Predatory Lending and Hidden Risks

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Abstract

We study a specific practice of predatory lending: borrowers being rejected and approved in rapid succession by the same lender. We show that in such cases borrower and contract characteristics and ex-post performance are consistent with predatory steering. Steered borrowers are associated with groups with lower financial sophistication. They are more likely to enter non-amortizing contracts with high profit margins that are quickly securitized. Steered borrowers default less in boom years when refinancing is easy. However, their performance deteriorates sharply once falling prices trap them in contracts with rising payments, reflecting the long-term costs of predatory lending.

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1 Introduction

Predatory lending practices were common at the height of the housing market boom of the 2000s (Renuart, 2004; Financial Crisis Inquiry Commission, 2010). Engel and McCoy (2001) define predatory lending as "...onerous lending practices, which are often targeted at vulnerable populations and result in devastating personal losses, including bankruptcy, poverty, and foreclosure." Most of the existing literature identifies predatory lending either by ex-post contract characteristics—such as excessive fees, high interest rates, obscured prepayment penalties, or clauses barring borrowers from seeking judicial redress—or by ex-post mortgage performance (e.g., Engel and McCoy, 2001; Carr and Kolluri, 2001; White, 2008). These approaches potentially conflate predatory practices, optimal contract choices, and risk exposure.[1] They also offer little systematic evidence about the methods for implementing predatory practices or the mechanisms through which such practices inflict costs on borrowers and investors.

This study provides new evidence about the origination of predatory mortgages and their subsequent performance over the real estate cycle. We identify predatory loans not by the features of the eventual contract but by the process through which a loan was originated. Specifically, we analyze a particular business practice in which borrowers' mortgage applications are initially rejected but approved soon thereafter without meaningful changes in borrower income, loan amount, or property value. A very short time window between the two outcomes (less than two weeks, on average) also makes improvements in applicant credit scores unlikely. We contrast the outcomes of two sets of observationally equivalent

[1] Bond, Musto, and Yilmaz (2009) model predatory lending as a reverse asymmetric information problem, where the lender has more information about the borrower than the borrower has about herself.

borrowers—those who successfully obtained credit with a new lender and those who got a loan from the same lender to which they originally applied. Closely matching borrower characteristics in the two groups allows us to ascribe the difference in outcomes to lender behavior rather than to underlying borrower preferences. Whereas new lenders potentially employ a different underwriting framework, the original lender is likelier to have gotten to an approval by granting a manual exception or tweaking the contract form. This latter case opens a possibility of the first application being strategically denied to steer the borrower into a predatory contract.

Our empirical approach is motivated by background conversations with several mortgage practitioners active during the lending boom that preceded the Global Financial Crisis (GFC). These lenders and mortgage officers recounted practices whereby a loan officer could reject an application and then use substantially similar data to get approval by changing terms or contract type. The approved contract could be presented simultaneously with notifying the borrower of the rejection of the original application. An application rejected through an automated underwriting system would generate a Home Mortgage Disclosure Act (HMDA) record, as would an application that eventually got approved. While far from definitive, these anecdotes present a potential path to identifying predatory lending practices.

We use 2003–2006 transaction-level data from HMDA filings to flag borrowers whose rejected applications received subsequent approval without meaningful recorded changes. We find that borrowers who stayed with the original lender—those who were potentially steered—had systematically different demