the existence of government policies designed to increase competition, mortgage insurance and securitization, and advances in information technology, consistent with the findings in (Buchak, Matvos, Piskorski, and Seru 2018). Unlike the big banks, these lenders are not directly subject to prudential regulation and supervision; they typically have lower levels of capital and contingent liquidity, holding roughly 40–90 cents of capital for every \$100 of mortgages underwritten (see Coletti et al. (2016)). As a result, these lenders have less 'skin-in-the-game' relative to traditional lenders, and therefore might have different lending criteria. That being said, since most of their mortgages are insured and then either securitized or sold off, MFCs

available). Each 5-year amortization extension increases the premium by 20 bps. Premiums are typically rolled into the loan, rather than paid upfront.

are subject to the same mortgage-insurance rules as traditional lenders. In other words, for the set of mortgages that we study, MFCs face the same lending criteria in terms of minimum credit scores and maximum loan-to-value and debt-to-income ratios. However, their criteria for what is considered a profitable mortgage can be different than for a traditional lender.

2.3 Mortgage brokers

Brokers have been present in the Canadian mortgage market going back to the 1970s, but really only penetrated the market starting in the mid 1990s, establishing a national broker association (CIMBL) in 1994. By 2005, brokers were responsible for negotiating roughly 40% of all insured contracts, and nearly 50% of contracts for first-time buyers.

Industry surveys (Maritz (2012) and Dunning (2011)) suggest that mortgage brokers contact on average 4.5 lenders for each contract. These survey results are confirmed using administrative data from the Financial Services Regulatory Authority of Ontario, who document a median of 4 lender contacts per contract in the province. In contrast, potential borrowers searching on their own contact just over 2 lenders, typically traditional banks (Allen et al. (2014a)). Brokers, however, include non-traditional lenders (MFCs) in the search set in order to generate more quotes. Finally, during our sample period, two of the big national banks did not originate mortgages through the broker channel. Lenders face a trade-off between a higher volume generated by accepting broker business and an increase in costs via the compensation structure.

Brokers in Canada have a fiduciary duty to their clients. They are compensated by lenders, but "hired" free of charge by borrowers to gather multiple quotes. The broker arrangement in Canada differs from other jurisdictions. In the U.S., brokers receive both a cash-fee from the borrower and a yield-spread premium from the lender. The yield-spread premium is an increasing function of both the loan size and the interest rate, therefore brokers in the U.S. do not have an incentive to find borrowers the lowest rate (e.g., Hall and Woodward (2012)). In the U.K., (Robles-Garcia 2020) documents that over 70% of first-time buyers use a broker and compensation is split between the lender and borrower (and there is no fiduciary duty to the borrower).

The compensation structure of brokers differs from that of local branch loan officers, who are typically paid a fixed wage.[11] Normally, for every mortgage they arrange, brokers receive an upfront commission from lenders (50–120 bps of the loan amount), such that they clearly benefit when borrowers take out larger loans. According to Financial Services Regulatory Authority of Ontario, 46% of brokers receive a volume bonus, and 3% receive some sort of non-monetary compensation (this can be in the form of points used to 'buy' lower rates, tickets to sporting events, trips and other gifts).

Brokers can also benefit from borrowers choosing longer amortization. Although the maximum amortization length is between 25 and 40 years, loan terms are typically just five years. As a result,

[11] In addition to the fixed wage they receive, branch loan officers might also get annual bonuses tied to total volumes.

borrowers must regularly renew their mortgage to receive a new rate for the outstanding balance. At renewal, borrowers can choose to either stay with their current lender or switch to a different mortgage provider. Typically, at renewal brokers receive relatively low commissions if borrowers remain with their current lender. In contrast, if borrowers switch lenders, brokers would obtain the higher commissions associated with new lending. This creates incentives for brokers to recommend switching lenders at renewal. Lenders have in part responded to this agency problem by introducing a trailer-fee compensation structure—small upfront commission at origination but annual payments for the duration that the borrower stays with the same lender.[12] The compensation structures imply a number of reasons that brokers prefer products with longer amortization. First, if they receive trailer fees for every year that borrowers stay with the same lender, longer amortization potentially extends the period during which brokers get paid. Second, note that outstanding balances decline more slowly for mortgages with longer amortization due to smaller monthly payments. Since trailer fees are a fixed fraction of outstanding balances, the annual commissions are larger if amortization is longer. Lastly, (Allen and Li 2023) find that Canadian borrowers with longer amortizing mortgages are more likely to switch lenders at renewal.[13] Therefore, even under the upfront compensation structure, brokers have an incentive to recommend products with longer amortization since they expect more switching and hence higher commissions at renewal. In contrast, lenders are hurt by the higher switching rates associated with longer-amortization mortgages, exacerbating the misalignment of incentives between branch and broker.

The following example provides a sense of how broker compensation varies across products. We focus on the sub-sample of borrowers who have access to 100% LTV and 40-year amortization. Consider an average broker-client who purchases a house valued at $218,985, with mortgage interest rate of 5.53%. We assume the following trailer-fee commission structure: brokers receive 75 bps of the loan size at origination, 8 bps of the outstanding balance annually in years 2-5, and then 20 bps annually afterwards. Product commissions are discounted using a discount factor of 0.95 and presented in Table 1.

We can see that amortization appears to be quantitatively more important for broker compensation than LTV. Fixing amortization at the most popular length of 25 years, we can evaluate the increase in total commissions as LTV increases. Moving from LTV of 95% to 100% increases broker compensation by $246 (= $4916 - $4670). Next, we fix LTV at 95% and compare total commissions as amortization length increases. Moving from a 25- to a 30-year amortization increases commission by $576. The difference is even more significant when we move from a 25- to a 40-year

[12]For example, Merix Financial, one of the largest lenders operating in the broker channel, offers two compensation structures. The upfront compensation structure pays 100 bps at origination and nothing in following years even if borrowers stay at renewal. The trailer-fee structure pays 75 bps at origination, and then 8–20 bps of the outstanding balance annually for the duration of the borrower-lender relationship.

[13]This can be explained by larger potential savings in interest costs from switching to lenders with better rates. It is also consistent with (Fisher, Gavazza, Liu, Ramadorai, and Tripathy 2023), who find that UK borrowers are more likely to refinance for better rates when the outstanding balance is higher and remaining amortization period is longer.

amortization, which has the largest market share among longer-amortization ($\geq$ 30Y) mortgages. Broker commissions increase by $1,528. Note that these calculations assume that borrowers never switch lenders. If we allow for switching at renewal and we take into account the fact that borrowers with longer amortization switch more, longer amortization would matter even more for broker commissions than higher LTV.

Table 1: Discounted sum of broker commission by product

	LTV					Upfront
	80%	85%	90%	95%	100%	Commission (%)
AMT=25Y	3933	4178	4424	4670	4916	33.4
AMT=30Y	4418	4694	4970	5246	5522	29.7
AMT=35Y	4845	5148	5451	5754	6057	27.1
AMT=40Y	5219	5546	5872	6198	6524	25.2

Note: This table presents the present value of broker commissions by mortgage products. Units are Canadian dollars. We fix the house price and mortgage rate at their mean—$218,985 and 5.53%, respectively. Brokers receive 75 bps of the loan size at origination, 8 bps of the outstanding balance annually in years 2-5, and then 20 bps annually afterwards. We assume an annual discount factor of 0.95. The last column shows the fraction of commissions received upfront at origination, which does not vary across LTV choices.

3 Data and descriptive analysis

3.1 Data

Our main dataset is a 25% random sample of insured mortgage contracts from the CMHC, from January 2005 to December 2007. The dataset contains information on over a dozen household/mortgage characteristics, including the financial characteristics of the contract (i.e., lender, rate, application date, closing date, loan size, house price, debt ratio, risk type), and some demographic characteristics such as income, prior relationship with the lender, source of down-payment (cash, savings, loan, gift), residential status (renter, living with parents, previous home owner), and dwelling type (detached, semi-detached, condo, etc.). In addition, we observe the location of the purchased house up to the forward sortation area (FSA).[14] Importantly, we know whether the borrower used a broker or branch to intermediate the mortgage.[15]

The dataset contains lender identity information for 13 mortgage providers during our sample period. Mortgage contracts for which we do not have a lender name but only a lender type are coded as "Other credit union," "Other trusts," or "Other bank." These three categories are fragmented

[14]The FSA is the first half of a postal code. We observe 1,482 FSAs in the sample. While the average FSA has a radius of 7.6 kilometers, the median is much lower at 2.6 kilometers.

[15]We also observe, in less than 1% of cases, loans intermediated by either a real estate agent or construction company. We drop these contracts from our analysis.

and contain mostly regional financial institutions. We therefore combine them into a single "Other Lender" category. All together, consumers face 14 lending options.

We restrict our sample to contracts with relatively homogeneous terms. In particular, we restrict our sample to contracts with the following characteristics: (i) 5-year fixed-rate term, (ii) 25-year or longer amortization, (iii) LTV $\geq 80\%$, and (iv) first-time home buyers' newly issued mortgages (i.e., excluding refinancing, renewal, and repeated purchase).[16] We trim the top and bottom 0.5% of borrowers in terms of income and house price. The final sample includes 48,391 observations.

For each borrower, we define the relevant market as a 10 KM circle around the centroid of her FSA. We obtain annual data on bank branch locations from Payments Canada. We also collected information on broker locations from a directory of brokers gathered annually by CAAMP. The directory has information on the broker and his/her associated firm. For the province of Ontario we also confirm the accuracy of this directory by comparing it to administrative data collected by the Financial Services Regulatory Authority of Ontario. We then count the number of banks and brokers in each borrower's local market. Lastly, since we do not observe individual-level savings, we obtain the average level of savings for each economic region (there are 92 of them in our sample) using the Canadian Financial Monitor surveys during the sample period.

3.2 Descriptive evidence

In this section we provide descriptive evidence that consumers transacting through mortgage brokers are observationally different from consumers transacting directly with financial institutions. Table 2 describes the main financial and demographic characteristics of the borrowers in our sample, broken down by broker and branch transactions. Notice that slightly more than half of the borrowers in our sample obtain their mortgages via brokers. The top part of the table shows that broker-clients are on average riskier than branch-clients. Specifically, they have lower income and lower FICOs, but buy more expensive houses using longer amortization periods to smooth-out monthly loan payments. Broker-clients are also more likely to be constrained by the maximum allowable TDS ratio.[17] This is the case despite broker-clients having lower monthly payments towards non-mortgage debt such as credit cards, auto loans, etc.

Table 2 also presents summary statistics for market structure variables. These are employed

[16] In analysis not reported here we examined whether repeat-buyers were different than first-time buyers. Conditional on observable borrower characteristics, repeat-buyers are 7.5 percentage points less likely to use a broker than first-time buyers. Conditional on using a broker, however, they have similar outcomes to first-time buyers. It could be interesting to investigate whether repeat-buyers learn from their past broker experience and whether their product choices are less influenced by brokers. Unfortunately, such an analysis would require a dynamic model of channel and product choices as well as a panel of borrowers for whom we observe the broker choices and mortgage contracts repeatedly, which is beyond the scope of this paper.

[17] In the data, we observe relatively few consumers with TDS constraint binding at 45%. In the model, consumers can adjust debt exactly to match the constraint, but in reality this adjustment can be discrete or random, and consumers might want to "over" adjust in order to avoid hitting the constraint at closing. Therefore, we assume that constrained consumers are those with TDS $\in (40\%, 45\%]$.

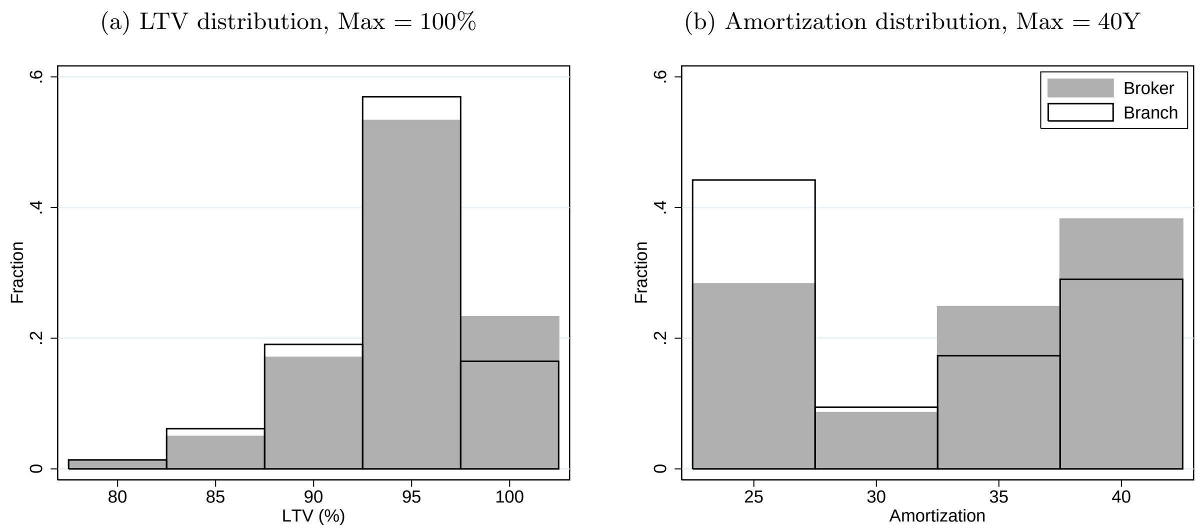
Table 2: Summary statistics by origination channel

	Branch	Broker	Diff	T Stat
Borrower characteristics				
Income ($1,000)	70.462	69.621	0.841	3.25
Borrower age	33.151	33.849	-0.697	-8.02
I(Low Risk)	0.807	0.777	0.031	8.09
House price ($1,000)	181.278	202.939	-21.661	-27.64
Other debt payment	931.390	849.099	82.290	15.04
ER saving ($1,000)	25.578	26.835	-1.257	-17.41
Mortgage features				
Interest rate(%)	5.422	5.277	0.145	26.05
Mortgage payment	1003.678	1102.180	-98.503	-23.94
Bond rate (%)	4.241	4.231	0.010	2.26
Rate premium (%)	1.440	1.436	0.004	3.49
Loan ($1,000)	168.587	189.459	-20.872	-28.83
Amortization (years)	27.768	28.799	-1.031	-20.71
LTV (%)	93.354	93.636	-0.281	-7.96
TDS (%)	33.365	34.068	-0.703	-13.03
I(Max Amortization)	0.492	0.569	-0.077	-17.10
I(Max LTV)	0.481	0.525	-0.044	-9.68
I(Max TDS)	0.093	0.131	-0.038	-13.17
Market structures				
Nb. banks	6.007	6.405	-0.399	-17.36
I(Broker presence)	0.807	0.901	-0.094	-29.63
Nb. brokers	15.578	20.403	-4.825	-22.42
Share excluding brokers	0.206	0.211	-0.005	-3.82
Obs	23,609	24,782		

Note: This table presents the mean of transaction characteristics in both branch and broker channels, as well as the differences between channels. The t-statistics indicate that most of the mean differences are statistically significant at the 0.1% level. Income is household gross annual income. The indicator variable, I(low risk), is equal to 1 if the credit score is equal to or higher than 680 and 0 otherwise. We observe granular FICO credit score buckets in the data, which we use in estimation. ER saving is the average level of savings at an economic-region level. Rate premium is the difference between the medium posted rate of the biggest six national banks and the "no-haggle rate" set by broker-lenders. The indicator variable, I(Max amortization), is equal to 1 if the borrower chose the maximum allowable amortization at the time of origination. The indicator variable, I(Max LTV), equals 1 if the borrower chose the maximum allowable loan-to-value ratio at the time of origination. The indicator variable, I(Max TDS), equals 1 if the borrower has a total-debt-service ratio greater than 40%. For each borrower, we define the local market as a 10 KM circle around the FSA centroid, and then obtain the number of banks and brokers and calculate the share of branches belonging to the banks that exclude brokers in her local market. The indicator variable, I(Broker presence) equals 1 if there exists at least one broker in a borrower's local market.

as shifters for borrower choice of origination channel and mortgage rates to deal with the selection problem in Section 5. Broker-clients are more exposed to both banks and brokers in their neighborhoods. Finally, we calculate the share of bank branches owned by lenders that do not intermediate with brokers in each borrower's local market. For branch-clients the share of bank branches in their local market that excludes brokers is 20.6% and for broker-clients the share is 21.1%.

Figure 1: LTV and amortization distributions by origination channels



Note: This figure presents the distributions of LTV and amortization choices in both branch and broker channels. Panel (a) focuses on the sample period when 100% LTV is available; while panel (b) uses the period during which borrowers have access to 40-year amortization.

In Figure 1, we present the distributions of LTV and amortization for both the branch and broker channels, focusing on the sample periods during which the most lax guidelines were in place. Both distributions are shifted to the right for broker-clients relative to branch-clients. A larger fraction of broker-clients choose the maximum LTV allowed (zero down-payment) and the maximum amortization length (40 years).

Next, Table 3 highlights that brokers, on average, negotiate better rates. This difference is robust to controlling for a host of observable characteristics as well as year, quarter, region, product, and lender fixed effects.[18] In Section 6, we further control for selection into different origination channels using local market structure variables as instruments, and find an even larger rate reduction (26 bps) in the broker channel. This highlights that, in order to estimate the causal effects of brokers, it is essential to account for how unobserved consumer heterogeneity affects origination channels, rates, and product choices.

[18] Note that a "region" is larger than the "economic region" that we introduce in subsection 3.1. We have 15 regions in total: British Columbia, Alberta, Quebec and Ontario are split into 2, 3, 3 and 5 regions, respectively. We combine Saskatchewan and Manitoba into one region. Four Atlantic provinces are grouped as a single region. In contrast, we have 92 economic regions.

Table 3: Broker-clients pay less than branch-clients

	Dependent variable: mortgage contract rate			
I(broker)	-0.100***	-0.093***	-0.098***	-0.165***
	(0.006)	(0.006)	(0.006)	(0.007)
Other controls	Y	Y	Y	Y
Year FE	N	Y	Y	Y
Quarter FE	N	Y	Y	Y
Region FE	N	Y	Y	Y
Product FE	N	N	Y	Y
Lender FE	N	N	N	Y
R^2	0.344	0.369	0.377	0.395

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors clustered at the FSA level. Other controls include FICO score, income (log), borrower age, house price (log), bond rate, rate premium, I(house age≤5 year), and average saving at economic-region level (log). There are 48,391 observations.

In Table 4, we investigate whether variation in observed characteristics can fully explain the correlation between broker usage and product choice. We restrict attention to borrowers who have access to products with 100% LTV or products with amortization longer than 25 years. We find that, after controlling for a rich set of observable characteristics, broker-clients are still more likely to choose products with higher LTV and longer amortization when they are available. The results hold even if we include lender fixed effects or focus on big lenders that originate in both the branch and broker channels. This is not surprising, given our focus on insured mortgages and that all lenders need to apply the same minimum qualification rules mandated by the government.

These findings suggest that there is either selection on unobservable characteristics, or that brokers influence borrowers towards these products. For example, borrowers selecting into the broker channel might have different characteristics unobserved by the econometrician but potentially observed by lenders and brokers (e.g., savings, checking account activity), which could lead them to prefer higher LTV and longer amortization products. On the other hand, brokers might directly influence borrowers towards products that are more profitable to them. Finally, brokers tend to generate more quotes and better rates, which can indirectly affect product choices. In the next section, we build a structural model to account for these possible explanations for the observed differences in product choice across origination channels: selection on observables, selection on unobservables, and the causal effect of brokers (direct influence and indirect rate effect).

Table 4: Broker-clients are more likely to choose LTV>95% and amortization>25Y

	Panel A: I(LTV>95%)			
I(broker)	0.086***	0.083***	0.093***	0.080***
	(0.006)	(0.006)	(0.007)	(0.009)
R^2	0.085	0.094	0.114	0.109
Obs	19160	19160	19160	7975

	Panel B: I(AMT>25Y)			
I(broker)	0.090***	0.107***	0.101***	0.062***
	(0.006)	(0.005)	(0.006)	(0.008)
R^2	0.149	0.304	0.308	0.314
Obs	30840	30840	30840	13617
Other controls	Y	Y	Y	Y
Year FE	N	Y	Y	Y
Quarter FE	N	Y	Y	Y
Region FE	N	Y	Y	Y
Lender FE	N	N	Y	Y

Note: Panel A focuses on the subsample of borrowers who have access to products of 100% LTV at time of mortgage origination; while panel B focus on the subsample of borrowers who have access to products of more than 25-year amortization. The last column considers the biggest five lenders who originate in both branch and broker channels. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors clustered at FSA-level. Other controls include FICO score, income (log), borrower age, house price (log), bond rate, rate premium, I(house age≤5 year), and average saving at economic-region level (log). The means of the dependent variables are 0.20 and 0.64, respectively.

4 A model of mortgage-product choice

In this section we develop a model of mortgage-product choice. Taking as given the decision of whether or not to use a broker and the mortgage rate, the borrower makes a discrete choice over products characterized by two features: amortization length and LTV. In Section 5, we use a control function approach to handle the endogeneity in mortgage rates and choices of origination channel.

Given the best interest rate offer p in the chosen origination channel (branch or broker), the borrower makes a discrete choice among mortgage products with different LTV and amortization.[19]

The total set of mortgage products available is denoted as $\mathcal{J} \equiv \{80\%, 85\%, 90\%, 95\%, 100\%\} \times$

[19]We assume that the mortgage rate received by each individual borrower is fixed and does not depend on their product choice. In an alternative specification, we allow for rate differences across products. We infer the rates of unchosen options for each borrower based on the average rate differences estimated from a regression framework controlling for a rich set of observable characteristics. Since the rate differences are small, the model estimation results are robust.

$\{25Y, 30Y, 35Y, 40Y\}$. As mentioned in Section 2, our sample period featured a number of changes to macroprudential policies (relaxing the maximal amortization to 40 years and allowing for zero down-payment loans), and so certain choices in $\mathcal{J}$ might not be available when the borrower originates her mortgage. The borrower-specific choice set $\mathcal{J}_i$, therefore, can be smaller than $\mathcal{J}$.[20]

The borrower chooses the product that maximizes her indirect utility, which consists of her expected consumption as well as payoffs that depend on the characteristics of the mortgage. Given a rate of p, the associated monthly mortgage payment per dollar of mortgage loan is P_{AMT_j}, which is decreasing in amortization. We focus on the market for insured mortgages, hence the total loan size is $L_{ij} = (1 + \Delta_j) \cdot LTV_j \cdot h_i$, where Δ_j is the insurance premium and h_i is the house price.[21] Then, $R_j = P_{AMT_j} \cdot (1 + \Delta_j) \cdot LTV_j$ denotes the monthly payment per dollar of house price. Borrowers also have access to other non-mortgage debt, OD_i (e.g., auto loans and credit cards) at a fixed rate of w, such that the monthly payment on other debt is given by $d_i = OD_i \cdot w$. Hence, we characterize consumption as:

$$c_{ij} = y_i - R_j h_i + OD_i - d_i = y_i - R_j h_i + d_i \left(\tfrac{1}{w} - 1\right).$$

Loan qualification: In order to qualify for mortgage insurance, and therefore a loan, a borrower has to meet a TDS requirement—the total monthly payment on all debt should be less than 45% of gross income. The constraint limits the maximum monthly payment on non-mortgage debt:

$$\frac{R_j h_i + d_i}{y_i} \leq 0.45 \Rightarrow d_i \leq (0.45 \times y_i - R_j h_i) \equiv d_{ij}^{\max}. \tag{1}$$

We assume that d_i is drawn from a distribution $F_d(\cdot)$ after the contract is signed. This captures the uncertainty in non-mortgage debt accumulation post-origination. The post-contractual monthly payment is $\min\{d_i, d_{ij}^{\max}\}$.[22] Therefore, the TDS constraint affects product choices via its impact on consumption.

[20] The choice set does not depend on the origination channel. That is, every lender and broker offers the same menu of products in $\mathcal{J}_i$. This assumption seems reasonable given our focus on a set of relatively homogeneous products.

[21] We assume that the value of a borrower's housing choice is predetermined, i.e., borrowers have a rough idea about the neighborhood they wish to purchase in and therefore the approximate price of the house.

[22] Lenders and borrowers observe a one-time realization of d_i at origination. However, this does not mean that the borrower will keep making the same monthly payment on other debt. Rather, borrowers understand that this is just one draw from the distribution $F_d(\cdot)$, and hence need to form expectations about future realizations in order to calculate expected monthly consumption. Notice that we assume the TDS constraint is in effect even after mortgage origination. This implies that for borrowers at the TDS constraint, they cannot accumulate more debt. This is a reasonable assumption since non-mortgage lenders also look at a borrower's ability to service their debt when making approval/rejection decisions.

The expected consumption of borrower i who has chosen product j is as follows:

$$\begin{aligned}\mathbb{E}[c_{ij}] &= y_i - R_j h_i - \mathbb{E}[\min\{d_i, d_{ij}^{\max}\}] \cdot (1 - \tfrac{1}{w}) \\ &= y_i - R_j h_i - \left[\big(1 - F(d_{ij}^{\max})\big) \cdot d_{ij}^{\max} - \int_{-\infty}^{d_{ij}^{\max}} d_i \cdot dF(d_i)\right] \cdot \big(1 - \tfrac{1}{w}\big) \\ &= y_i - D_{ij}(p),\end{aligned}$$

where $D_{ij}(p) = R_j h_i + \mathbb{E}[\min\{d_i, d_{ij}^{\max}\}] \cdot (1 - \frac{1}{w})$ is the expected net debt payment conditional on the mortgage rate, p.

In addition to the utility derived from expected consumption, borrower payoffs also depend on other mortgage characteristics. We parameterize the indirect utility from choosing mortgage product $j \in \mathcal{J}_i$ (conditional on the origination channel *broker* and the rate offer p) as follows:

$$U_{ij}(p, broker) = \mathbb{E}[c_{ij}] - \pi_i \left[\underbrace{\frac{(1 - LTV_j) \cdot h_i + \mathcal{C}(h_i)}{s_i}}_{\frac{\text{lump-sum downpayment}}{\text{saving}}} \right]^2 - \delta_i I_j + \mu_{j,broker}. \tag{2}$$

The second component represents the borrower's disutility of making an upfront payment from her savings, s_i. This lump-sum payment consists of a down-payment, $(1 - LTV_j) \cdot h_i$, as well as closing costs $\mathcal{C}(h_i)$, assumed to be 3% of the house value.[23] Hence, borrowers face a trade-off between the size of the down-payment and consumption: increasing the LTV leads to a smaller down-payment but higher monthly mortgage payments. Borrowers with very high savings prefer low-LTV contracts. As s_i falls, the cost of raising the required lump-sum payment increases, and borrowers are more likely to choose options with a higher LTV. Since we do not observe s_i, we denote $\theta_i = \dfrac{\pi_i}{s_i^2}$ as a borrower-specific coefficient reflecting the heterogeneity in marginal disutility from the lump-sum payment. Besides savings, this coefficient also captures the opportunity cost of making a down-payment. Borrowers with better outside investment opportunities will have a higher disutility of making a large lump-sum payment.[24]

The third component in equation (2), $\delta_i I_j$, captures disutility from high interest rates beyond the direct effect of lowering monthly consumption. Specifically, $I_j \equiv I(p, (1 + \Delta_j) \cdot h_i \cdot LTV_j, AMT_j)$ is the total interest cost associated with product j over the amortization period. This creates a natural trade-off, as products with higher amortization have a smaller monthly payment but larger total interest costs. We allow for borrower-specific marginal disutility from interest costs, given by δ_i. This coefficient captures, in a reduced-form way, differences in borrowers' prepayment probabilities.[25]

[23]See for example https://www.canada.ca/en/financial-consumer-agency/services/buying-home.html and https://www.rbcroyalbank.com/mortgages/budgeting-for-closing-costs.html.

[24]More generally, the marginal disutility of lump-sum payments can vary in borrower discount factors.

[25]Borrowers need not strictly follow the amortization schedule. For example, a borrower choosing a mortgage with

Finally, $\mu_{j,broker}$ captures other non-monetary payoffs from choosing product j in origination channel $broker \in \{0, 1\}$. We allow these product fixed effects to differ across the origination channel, normalizing to 0 for the baseline product with amortization of 25 years and 95% LTV. Therefore, $\mu_{j,broker=0}$ measures the non-pecuniary benefit or cost of choosing product j relative to the baseline product in the branch channel. For instance, the fixed effects could be negative for riskier products because borrowers internalize the associated risks or because it requires more effort to get approved.[26] On the other hand, $\mu_{j,broker=0} > \mu_{j,broker=1}$ means that, all else equal, the borrower derives higher utility from product j relative to the baseline product if she obtains it from the branch channel. We therefore interpret differences in the product fixed effects across channels as the *direct broker influence*.

Given the mortgage rate p and origination channel $broker$, the borrower's problem is to choose the mortgage product that maximizes the indirect utility, which generates the value function below:

$$U_i^*(p, broker) = \max_{j \in \mathcal{J}_i} U_{ij}(p, broker).$$

5 Empirical specification

In this section, we parameterize the mortgage-product choice model to incorporate heterogeneity in observable characteristics. Conditional on the origination channel and mortgage rate, our model predicts product choice. However, since unobserved borrower heterogeneity in the taste parameters (capturing savings and prepayment risks) can simultaneously affect product choice, origination channel, and mortgage rates, ignoring the endogeneity in origination channel and mortgage rate could bias the estimates of the product choice model. In order to control for the selection bias, we adopt a control function approach similar to (Adams, Einav, and Levin 2009), (Crawford, Pavani, and Schivardi 2018), and (Ioannidou, Pavanini, and Peng 2022). Specifically, we use first-stage regressions for broker usage and mortgage rates to construct control variables that capture the selection due to unobservables. Then in the second stage, we add these control variables to the taste parameter specifications and estimate the product choice model via maximum likelihood. We discuss identification at the end of this section.

5.1 Empirical specification and two-stage estimation strategy

We estimate the model in two stages, and start by describing the second. Our model predicts that a borrower's choice of product j is a function of observable and unobservable borrower characteristics.

a 40-year amortization might not be sensitive to the total interest cost over the full amortization period if she plans to sell the house after 5 years and exit the mortgage market. Alternatively, she can make accelerated payments that reduce the effective amortization.

[26] As another example, some borrowers may have strong preference for low-LTV products because they receive gifted funds from parents to make down payments. (Benetton, Kudlyak, and Mondragon 2022) shows that gifted down payments (from parent equity extraction) has important effects on child homeownership and LTV choice.

In particular, the borrower-specific taste parameters, (θ_i, δ_i), represent the disutility from making lump-sum payments (capturing borrower savings or outside investment opportunities) and the disutility from total interest costs (capturing prepayment risks), respectively. We parameterize them as functions of observable characteristics $\boldsymbol{x}_i$ (FICO score, borrower age, income (log), I(house age≤5 year), house price (log), bond rate, rate premium, ER savings, region, year, and quarter fixed effects):

$$\ln \theta_i = \boldsymbol{x}_i'\boldsymbol{\theta} + u_{1i}, \tag{3}$$

$$\ln \delta_i = \boldsymbol{x}_i'\boldsymbol{\delta} + u_{2i}. \tag{4}$$

We denote the error terms $\boldsymbol{u}_i = (u_{1i}, u_{2i})$, which captures the variation in the random coefficients that cannot be explained by the observable borrower characteristics $\boldsymbol{x}_i$.

Next, we specify that the monthly payment on non-mortgage debt, d_i, is log-normally distributed with location parameter $\bar{d}_i$ and variance σ_d^2. The location parameter is modeled as a function of observed characteristics $\boldsymbol{x_i}$, as well as income (y_i) and unobserved savings (through θ_i):

$$\bar{d}_i = \boldsymbol{x}_i'\boldsymbol{\lambda} + \lambda_0 y_i \theta_i.$$

Let $\boldsymbol{\beta}_2 = (\boldsymbol{\mu}, \boldsymbol{\theta}, \boldsymbol{\delta}, \boldsymbol{\lambda}, \lambda_0, \sigma_d)$. Depending on whether the TDS constraint is binding, the probability (density) of observing a monthly payment on non-mortgage debt $\tilde{d}_i$ is given by

$$\begin{aligned} P_i(\tilde{d}_i) &\equiv P(\tilde{d}_i | p_i, broker_i, \boldsymbol{x_i}, \theta_i, \delta_i; \boldsymbol{\beta}_2) \\ &= P(\tilde{d}_i | p_i, broker_i, \boldsymbol{x_i}, \boldsymbol{u}_i; \boldsymbol{\beta}_2) = \begin{cases} 1 - F_d(\tilde{d}_i), & \text{if } TDS_i = T\bar{D}S \\ f_d(\tilde{d}_i), & \text{if } TDS_i < T\bar{D}S. \end{cases} \end{aligned}$$

Given the observed characteristics $\boldsymbol{x_i}$, the origination channel, the mortgage rate, the model parameters, and random coefficients (θ_i, δ_i), the model deterministically predicts product choices. To smooth the likelihood function for estimation, we introduce an IID preference shock for each product choice, ε_{ij}, drawing from a Type-1 extreme value distribution with scale parameter of σ_ε and mean of 0. We can rewrite borrower i's utility for product j as following:

$$\begin{aligned} U_{ij} \ &= y_i - Pmt(p_i, (1+\Delta_j)h_i \cdot LTV_j, AMT_j) - \mathbb{E}[\min\{d_i, d_{ij}^{\max}\}] \cdot (1 - \tfrac{1}{w}) \\ &\quad - \theta_i \big[(1 - LTV_j + 3\%) \cdot h_i\big]^2 - \delta_i I(p_i, (1+\Delta_j)h_i \cdot LTV_j, AMT_j) \\ &\quad + \mu_{j,broker} + \varepsilon_{ij}, \end{aligned} \tag{5}$$

where we rewrite the monthly mortgage payment $R_j h_i$ as $Pmt(p_i, (1+\Delta_j)h_i \cdot LTV_j, AMT_j)$ to highlight its dependence on mortgage rate, loan size, and amortization. Then for each borrower i, given her origination channel and mortgage rate, the probability of choosing product j can be expressed in a standard logit form:

$$P_i(j) \equiv P_i(j|p_i, broker_i, \boldsymbol{x_i}, \theta_i, \delta_i; \boldsymbol{\beta}_2)$$
$$= P_i(j|p_i, broker_i, \boldsymbol{x_i}, \boldsymbol{u}_i; \boldsymbol{\beta}_2) = \frac{\exp(U_{ij}/\sigma_\varepsilon)}{\sum_{k\in\mathcal{J}_i}\exp(U_{ik}/\sigma_\varepsilon)}.$$

We choose a small scale parameter $\sigma_\varepsilon = 0.02$ to ensure that the idiosyncratic taste shocks have little effect on borrower choices.[27]

Therefore, conditional on the observed characteristics $\boldsymbol{x}_i$, the origination channel $broker_i$, and interest rate p_i, the likelihood contribution of borrower i, who has non-mortgage debt payment $\tilde{d}_i$ and chooses mortgage product j, is given by

$$\ell_i(j, \tilde{d}_i, p_i, broker_i, \boldsymbol{x}_i; \boldsymbol{\beta}_2)$$
$$= \int P_i(j, \tilde{d}_i|p_i, broker_i, \boldsymbol{x}_i, \boldsymbol{u}_i; \boldsymbol{\beta}_2) \cdot f(\boldsymbol{u}_i|p_i, broker_i, \boldsymbol{x}_i)\, d\boldsymbol{u}_i$$
$$= \int P_i(j)P_i(\tilde{d}_i) \cdot f(\boldsymbol{u}_i|p_i, broker_i, \boldsymbol{x}_i)\, d\boldsymbol{u}_i,$$

where $f(\boldsymbol{u}_i|p_i, broker_i, \boldsymbol{x}_i)$ is the conditional probability density function of $\boldsymbol{u}_i$. Recall that $\boldsymbol{u}_i$ captures the variation in the random coefficients (θ_i, δ_i) that cannot be explained by the observable borrower characteristics $\boldsymbol{x}_i$. More intuitively, it contains the borrower's private information regarding her savings and prepayment risk, which may be observable to lenders/brokers but not to us. Naturally, such private information also affects the borrower's profitability and hence her choice of origination channel as well as the mortgage rate, what we call *selection on unobservables*. Ignoring this could lead to biased estimates for parameters $\boldsymbol{\beta}_2$ in the product choice model, and especially for $\boldsymbol{\mu}$, which informs as to the *direct influence of brokers* on product choices.

For example, a borrower with higher prepayment risk would seem less profitable from a lender's perspective and hence is more likely to use a broker to obtain a mortgage, since it might be too costly for her to search for approval on her own. Meanwhile, the borrower is more likely to choose mortgage products with longer amortization, since she worries less about the total interest cost over the full amortization period. In this case, a model ignoring self-selection into the broker channel due to unobserved prepayment risk would attribute the choice of longer amortization to brokers, overestimating the influence of brokers on borrower choices.

How can we control for the potential selection bias introduced by the endogeneity in mortgage rates and origination channels? We now turn to our first stage to construct control variables that capture the selection on unobservables.

We estimate the reduced-form broker choice equation (6) and pricing equation (7). The bro-

[27]This type of smoothing is used to approximate pure characteristic models of demand ((Berry and Pakes 2007)). Notice that we do not try to identify the scale parameter σ_ε. One can assume a different value of σ_ε and then adjust all utilities accordingly to keep the ordering across products unchanged and hence the model implication unaffected.

ker choice is a function of observable characteristics, $\boldsymbol{z} = [\boldsymbol{z}_1, \boldsymbol{z}_2, \boldsymbol{x}]$, which include instrumental variables not in $\boldsymbol{x}$. We explain how these exclusion restrictions help identification in Section 5.2.

$$broker_i = \begin{cases} 0, & \text{if } \boldsymbol{z}_i' \boldsymbol{\gamma}_1 + e_{1i} < 0 \\ 1, & \text{if } \boldsymbol{z}_i' \boldsymbol{\gamma}_1 + e_{1i} \geq 0. \end{cases}, \quad e_{1i} \sim \mathcal{N}(0,1). \tag{6}$$

We estimate equation (6) using a Probit model. We then obtain the generalized residuals as the inverse Mills ratio:

$$\hat{e}_{1i} \equiv e_1(\boldsymbol{z}_i, broker_i) = \begin{cases} -\phi(-\boldsymbol{z}_i'\hat{\gamma}_1)/\Phi(-\boldsymbol{z}_i'\hat{\gamma}_1), & \text{if } broker_i = 0 \\ \phi(-\boldsymbol{z}_i'\hat{\gamma}_1)/(1 - \Phi(-\boldsymbol{z}_i'\hat{\gamma}_1)) & \text{if } broker_i = 1, \end{cases}$$

where $\phi(\cdot)$ and $\Phi(\cdot)$ denote the probability density function and cumulative distribution function of a standard Normal distribution, respectively.

The mortgage rate in each channel is assumed to be a function of observable characteristics $[\boldsymbol{z}_2, \boldsymbol{x}]$. We also include the inverse Mills ratio $\hat{\boldsymbol{e}}_1$ obtained above to control for borrower selection into different origination channels.

$$p_i = \begin{cases} [\boldsymbol{z}_{2i}, \boldsymbol{x}_i, \hat{e}_{1i}]' \boldsymbol{\gamma}_2^{broker=0} + e_{2i}, & \text{if } broker_i = 0; \\ [\boldsymbol{z}_{2i}, \boldsymbol{x}_i, \hat{e}_{1i}]' \boldsymbol{\gamma}_2^{broker=1} + e_{2i}, & \text{if } broker_i = 1. \end{cases} \tag{7}$$

We estimate the pricing equation (7) by ordinary least squares using the subsamples of branch-clients and broker-clients separately. Given the estimates $(\hat{\boldsymbol{\gamma}}_2^{broker=0}, \hat{\boldsymbol{\gamma}}_2^{broker=1})$, we obtain the residuals $\hat{e}_{2i} \equiv e_2(\boldsymbol{z}_{2i}, \boldsymbol{x}_i, \hat{e}_{1i}, p_i, broker_i) = p_i - [\boldsymbol{z}_{2i}, \boldsymbol{x}_i, \hat{e}_{1i}]' \hat{\boldsymbol{\gamma}}_2^{broker=broker_i}$.

The residuals $(\hat{e}_{1i}, \hat{e}_{2i})$ contain information on the unobserved heterogeneity in borrower savings and prepayment risks, which endogenously affect borrowers' mortgage rates, origination channel, and product choices. Therefore, we use these residuals as control variables in the random coefficients (θ_i, δ_i). Specifically, we assume that the error terms in equations (3) and (4) are linear in $\hat{e}_{1i}, \hat{e}_{2i}$ and their interaction term. We can rewrite the random coefficient specification as follows:

$$\ln \theta_i = \boldsymbol{x}_i' \boldsymbol{\theta} + \underbrace{\rho_1 \hat{e}_{1i} + \rho_2 \hat{e}_{2i} + \rho_3 \hat{e}_{1i} \hat{e}_{2i} + \tilde{u}_{1i}}_{u_{1i}}, \tag{8}$$

$$\ln \delta_i = \boldsymbol{x}_i' \boldsymbol{\delta} + \underbrace{\tau_1 \hat{e}_{1i} + \tau_2 \hat{e}_{2i} + \tau_3 \hat{e}_{1i} \hat{e}_{2i} + \tilde{u}_{2i}}_{u_{2i}}, \tag{9}$$

where $\tilde{u}_{1i} \sim \mathcal{N}(0, \sigma_\theta^2)$ and $\tilde{u}_{2i} \sim \mathcal{N}(0, \sigma_\delta^2)$ are independent of mortgage rates and the origination channels.

Denote $\boldsymbol{\beta} \equiv (\boldsymbol{\mu}, \boldsymbol{\theta}, \boldsymbol{\delta}, \boldsymbol{\lambda}, \lambda_0, \boldsymbol{\rho}, \boldsymbol{\tau}, \sigma_\theta, \sigma_\delta, \sigma_d)$ the full vector of parameters for the second-stage product choice model. With the constructed residuals $(\hat{e}_{1i}, \hat{e}_{2i})$ from the first stage, we can rewrite the likelihood contribution of a borrower who has non-mortgage debt payment $\tilde{d}_i$ and chooses mortgage product j:

$$\begin{aligned}
&\ell_i(j, \tilde{d}_i, p_i, broker_i, \boldsymbol{x}_i, \hat{e}_{1i}, \hat{e}_{2i}; \boldsymbol{\beta}) \\
&= \int P_i(j, \tilde{d}_i | p_i, broker_i, \boldsymbol{x}_i, \hat{e}_{1i}, \hat{e}_{2i}, \tilde{\boldsymbol{u}}_i; \boldsymbol{\beta}) f(\tilde{\boldsymbol{u}}_i | p_i, broker_i, \boldsymbol{x}_i, \hat{e}_{1i}, \hat{e}_{2i}) \, d\tilde{\boldsymbol{u}}_i \\
&= \iint P_i(j | p_i, broker_i, \boldsymbol{x}_i, \theta_i, \delta_i; \boldsymbol{\beta}) P_i(\tilde{d}_i | p_i, broker_i, \boldsymbol{x}_i, \theta_i, \delta_i; \boldsymbol{\beta}) \ \cdots \\
&\qquad\qquad\qquad\qquad \times \phi_{\tilde{u}_{1i}}(\tilde{u}_{1i}) \phi_{\tilde{u}_{2i}}(\tilde{u}_{2i}) \, d\tilde{u}_{1i} d\tilde{u}_{2i}
\end{aligned}$$

To obtain the estimate for $\boldsymbol{\beta}$, we maximize the log-likelihood $\mathcal{L} = \sum_i \ln \ell_i(j, \tilde{d}_i, p_i, broker_i, \boldsymbol{x}_i, \hat{e}_{1i}, \hat{e}_{2i}; \boldsymbol{\beta})$ given all observations in our sample.

5.2 Identification

We now provide a heuristic discussion of identification of the model parameters. Recall that both broker choices and rates are functions of observable characteristics that include all control variables in $\boldsymbol{x}$ and hence allow us to control for borrower selection into brokers due to observable heterogeneity, as well as borrower-specific pricing algorithms.

In addition, in the broker choice equation (6), we include instrumental variables $[\boldsymbol{z}_1, \boldsymbol{z}_2]$ that are not in $\boldsymbol{x}$. These variables are related to local market structure: (i) number of banks in a local market, (ii) an indicator variable that equals 1 if at least one broker is available in the local market, (iii) number of brokers in log, (iv) share of bank branches excluding the broker channel, (v) the interaction between (iii) and (iv), as well as (vi) the interaction between logged number of brokers and rate premium. In the pricing equation (7), we include only one instrumental variable $\boldsymbol{z}_2$—number of banks in the local market.[28]

Our exclusion restriction assumption requires that these instrumental variables affect the random coefficients (θ_i, δ_i) through the constructed residuals in the first-stage regressions ($\tilde{\boldsymbol{u}}$ is independent of $\boldsymbol{z}$). For instance, conditional on $\boldsymbol{x}$, the number of banks in a local market does not directly affect borrower savings or prepayment risks.[29] However, borrowers with access to more

[28] The idea is that the presence of brokers does not directly influence rates. A broker has access to a set of lenders, which determines the rates for their own products. However, the number of brokers can indirectly affect rates by changing a borrowers probability of using the broker channel.

[29] The assumption would be violated if, for example, competition in local markets also affects deposit rates and hence household savings. However, unlike individualized mortgage rates, financial institutions determine and post their savings rates nationally. Therefore, local market structure has little effect on households' incentives to save. In addition, note that by including our measure of average economic region savings as a control variable in $\boldsymbol{x}$, we help alleviate the concern over the validity of our instruments—idiosyncratic deviations of household savings from the average is even less likely to be correlated with local market structure. In Table A1, we provide further supporting evidence for the exclusion restriction assumption. Using data from CFM surveys between 2005 and 2007, we do not find a statistically significant relationship between household savings and local market structure variables. One may also be concerned that more local lenders might directly increase prepayment risks because lenders compete more aggressively for rivals' clients. Indeed, (Allen and Li 2023) show that more competition in local markets can increase

banks are more likely to use a branch (e.g., due to existing banking relationships), which creates variation in the constructed residuals $(\hat{e}_{1i}, \hat{e}_{2i})$ that are independent of $\boldsymbol{x}_i$. Therefore, the exclusion restrictions allow us to separately identify the effect of observable characteristics $\boldsymbol{x}$ on the random coefficients and the effect of the constructed residuals (selection on unobservables).

We briefly discuss the identification of the remaining parameters. The distribution of d_i is identified from the observed non-mortgage debt payment and TDS constraint, as well as correlations of these variables with observed characteristics. The exogenous variation in choice sets helps to pin down the average taste parameters—the intercepts of the random coefficients. This variation comes from two sources: (i) macroprudential policy changes making more products available, and (ii) changes in the insurance-premium schedule that affect the relative differences across LTV choices. The slope parameters in the random coefficient θ_i are identified from the correlation between the lump-sum payment of the chosen product, observed borrower characteristics $\boldsymbol{x}_i$, and constructed residuals $(\hat{e}_{1i}, \hat{e}_{2i})$ from the first-stage regressions. For example, if we observe that borrowers with higher credit scores are more likely to choose products with lower LTV (larger down-payment), then we can infer that a higher credit score is associated with lower disutility from a lump-sum payment (lower θ_i and higher savings). Similarly, correlation between total interest costs associated with the chosen product and $\boldsymbol{x}_i$ as well as $(\hat{e}_{1i}, \hat{e}_{2i})$ identifies the slope parameters in δ_i. The main parameter of interest is $\boldsymbol{\mu}$. It is identified from the differences between the probabilities of choosing products across different channels that are not explained by borrower preferences over expected consumption, lump-sum payments, and total interest costs.

6 Estimation results

In this section we present our model estimates (benchmark model). We then estimate restricted versions of the benchmark model to test for whether or not pricing and broker-use are endogenous to product choice and whether or not brokers directly influence borrowers.

6.1 Benchmark estimates

Table 5 displays the first-stage regression results. We find that local market structure affects the choice of origination channel. Each additional bank in a borrower's neighbourhood decreases the probability of using a broker by 1.7 p.p. The total negative marginal effect of the neighborhood share of lenders excluding brokers suggests that borrowers are less likely to use a broker when there are more branches of the excluding banks. Borrowers who have a broker in their neighborhood are

the probability of switching lenders at renewal. However, in our model, borrowers do not equate switching with prepayment—their outstanding balance is renewed regardless of lender, and continues to incur interest costs. Rather, borrowers' prepayment probabilities depend on the likelihood of moving and selling, transitioning from owning to renting, defaulting, etc., which are reasonably unrelated to the local market structure. Of course, lenders care about the switching probabilities and would adjust their pricing accordingly. These effects are captured in the first-stage regressions.

Table 5: First-stage regression results

	Broker (Probit)	Rate: Branch	Rate: Broker	Rate: All
Instrumental Variables				
I(Broker presence)	0.174***			
	(0.047)			
Nb. brokers (log)	0.270***			
	(0.059)			
Share excluding brokers	0.262**			
	(0.099)			
Share excluding brokers	-0.298***			
× Nb. brokers (log)	(0.057)			
Rate premium (%)	-0.037			
× Nb. brokers (log)	(0.039)			
Nb. banks	-0.045***	-0.013***	-0.007***	-0.011***
	(0.009)	(0.002)	(0.002)	(0.001)
Control Variables				
Rate premium (%)	0.092	0.328***	0.323***	0.330***
	(0.106)	(0.039)	(0.034)	(0.025)
Bond rate (%)	0.110***	0.536***	0.563***	0.551***
	(0.025)	(0.015)	(0.013)	(0.010)
Income (log)	-0.503***	0.097***	0.102***	0.102***
	(0.022)	(0.020)	(0.020)	(0.014)
FICO $\in$ [680,717]	-0.079***	-0.058***	-0.047***	-0.053***
	(0.018)	(0.012)	(0.011)	(0.008)
FICO $\in$ [718,759]	-0.138***	-0.116***	-0.126***	-0.122***
	(0.017)	(0.011)	(0.010)	(0.008)
FICO $\geq$760	-0.193***	-0.183***	-0.174***	-0.181***
	(0.017)	(0.012)	(0.011)	(0.008)
Borrower age	0.002**	0.001**	0.002***	0.002***
	(0.001)	(0.000)	(0.000)	(0.000)
House price (log)	0.487***	-0.262***	-0.204***	-0.236***
	(0.027)	(0.022)	(0.021)	(0.016)
New property	-0.133***	-0.049***	-0.029***	-0.039***
	(0.017)	(0.009)	(0.008)	(0.006)
ER saving (log)	-0.011	-0.066**	0.005	-0.030
	(0.056)	(0.022)	(0.019)	(0.016)
$\hat{e}_1$		0.082	0.104*	0.103**
		(0.052)	(0.050)	(0.038)
I(broker)				-0.257***
				(0.060)
R^2		0.362	0.372	0.371
Obs	48391	23609	24782	48391

Note: Variable definitions are given in Table 2. $\hat{e}_1$ is the inverse Mills ratio obtained after estimating the Probit model given by equation (6). * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Region, year, quarter fixed effects are included. Standard errors clustered at FSA level.

6.4 p.p. more likely to use a broker, and the number of brokers is positively correlated with broker choice. Additional controls are also statistically significant. An increase in the bond rate represents an increase in the cost of funding, and this is correlated with an increase in broker-use. Borrowers are also more likely to use a broker if they are purchasing a more expensive house. Variables that are negatively correlated with broker-use include income and credit score.

Focusing on columns (2) and (3), we find that the presence of more banks in a neighborhood is correlated with lower mortgage rates in both branch and broker channels. Borrowers who are more likely to use brokers (higher $\hat{e}_1$) tend to pay higher rates. Higher income borrowers pay higher rates and higher credit score borrowers pay lower rates, and the differences between branch and broker are economically small. Finally, the last column finds that after controlling for selection into different origination channels using $\hat{e}_1$, brokers on average reduce mortgage rates by 26 bps. In general, our regression results are consistent with consumer-based pricing (c.f., (Allen, Clark, and Houde 2014b) and (Allen, Clark, and Houde 2019)), who find that rates are a function of (unobservable) search costs, and that higher-income individuals, who have higher search costs, pay higher rates.

Table 6 presents the Maximum Likelihood estimates of the mortgage-product choice model. Recall that θ represents a consumer's marginal disutility of upfront payment—which is decreasing in the consumer's savings and increasing in their outside investment opportunities. We estimate lower disutility from making a lump-sum payment for borrowers who are buying more expensive houses, are more creditworthy (FICO ≥ 760), and are older. These estimates can be rationalized by the fact that these characteristics are positively correlated with higher savings. In addition, ceteris paribus, we find higher disutility from lump-sum payments for borrowers with higher income and for those entering the market when the bond rate is higher. These borrowers likely have better outside investment opportunities.

From the coefficients on the control residuals ($\hat{e}_1$, $\hat{e}_2$), we find that high θ (lower savings or better outside investment opportunities) are associated with use of brokers and higher mortgage rates. In addition, the estimate on the interaction term $\hat{e}_1\hat{e}_2$ suggests that at the broker channel ($\hat{e}_1$ is high), the positive relationship between θ and rate is weaker. A possible reason for this is that brokers are monoline intermediaries and therefore cross-selling is rare. Therefore, even clients with low θ (high savings or bad outside investment opportunities), may not enjoy significantly better rates since lenders and brokers cannot earn extra profits from cross-selling other products (e.g., mutual funds).

The estimates in column (2), which are for the location parameter for non-mortgage debt, mostly have the same sign as those in column (1). This is consistent with borrowers with higher savings tending to have lower non-mortgage debt. Finally, the random coefficient in column (3), δ, captures borrower prepayment risks (or marginal disutility from total interest costs). The most important coefficients are for the control residuals, which show that higher rates and broker-use

Table 6: Product choice model estimates

	(1)	(2)	(3)
	$\ln\theta$	$\bar{d}$	$\ln\delta$
FICO∈[680,717]	0.2659 (0.0124)	0.103 (0.0072)	0.2831 (0.0228)
FICO∈[718,759]	0.1547 (0.0109)	0.0507 (0.0064)	0.2808 (0.021)
FICO≥760	-0.1862 (0.0106)	-0.0978 (0.006)	0.0704 (0.0209)
Borrower age	-0.0044 (0.0004)	0.0001 (0.0002)	-0.0035 (0.0007)
Income (log)	0.1235 (0.0119)	1.4838 (0.0073)	0.1825 (0.0237)
New property	-0.0183 (0.0088)	0.0504 (0.0051)	0.1681 (0.0161)
House price (log)	-1.9214 (0.0142)	-0.6544 (0.008)	-0.4299 (0.0273)
Bond rate	0.1842 (0.0147)	0.0046 (0.0087)	-0.2034 (0.0296)
Rate premium	-0.0095 (0.0389)	-0.0196 (0.0241)	-0.3352 (0.0785)
ER saving (log)	-0.0648 (0.0209)	-0.0334 (0.0128)	-0.1912 (0.0407)
$y\theta$		-0.0387 (0.0014)	
e_1	0.0504 (0.0098)		-0.0641 (0.0087)
e_2	0.1822 (0.0058)		-0.2103 (0.0079)
e_1e_2	-0.0278 (0.0065)		-0.0554 (0.0097)
σ_θ	0.5723 (0.0059)		
σ_d		0.5106 (0.0013)	
σ_δ			0.8255 (0.0091)
Log likelihood		-95,622.96	

Note: The omitted baseline FICO category is below 680. Estimates on year, quarter, and region dummies are not reported. Standard errors in parentheses. The interest rate for non-mortgage debt is fixed at 3%. $\hat{e}_1$ is the generalized residuals obtained from the Probit regression of broker choices reported in column (1) of Table 5. $\hat{e}_2$ is the residuals obtained from rate regressions reported in columns (2) and (3) of Table 5. These residuals and their interaction are used to control for the endogeneity of broker choices and mortgage rates.

are associated with higher prepayment risks (and hence lower disutility from total interest costs).

6.2 Model fit

Using our model estimates, we focus on the period when all mortgage products are available and simulate the choices for 100,000 broker-clients and 100,000 branch-clients. We then compare the resulting distributions of amortization, LTV, and TDS to those observed in the data. Amortization and LTV are product choices while TDS is an outcome. We present goodness of fit for a version of the model without the logit (taste) shocks. These shocks are only needed to smooth the likelihood function in estimation; not in model simulation. Results are presented in Table 7. Consistent with the data, the share of longer amortization and higher LTV mortgages originated via brokers is higher than through branches. Quantitatively, the shares in each cell are similar for the data and model. In addition, the model is able to reproduce the difference in TDS distribution across channels.

Table 7: Benchmark model fit

	Data		Model	
	Branch	Broker	Branch	Broker
AMT=25Y	44.46	28.23	46.07	28.13
AMT=30Y	9.39	8.59	10.08	10.56
AMT=35Y	17.28	24.86	17.04	24.02
AMT=40Y	28.86	38.32	26.81	37.30
LTV=80%	1.25	1.29	1.61	1.65
LTV=85%	6.06	4.79	6.24	5.50
LTV=90%	18.83	17.02	18.69	16.94
LTV=95%	56.84	52.82	56.09	52.06
LTV=100%	17.03	24.08	17.38	23.84
TDS∈(5%,15%]	0.48	0.19	0.18	0.12
TDS∈(15%,25%]	8.62	6.66	10.61	8.45
TDS∈(25%,35%]	39.81	38.60	42.48	41.77
TDS∈(35%,45%]	51.09	54.55	46.73	49.66

Note: the first two columns show the distribution of products in the data. The next two columns present the simulated distribution from the benchmark model for broker and branch channels.

6.3 Endogeneity in pricing and broker usage

As described in Section 5.1, our empirical model accounts for both the endogeneity in pricing and choice of origination channel using a control function approach. To quantify the importance of selection bias created by this endogeneity problem, we estimate a restricted version of the model in which the coefficients on the residuals obtained from the first-stage regressions ($\hat{e}_1$, $\hat{e}_2$) are set to 0, i.e., assuming that there is no selection on unobservables in the data generating process. See Appendix C for estimation results. The likelihood ratio test-statistic for the null hypothesis that the coefficients on our control residuals are equal to zero is 941.8. The critical value of $\chi^2(6)$ distribution associated with the 0.1% significance level is 22.46, and so we reject the restricted model. This result implies that controlling for endogeneity of prices and origination channel is important.

In Section 7 we focus on quantifying the importance of different explanations for product choices in our benchmark model. In Appendix C we do the same using this restricted model. The exercise further highlights that, if one does not account for endogeneity of prices and origination channel, the estimated broker influence could be biased. We show that the restricted model overestimates the contribution of direct broker influence on LTV and amortization choices. We discuss this in more detail in section 7.

6.4 Is there a direct influence of brokers on borrower choice?

Next, we use our model to investigate whether there is evidence that brokers directly influence borrowers. Table 8 presents product-specific fixed effects in the branch channel ($\mu_{j,broker=0}$) and the estimated difference between origination channels: $\mu_{j,broker=1} - \mu_{j,broker=0}$. All coefficients are relative to a reference product with amortization of 25 years and LTV of 95%. For example, consider the estimates for the 40-year amortization and 95% LTV product: (-10.1, 4.7). The negative sign on the first number implies that for branch borrowers, holding all things equal across product choices,[30] the product (95%,40Y) generates lower utility than the baseline product (95%,25Y). In terms of monetary values, branch borrowers on average require a monthly compensation of $|-10.1 \times \$1,000/50| = \$202$ to choose the product (95%,40Y) over the baseline product.[31] The second number in the cell captures the difference in product preferences across channels. In this example, it implies that borrowers using the broker channel on average require a monthly compensation of $|(-10.1 + 4.7) \times \$1,000/50| = \$108$ to choose the product (95%,40Y) over the baseline product. Since this number is smaller than the compensation required in the branch channel (\$202), brokers affect borrower preferences relative to the baseline product. The marginal broker influence in dollar value is $\$202 - \$108 = \$94$ per month.[32]

Table 8: Estimates of product fixed effects across branch and broker channels

	LTV				
AMT	80%	85%	90%	95%	100%
25Y	(44.3,5.6)	(34.8,2.7)	(18.4,1)	(0,0)	(-41.6,4.6)
30Y	(41.9,6.6)	(29.4,4.6)	(10.9,3.5)	(-7.7,2.4)	(-44.4,6.4)
35Y	(42.7,7.9)	(29.1,6.1)	(9.9,5.1)	(-9.2,4.6)	(-43.6,7.7)
40Y	(41.1,9.9)	(29.3,5.9)	(9.4,5.1)	(-10.1,4.7)	(-42.1,7.6)

Note: In each cell, the first number is the estimated product preference at branch channel ($\mu_{j,broker=0}$), while the second number is the estimated difference between origination channels ($\mu_{j,broker=1} - \mu_{j,broker=0}$).

Our main objective is to investigate whether, after controlling for heterogeneity in consumer characteristics, preferences, and heterogeneous interest rate offers, brokers exert any direct influence

[30] All things being expected consumption, lump-sum payment, and total interest cost.

[31] Since we use a small scale parameter $\sigma_\varepsilon = 0.02$ for the T1EV idiosyncratic preference shock distribution, after normalization the marginal disutility of \$1,000 monthly payment is 50.

[32] Table A2 presents the difference in estimated product fixed effects across channels in dollar terms for all product choices.

on borrowers' product choices. Specifically, we test the null hypothesis: $\mu_{j,broker=1} = \mu_{j,broker=0}, \forall\ j$. To do this we estimate a restricted version of the benchmark model under the null hypothesis that all product-specific fixed effects are the same in both channels. The likelihood ratio test-statistic for the null hypothesis that the product fixed effects are equal across origination channels is 248.9. The critical value of $\chi^2(19)$ distribution associated with a 0.1% significance level is 43.82; and so we reject the null. This result implies that brokers do exert direct influence on borrowers as to the mortgage product they purchase. In other words, borrowers end up with a product that might not be their optimal choice if they were instead using the bank-branch channel. However, simply from the entries in Table 8, it is difficult to infer the overall broker influence, since brokers affect the relative preferences across all products. As a solution, in the next section we investigate how consumer choices would be affected if we remove the direct broker influence (i.e., set $\mu_{j,broker=1} = \mu_{j,broker=0}$).

7 Decomposition

We now formally decompose the contribution of the causal effect of brokers, selection on observables, and selection on unobservables for explaining the different distributions of product choice across origination channels. We further break down the causal effect of brokers into two components: (i) direct influence on product choices, and (ii) indirect effect due to different rate setting.

Table 9 presents the main results for product shares, and Table 10 reports summary statistics for key variables. Panel (A) of Table 9 describes product choices arising from the benchmark model. Each cell is a product share in the broker channel for (LTV, amortization) combinations. The most popular product has a 95% LTV and 40-year amortization (18.3% share). Choices of products with an LTV below 90% are relatively rare. Panels (B)-(E) also present product shares, but they are generated from different model simulations. In each case, we use our model estimates to simulate the choices of 100,000 broker-clients under different scenarios. Each scenario builds on the previous panel. Specifically, panel (B) removes the brokers' direct influence on product choices (i.e., setting $\mu_{j,broker=1} = \mu_{j,broker=0}$), panel (C) removes both the brokers' direct influence and rate-setting differences across channels, panel (D) removes these first two channels and also selection on unobservables, and panel (E) removes the first three channels as well as differences in observable characteristics across branches and brokers.[33]

In panel (B) we remove brokers' direct influence on product choices, reporting product shares from a counterfactual in which we set the differences in product dummies across channels to zero. The key takeaway from this panel is that, in the absence of the direct influence of brokers, the share of 100% LTV and long amortization products falls. The share of products with 100% LTV falls from 23.84% to 20.52% and the share of products with 35- or 40-year amortization falls from 61.32% to 55.33%. In Table 10, we see that the average amortization decreases by 0.61 years and

[33]The exact sequence of removing differences across broker- and branch-clients is not important. Results are available upon request.

Table 9: Product shares in broker channel (%)

	LTV					**Total**
	80%	85%	90%	95%	100%	
	Panel A: Model					
AMT=25Y	0.78	2.10	6.24	15.04	3.97	28.13
AMT=30Y	0.23	0.68	1.93	5.22	2.50	10.56
AMT=35Y	0.34	1.24	3.72	13.49	5.24	24.02
AMT=40Y	0.30	1.49	5.05	18.31	12.14	37.30
Total	1.65	5.50	16.94	52.06	23.84	100.00
	Panel B: Model w/o direct broker influence					
AMT=25Y	0.63	2.25	7.21	19.72	3.97	33.78
AMT=30Y	0.22	0.66	1.84	6.05	2.12	10.89
AMT=35Y	0.26	0.88	2.96	11.03	3.63	18.77
AMT=40Y	0.13	1.56	5.03	19.03	10.81	36.56
Total	1.25	5.36	17.04	55.83	20.52	100.00
	Panel C: Model w/o direct broker influence, rate setting same as branch					
AMT=25Y	0.74	2.44	7.60	19.61	3.89	34.28
AMT=30Y	0.26	0.76	2.03	6.17	2.09	11.31
AMT=35Y	0.32	0.97	3.22	10.87	3.45	18.83
AMT=40Y	0.19	1.72	5.42	18.49	9.77	35.59
Total	1.52	5.88	18.27	55.14	19.19	100.00
	Panel D: Model w/o direct broker influence, branch-like control function variables, rate setting same as branch					
AMT=25Y	1.07	3.29	9.32	20.67	3.43	37.79
AMT=30Y	0.34	0.94	2.24	6.25	1.81	11.58
AMT=35Y	0.39	1.11	3.50	10.77	2.92	18.69
AMT=40Y	0.21	1.83	5.32	16.82	7.75	31.93
Total	2.01	7.17	20.39	54.51	15.92	100.00
	Panel E: Model w/o direct broker influence, branch-like control function variables, rate setting, and observable characteristics same as branch					
AMT=25Y	1.07	3.38	9.84	24.16	4.53	42.98
AMT=30Y	0.26	0.75	1.98	5.82	1.93	10.73
AMT=35Y	0.32	0.99	3.11	10.27	2.96	17.65
AMT=40Y	0.15	1.49	4.44	15.03	7.54	28.64
Total	1.79	6.60	19.38	55.27	16.96	100.00

Note: We focus on the period when all mortgage products are available. In each panel, we simulate the choices of 100,000 broker-clients. In panel A we present the predicted product shares in our benchmark model. Panel B presents product shares under the restriction that the product dummies across channels are equal. In panel C, we simulate broker borrowers' mortgage rates using the first stage rate regression estimates from branch borrowers (column (2) in Table 5). Panel D presents product shares in a version of the model where we set the control function variables to mimic those of the branch borrowers. Panel E draws observations from the branch borrower sample. The sampling scheme is weighted to keep the market-quarter shares unchanged.

LTV falls slightly by 0.1 p.p., while TDS increases. The two last rows of Table 10 document the share of broker-clients that switch products across different panels. Moving from the benchmark to panel (B), we see that 13.6% of broker-clients choose a different product once we remove the direct influence of brokers. Table 11 focuses on this subsample of affected borrowers and finds that their average amortization falls by 4.55 years and their monthly mortgage payment increases by \$49.82. In contrast, their LTV only decreases by 0.7 p.p. on average, suggesting that when brokers do influence choice, it is mainly influencing amortization.

Table 10: Summary statistics: Panel A to E

	Panel A	Panel B	Panel C	Panel D	Panel E
AMT (years)	33.52	32.91	32.79	32.24	31.60
LTV (%)	94.55	94.45	94.23	93.76	93.95
TDS (%)	34.99	35.11	35.49	35.34	34.57
GDS (%)	20.53	20.65	21.11	20.87	19.38
Rate (%)	5.53	5.53	5.76	5.64	5.64
Loan (\$1,000)	212.30	212.08	211.49	210.28	204.21
Mortgage payment	1162.50	1169.27	1194.05	1181.01	1152.72
θ	0.29	0.29	0.29	0.27	0.32
δ	0.47	0.47	0.47	0.52	0.54
Debt obligation	905.76	905.76	905.76	911.22	1002.93
Change choice (%)					
rel. to prior panel		13.60	6.79	16.88	
rel. to panel A		13.60	16.70	30.75	

Note: This table calculates the mean of variables of interest for broker-clients using simulated samples from Table 9. In the last two rows, we show the fraction of borrowers who change their product choices. θ is the random coefficient reflecting the marginal disutility of lump-sum payments. δ is the marginal disutility of total interest costs.

Table 11: Mean change in variables of interest for borrowers who switch product choices

	Panel B	Panel C	Panel D
Change in AMT (years)	-4.55	-1.75	-3.25
Change in LTV (%)	-0.71	-3.26	-2.79
Change in Rate (%)	0.00	0.24	-0.12
Change in Loan (\$)	-1638	-8697	-7171
Change in Mortgage payment (\$)	49.82	-2.58	-10.41
Change in Interest cost (\$)	-34196	-11615	-44931

Note: This table zooms in on the subsample of broker borrowers who change product choices in the decomposition exercise. As reported in Table 10, 13.6% of borrowers change choices when removing direct broker influence in panel B, 6.79% change choices when removing the indirect rate effect in panel C, and 16.88% change choices when removing selection on unobservables in panel D. This table calculates the mean change in variables of interest for these affected borrowers in each panel.

In the previous step, we had fixed the interest rates faced by borrowers. Recall that in the data we observe that broker-clients on average pay less. Panel (C) examines the following counterfactual:

if broker-clients were to visit a bank branch, what rates would they receive and how would the change in rates affect their product choices? Specifically, we use the first-stage rate setting equation from the branch channel—column (2) of Table 5—to predict rates for broker-clients. We plot the change in mortgage rates faced by broker-clients in Figure A1 of Appendix A. Table 10 shows that broker-clients on average pay about 23 basis points more if they were to use bank branches. The higher interest rates on average reduce amortization by 0.12 years and LTV by 0.22 p.p, leading to an increase in average mortgage payment by \$24.8. There are 6.8% of borrowers who change their product choices due to higher rates. Table 11 finds that, among these affected borrowers, the average LTV drops by 3.26 p.p. and the loan size decreases by \$8,697. The average amortization also decreases by 1.75 years. As a result of these choice adjustment, their monthly mortgage payment decreases by \$2.6.

In panel (D) we simulate a version of the model where we set the control function variables in the random coefficients to mimic those of the branch clients. This allows us to capture any selection on unobservables: broker-clients could be unobservably different in their disutility from lump-sum payments (θ) and from interest costs (δ), and these unobserved differences are captured by $\hat{e}_1$ and $\hat{e}_2$, the (generalized) residuals obtained from Table 5. Specifically, we obtain the generalized residuals $\hat{e}_1$ for broker-clients assuming that they had instead chosen to use a branch. For $\hat{e}_2$, we draw from the residual distribution following the rate regression in the branch channel (column (2) in Table 5), preserving the percentile ranking. This effectively pushes the broker-clients' taste preferences towards those of branch-clients. In addition, by changing $\hat{e}_1$ and $\hat{e}_2$, it also affects the interest rates that would be negotiated by the broker-clients in the branch channel. This counterfactual leads to a further decrease in the share of products with high LTV and long amortization—suggesting that these unobservable characteristics are an important determinant of product choice. In Table 10, we find the corresponding decrease in average amortization length and LTV are 0.55 years and 0.47 p.p., respectively. Moving from panel (C) to (D), we observe that 16.88% of broker-clients choose a different product once selection on unobservables is removed. For these borrowers, the average amortization falls by 3.25 years and the average LTV by 2.8 p.p. Overall, we find that selection on unobservables is the main driver in explaining the LTV difference across channels.

Finally, panel (E) reports product shares in a counterfactual where we eliminate differences in observable borrower characteristics (other than the region-quarter that borrowers belong to).[34] The changes in product shares moving from panel (D) to (E) can therefore be attributed to differences in observed characteristics between branch-clients and broker-clients, rather than to differences in

[34] Practically what this means is that we draw observations from the branch sample using a weighted sample scheme to ensure that the geographic composition remains the same. For example, suppose we only have two regions: Toronto and Montreal, each with 100 mortgages. In Toronto, 20 mortgages are originated by banks and 80 by brokers, while Montreal has 20 from brokers and 80 from banks. In the data, therefore, our broker-client sample has 80 from Toronto and 20 from Montreal. We wish to keep this composition in the simulation, which is achieved by assigning higher weight to Toronto branch clients. Note that if we draw 100 borrowers from the branch sample without weighting, we would have roughly 20 from Toronto and 80 from Montreal.

geographic composition between the two groups. The simulated product shares reported in panel (E) should closely match the product shares in the branch sample. For comparison these are reported in Table 12.

Table 12: Product shares in branch channel (%)

	LTV					**Total**
	80%	85%	90%	95%	100%	
	Panel A: Data					
AMT=25Y	0.75	2.96	10.00	25.60	5.15	44.47
AMT=30Y	0.12	0.74	1.66	5.26	1.61	9.39
AMT=35Y	0.26	1.07	2.94	10.33	2.68	17.28
AMT=40Y	0.11	1.29	4.23	15.65	7.58	28.86
Total	1.25	6.06	18.83	56.84	17.02	100.00
	Panel B: Model					
AMT=25Y	0.97	3.31	9.98	26.64	5.17	46.07
AMT=30Y	0.23	0.71	1.77	5.51	1.86	10.08
AMT=35Y	0.30	0.93	2.94	9.92	2.95	17.04
AMT=40Y	0.11	1.30	4.00	14.01	7.39	26.81
Total	1.61	6.24	18.69	56.09	17.38	100.00

We summarize the change in product shares across panels in two ways. First, we are interested in the fraction of borrowers choosing high amortization products (AMT≥35Y) and high LTV products (LTV≥95%). Table 13 calculates the total changes in shares of these two product categories as we move from Panel A to Panel E. We also calculate changes due to specific factors: direct broker influence (Panel A to B), rate-setting differences (Panel B to C), unobservables (Panel C to D), and observables (Panel D to E). A negative number implies that product shares fall as we move from panel to panel, making our broker-clients more and more similar to branch borrowers. Overall, we find that, once removing all difference across channels, the share of high-amortization products would fall by about 15 p.p., 40% of which can be explained by direct broker influence. On the other hand, the change in the high-LTV product share is mainly driven by selection on unobservables. Brokers directly influence borrowers towards high-amortization products but not high-LTV products. In contrast, the indirect rate effect encourages more broker-clients to chose higher LTV but has less impact on amortization choices.

To further highlight the role of selection on unobservables, we can compare the benchmark model predictions in Table 13 to the restricted model predictions presented in Table C4 of Appendix D. Recall that this restricted model (discussed in Section 6.3) assumes away selection on unobservables by excluding the control residuals in the random coefficient specifications. Compared to the benchmark model predictions in Table 13, the restricted model attributes, at least partially,

Table 13: Changes in product shares from Panel A to E

	I(AMT≥35Y)	I(LTV≥95%)
Total change	-15.03 (100%)	-3.67 (100%)
Changes due to		
Broker influence	-5.99 (39.85%)	0.45 (-12.22%)
Rate setting difference	-0.91 (6.05%)	-2.03 (55.14%)
Selection on unobservables	-3.79 (25.22%)	-3.89 (105.99%)
Selection on observables	-4.34 (28.88%)	1.8 (-48.91%)

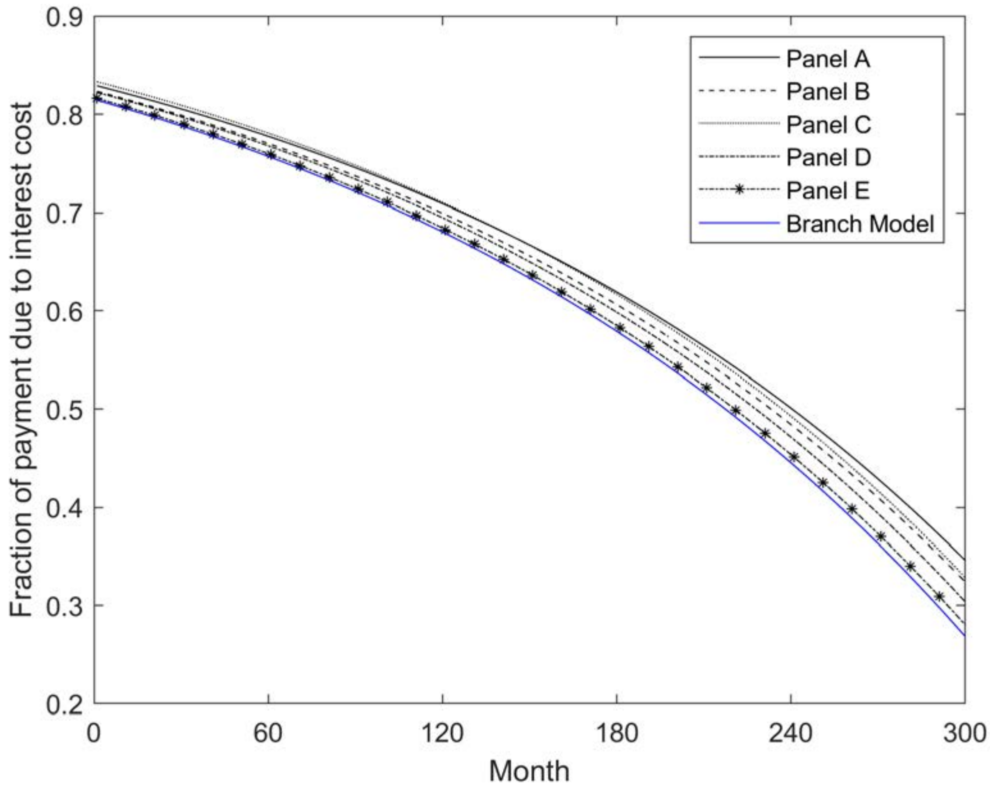
Note: The first row shows the percentage point change in product share from Panel A to Panel E in Table 9. The remaining rows further break this down into changes due to broker influence (Panel A to B), rates setting difference (Panel B to C), unobservables (Panel C to D), and observables (Panel D to E). The fraction of the total change that can be attributed to different factors is presented in parentheses.

the effect of selection on unobservables to direct broker influence. For instance, the contribution of direct broker influence towards high-amortization products is close to the sum of the contribution from both direct broker influence and selection on unobservables. More striking, under the restricted model, direct broker influence becomes the main driver of high-LTV choices.

Given that brokers seem to largely influence the average amortization length, our second approach for highlighting our findings is to graphically illustrate the impact on borrowers' total interest costs as a result of using a broker. Figure 2 shows the amortization schedule (fraction of the mortgage payment that is interest rather than principal) in the benchmark model versus the simulated models defined above. Moving from 'Panel A' (broker model) to 'Branch Model' we see that borrowers pay down their mortgage faster and as a result pay less in terms of interest.

Next, we explore in more detail the 13.6% of borrowers whose choices are directly influenced by brokers. Among them, 76% choose longer amortization due to the causal effect of brokers, 25% increase their LTV, and 11% decrease their LTV. Our results are presented in Figure 3, which contains two panels. Panel (A) reproduces the amortization schedule shown in Figure 2 for influenced borrowers only. Removing the direct effect of brokers leads borrowers to take out shorter-term mortgages. As a result, the share of their monthly payment that is interest relative to principal changes quite drastically. After 25 years, 65% of a influenced borrower's payment goes towards principal, versus over 80% in the counterfactual. Over the lifetime of the mortgage, these borrowers can save $34,196 in interest costs if there were no direct influence of brokers on product choices. In panel (B) we plot the difference in outstanding balance at renewal for a borrower in the benchmark model versus the simulated model without broker influence. On average, if borrowers were not influenced, they would on average have $5,579 less to refinance after five years of paying down their mortgage. There is, however, substantial dispersion, with some borrowers having over

Figure 2: Amortization schedules



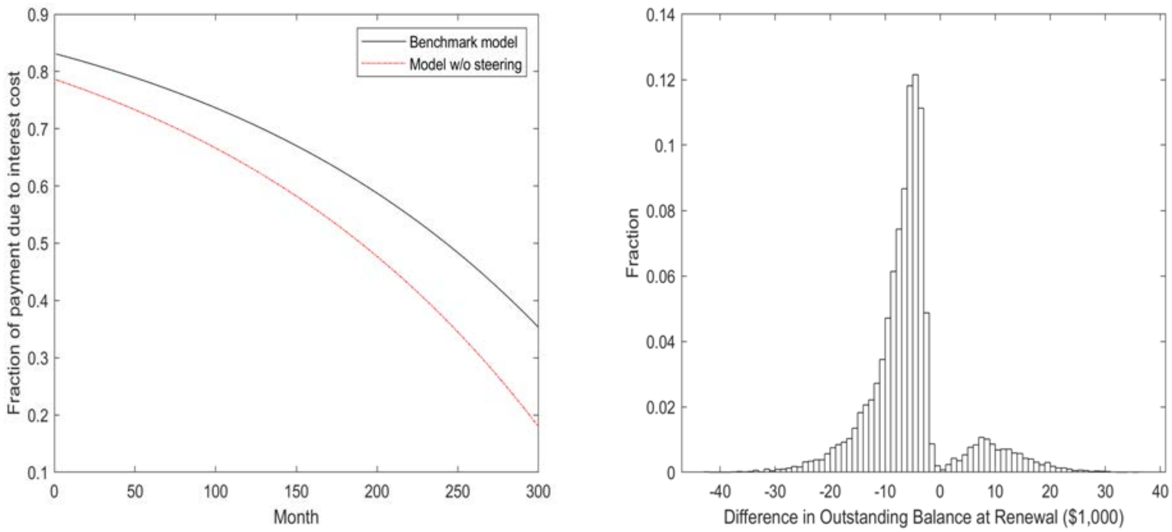
Note: This figure plots the fraction of borrowers' monthly mortgage payments that goes towards their interest costs. The calculations are based on simulated broker borrower samples reported in Panels A to E in Table 9. The solid blue line ('Branch Model') shows the amortization schedule for simulated branch clients in panel B of Table 12.

$30,000 less to refinance at renewal and some over $20,000 more.

It is not surprising that brokers might directly influence some borrowers towards higher-LTV products—larger loans are directly associated higher commissions. But why are some borrowers influenced by brokers to choose a lower LTV product? We find that these broker-clients have a relatively low θ (i.e., high savings or bad outside investment opportunities). If they were to visit a bank branch, a high LTV mortgage bundled with an investment product might be recommended to them. Since brokers cannot cross-sell, they likely provide a different recommendation: invest more in housing with a low LTV mortgage. Such a recommendation reflects brokers' fiduciary duty and does not necessarily create higher profits.

It might seem puzzling that brokers have a stronger influence on borrowers' amortization choices than on LTV. However, this is consistent with the compensation structure illustrated in Table 1 of subsection 2.3. We can see that amortization appears to be quantitatively more important for broker compensation than LTV. In addition, (Allen and Li 2023) find that borrowers with longer amortization are more likely to switch lenders at renewal, which generates higher commissions for

Figure 3: Amortization schedules and outstanding balances for influenced borrowers



(a) (b)

Note: This figure focuses on the 13.6% borrowers who change their product choices after removing direct broker influence. Panel (a) plots the fraction of a borrower's monthly mortgage payment that is interest cost (amortization schedule). The solid line is in the benchmark model and the dashed line is in the simulated model where we set the difference in product dummies across origination channels to be zero. Panel (b) plots the difference in outstanding balances five years after origination between the baseline model and the model without the direct broker influence.

brokers but hurts incumbent lenders. Therefore, relative to bank branches, this provides extra incentives for brokers to influence borrowers towards longer amortization. There could, of course, be other (behavioral) explanations. For example, it might be easier to convince borrowers to extend their amortization than to increase their LTV. This is the result of the flexibility offered by longer amortization, which is not present with higher LTV. With a 30-year amortization, a borrower always has the option to make a prepayment, which would essentially allow them to get on a 25-year schedule. On the other hand, given that in our setting the house choice is determined before borrowers make their product choices, households may have already saved the necessary funds to make a down payment. Therefore, to recommend higher-LTV products, brokers need to convince their clients to only use part of their savings for the down payment and invest the rest—which seems unlikely given that brokers do not cross-sell. Another possible explanation is that, from a borrower's perspective, the association between broker compensation and high-LTV products might be more salient than the link between broker compensation and high-amortization products. In such a case, borrowers could be particularly cautious regarding brokers' recommendations towards higher LTV while being more receptive to advice on amortization.

8 Conclusion

In this paper we study the role of intermediaries in credit markets. Using data from the Canadian mortgage market, we document that borrowers who transact through brokers are observationally riskier (have lower income and credit scores) and obtain riskier products (with higher amortization and LTV). We propose two possible explanations for these observations. First, unobserved borrower characteristics may drive both product choices and decisions to use brokers, creating a correlation between them. Second, brokers may have a causal impact on broker choice. They affect the rate distribution that borrowers face, they have an incentive to steer borrowers to increase their profits, and they work with lenders who might have heterogeneous lending standards. To disentangle the importance of selection on unobservable consumer characteristics and broker influence, we develop and estimate a model of mortgage-product choice. Our decomposition exercise suggests that brokers mainly influence consumer choices of amortization length, while the difference in LTV distributions across channels is largely driven by selection on unobservables.

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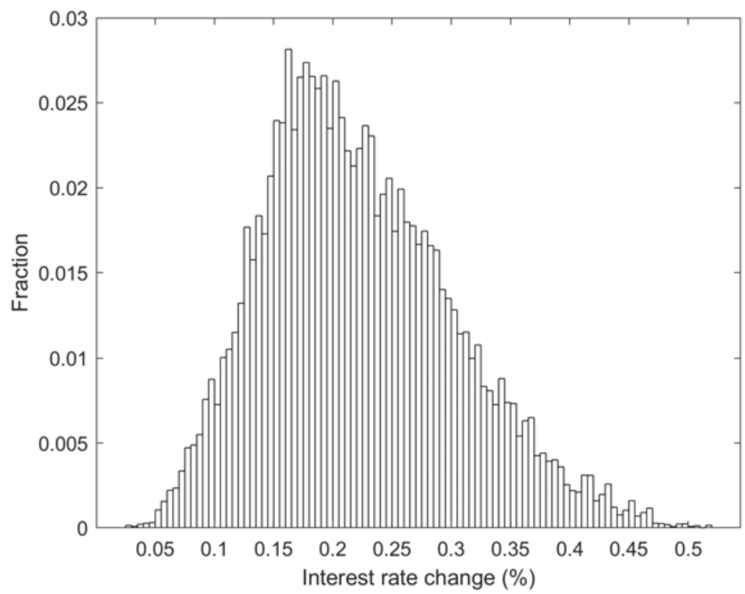
Appendix

A Additional tables and figures

Figure A1 plots the change in mortgage rates faced by broker-clients in a counterfactual where they pay the same rate as similar branch-clients. Table A1 reports results for the correlation between household savings and local bank branch and broker market structure. In Table A2, we calculate the difference in estimated product fixed effects across channels in dollar terms.

Figure A1: Distribution of rate changes moving from Panel B to Panel C



Note: The horizontal axis is measured in percentage points, i.e., 0.2 is 20 basis points. The histogram plots the change in mortgage rates that broker-clients would counterfactually face if they used a bank branch instead to originate their mortgage.

Table A1: Association between saving and local market structure

	Saving (log)		
Nb. banks	0.0001	0.003	0.005
	(0.012)	(0.012)	(0.012)
I(Broker presence)	-0.063	-0.055	-0.053
	(0.067)	(0.066)	(0.066)
Nb. brokers (log)	0.053	-0.005	-0.013
	(0.040)	(0.040)	(0.040)
Share excluding brokers	-0.134	-0.161	-0.160
	(0.157)	(0.152)	(0.150)
Share excluding brokers	-0.113	-0.084	-0.075
$\times$ Nb. brokers (log)	(0.105)	(0.104)	(0.104)
Control Variables			
Year FE	Y	Y	Y
Region FE	Y	Y	Y
Household-level controls	Y	Y	Y
FSA-level controls	N	Y	Y
ER saving (log)	N	N	Y
R^2	0.222	0.222	0.222
Obs	32972	32753	32753

Note: This table examines the association between household savings and local market structure using data from CFM surveys between 2005 and 2007. The first column controls for household income category and the age of household head. The second column controls for FSA-level characteristics derived from our main dataset: average house price (log), share of new properties, and share of borrowers in each FICO bin. The last column adds the average saving at the economic-region level (log) as a control variable. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors clustered at the FSA level.

Table A2: Difference in estimated product fixed effects across channels in dollar terms

	LTV				
AMT	80%	85%	90%	95%	100%
25Y	112.0	54.0	20.0	0.0	92.0
30Y	132.0	92.0	70.0	48.0	128.0
35Y	158.0	122.0	102.0	92.0	154.0
40Y	198.0	118.0	102.0	94.0	152.0

Note: Each cell presents the difference in monthly compensation required between channels for borrowers to choose a product over the baseline option: $20\times(\mu_{j,broker=1} - \mu_{j,broker=0})$. A positive number implies that broker clients require less compensation.

B Choice of origination channel and rate determination

In section 5.1 we provide an argument for how our control function approach captures the choice of origination channel and the distribution of mortgage rates. Here we present one model that can rationalize our approach. Consider a first stage to the game where consumers choose their origination channel. That is, choose either to search on their own (obtaining quotes and finding the best interest rate) or outsourcing this process to a broker.

We first describe the procedure if a consumer searches on their own. We assume that the consumer knows their cost of contacting potential lenders, κ_i, realized from the distribution $F(\cdot)$. For simplicity, we assume that all 'own-search' consumers obtain the same number, n, of interest rate quotes. We parameterize the offer rate p_{ij} of bank j to consumer i as follows:

$$p_{ij} = c_i + \omega_j,$$

where c_i is a common lending cost and ω_j is a bank-specific cost-shock, distributed according to $G(\omega)$ with mean 0. While all mortgages are insured, the lending costs capture the cost of prepayment net of potential benefits to banks of obtaining a customer and cross-selling other products. We assume that this component is observed and known by consumers and banks. Note that we also assume that cost differentials across banks are random, so that there is no bank that consistently offers smaller/larger rates to different consumers.

The rate negotiation process we use is a simplified version (Allen, Clark, and Houde 2019), where banks compete for consumers in an English auction. The best offer is equal to the second smallest lending cost:

$$p_i = c_i + \omega^n_{(2)},$$

where $\omega^n_{(k)}$ represents the k-th smallest value of ω among n banks. Hence, if a consumer searches on their own, her expected utility is defined as the expected utility from the best mortgage product conditional on the interest rate net of search costs:

$$\mathbb{E}_\omega[U^*_i(p_i, broker_i = 0)] - \kappa_i.$$

Alternatively, consumers can outsource the search process to a broker. In this case the consumer does not have to pay a search cost, since brokers obtain the quotes and negotiate with the banks.[35] The broker provides an additional benefit—she can contact more banks, n^b, and hence potentially obtain lower offers. As a result, the best interest rate obtained through the broker channel is:

$$p^b_i = c_i + \omega^{n_b}_{(2)},$$

[35] In other words, we normalize the search costs through the broker channel to 0, and we can interpret κ_i as the difference between search costs through direct channel and through broker channel.

which generates expected utility $\mathbb{E}_\omega[U_i^*(p_i^b, broker_i = 1)]$.

As a result, the consumer decides to use the broker if the expected utility from the broker channel is higher than searching on their own:

$$\mathbb{E}_\omega[U_i^*(p_i^b, broker_i = 1)] \geq \mathbb{E}_\omega[U_i^*(p_i, broker_i = 0)] - \kappa_i.$$

This results in a cutoff rule, where consumers use a broker only if their realized search cost is high enough relative to the expected benefits from using a broker:

$$\kappa_i \geq \mathbb{E}_\omega[U_i^*(p_i^b, broker_i = 0)] - \mathbb{E}_\omega[U_i^*(p_i, broker_i = 1)].$$

Selection into the broker channel works through several mechanisms. First, consumers with high search costs are most likely to use brokers. Second, a broker's ability to negotiate on interest rates affects the consumer choice at the first stage in a heterogenous manner. While all consumers gain from lower interest rates, those who are unable to make a large down-payment, or who are sensitive to total interest costs, benefit more. More than that, the interest rate plays a crucial role in the TDS constraint, as high monthly mortgage payments constrain the amount of non-mortgage debt that a consumer can accumulate. Thus, the indirect effect of brokers negotiating lower interest rates is that consumers can more easily meet the TDS constraint ("qualify"). The effect is more pronounced for high-risk consumers with large debt, which plays a role in adverse selection into the broker channel.

C A model of product choice that does not correct for endogeneity of origination channel and rates

This section presents the estimates of the restricted model discussed in Section 6.3. The restricted model does not include the control function variables obtained from first-stage regressions in the random coefficient specifications, i.e., setting the coefficient of $\hat{e}_1$, $\hat{e}_2$, and their interaction to zero. Therefore, the restricted model shuts down the possibility of selection on unobservables in borrower product choices.

Table C1 reports the maximum likelihood estimates for this restricted model. The likelihood ratio test statistic rejects the restricted model at 0.1% significance level, suggesting that selection on unobservables is important for rationalizing the product choices observed in the data.

Table C2 reports the product-specific fixed effects in the branch channel ($\mu_{j,broker=0}$) and the estimated difference between origination channels: $\mu_{j,broker=1} - \mu_{j,broker=0}$. All coefficients are relative to a baseline product with amortization of 25 years and LTV of 95%. Compared to the benchmark product dummy estimates reported in Table 8, brokers in the restricted model seem to have stronger influence on borrower preferences relative to the baseline product.

Table C3 reports the predicted product shares given the restricted model under the different counterfactual scenarios described in Section 7. Notice that, although the restricted model does not include control function variables in the random coefficients, we still account for broker selection in the first-stage rate setting equations. Therefore, when we remove the difference in unobservables across channels (moving from panel C to D), we observe change in product choices due to change in rates.

Finally, Table C4 summarizes the contribution of broker influence for the observed product choices. Compared to the benchmark model predictions in Table 13, the restricted model seems to attribute the effect of selection on unobservables on product choices at least partially to direct broker influence, making it the dominant explanation for both long-amortization and high-LTV choices.

Table C1: Restricted model: Product choice model estimates

	(1)	(2)	(3)
	lnθ	$\bar{d}$	lnδ
ER saving (log)	0.0265 (0.0147)	-0.0278 (0.0123)	-0.0705 (0.0421)
FICO∈[680,717]	0.219 (0.009)	0.0934 (0.0069)	0.3019 (0.0227)
FICO∈[718,759]	0.1306 (0.0078)	0.0385 (0.0061)	0.2069 (0.021)
FICO≥760	-0.1544 (0.0076)	-0.1063 (0.0057)	0.0241 (0.0209)
Borrower age	-0.0046 (0.0003)	0.0003 (0.0002)	-0.0005 (0.0007)
Income (log)	0.2073 (0.0083)	1.4726 (0.0071)	0.2516 (0.024)
New property	-0.02 (0.0061)	0.0505 (0.0049)	0.1945 (0.0159)
House price (log)	-2.1189 (0.0094)	-0.6351 (0.0081)	-0.4566 (0.0274)
Bond rate	0.1805 (0.0105)	0.0155 (0.0084)	-0.1732 (0.0301)
Rate premium	-0.1113 (0.0274)	-0.0202 (0.023)	-0.0024 (0.0776)
$y\theta$		-0.0193 (0.0007)	
σ_θ	0.5885 (0.0065)		
σ_d		0.5094 (0.0012)	
σ_δ			0.9087 (0.0089)
Log likelihood		-96,093.86	

Note: This table presents the maximum likelihood estimates of a restricted model of borrower product choice, where we do not control for the endogeneity of mortgage rates and broker choices using the (generalized) residuals obtained from regressions reported in Table 5. Estimates on year and region dummies are not reported. Standard errors in parentheses. Given the log likelihood in Table 6 and Table C1, we can test the null hypothesis that the coefficients on the control function proxies are all 0. The LR statistic is $2 \times (96,093.86 - 95,622.96) = 941.8$. The critical value of $\chi^2(6)$ distribution associated with the 0.1% significance level is 22.46.

Table C2: Restricted model: Estimates of product fixed effects across branch and broker channels

	LTV				
AMT	80%	85%	90%	95%	100%
25Y	(117.5,-10.5)	(87,-8.6)	(46,-5.3)	(0,0)	(-78.1,13.7)
30Y	(112.9,-8.9)	(80.4,-6.5)	(37.5,-2.3)	(-8,3.1)	(-80.5,16.4)
35Y	(112.1,-7.2)	(78.7,-4.9)	(35.4,-0.5)	(-10.2,5.6)	(-79.1,18.1)
40Y	(109.1,-4.4)	(77.5,-4.6)	(33.9,-0.2)	(-11.9,6.1)	(-77.9,18.2)

Note: In each cell, the first number is the estimated product preference at branch channel ($\mu_{j,broker=0}$), while the second number is the estimated difference between origination channels ($\mu_{j,broker=1} - \mu_{j,broker=0}$). In order to test the null hypothesis: $\mu_{j,broker=1} = \mu_{j,broker=0}, \forall j$, we estimate the model under the null and obtain a likelihood ratio test statistic of 658.36. The critical value of $\chi^2(19)$ distribution associated with the 0.1% significance level is 43.82.

Table C3: Restricted Model: Product shares in broker channel (%)

	LTV					**Total**
	80%	85%	90%	95%	100%	
	Panel A: Model					
AMT=25Y	0.91	2.48	6.57	14.99	4.00	28.95
AMT=30Y	0.22	0.74	2.04	5.46	2.40	10.85
AMT=35Y	0.34	1.29	3.78	12.65	5.34	23.40
AMT=40Y	0.37	1.58	4.98	17.89	11.99	36.81
Total	1.84	6.09	17.36	50.99	23.72	100.00
	Panel B: Model w/o direct broker influence					
AMT=25Y	1.11	3.28	8.99	19.52	3.66	36.55
AMT=30Y	0.31	0.92	2.14	6.04	1.66	11.07
AMT=35Y	0.45	1.30	3.62	10.26	3.03	18.66
AMT=40Y	0.22	1.90	5.64	17.53	8.42	33.71
Total	2.08	7.41	20.40	53.35	16.77	100.00
	Panel C: Model w/o direct broker influence, rate setting same as branch					
AMT=25Y	1.22	3.43	9.23	19.39	3.63	36.90
AMT=30Y	0.34	0.99	2.32	6.13	1.66	11.44
AMT=35Y	0.50	1.34	3.79	10.11	2.90	18.64
AMT=40Y	0.26	2.03	5.86	17.02	7.84	33.02
Total	2.33	7.80	21.19	52.65	16.03	100.00
	Panel D: Model w/o direct broker influence, branch-like control function variables, rate setting same as branch					
AMT=25Y	1.17	3.35	9.08	19.47	3.65	36.72
AMT=30Y	0.32	0.97	2.24	6.04	1.65	11.23
AMT=35Y	0.49	1.33	3.68	10.18	2.98	18.66
AMT=40Y	0.25	2.02	5.74	17.28	8.11	33.39
Total	2.23	7.68	20.74	52.98	16.38	100.00
	Panel E: Model w/o direct broker influence, branch-like control function variables, rate setting, and observable characteristics same as branch					
AMT=25Y	1.16	3.43	9.70	22.77	4.75	41.81
AMT=30Y	0.25	0.74	1.95	5.57	1.69	10.19
AMT=35Y	0.46	1.14	3.26	9.98	3.10	17.93
AMT=40Y	0.17	1.61	4.91	15.37	8.02	30.08
Total	2.04	6.92	19.80	53.69	17.55	100.00

Note: In panel A we present the predicted product shares in our benchmark model. Panel B presents product shares under the restriction that the product dummies across channels are equal. In panel C, we simulate broker borrowers' mortgage rates using the first stage rate regression estimates from branch borrowers (column (2) in Table 5). Panel D presents product shares when we set the control function variables to mimic those of the branch borrowers. The change in the product distribution is purely due to the effect of selection on unobservables on rates, since the restricted model does not include control function variables in the random coefficients. Panel E draws observations from the branch borrower sample. The sampling scheme is weighted to keep the market-quarter shares unchanged.

Table C4: Restricted model: Changes in product shares from Panel A to E

	I(AMT≥35Y)	I(LTV≥95%)
Total change	-12.2 (100%)	-3.47 (100%)
Changes due to		
Broker influence	-7.83 (64.19%)	-4.6 (132.33%)
Rate setting difference	-0.71 (5.84%)	-1.43 (41.22%)
Selection on unobservables	0.39 (-3.2%)	0.68 (-19.52%)
Selection on observables	-4.05 (33.17%)	1.88 (-54.03%)

Note: The first row shows the percentage point change in product share from Panel A to Panel E predicted by the restricted model in Table C3. The remaining rows further break this down into changes due to broker influence (Panel A to B), rates setting difference (Panel B to C), unobservables (Panel C to D), and observables (Panel D to E). The fraction of the total change that can be attributed to different factors is presented in parentheses.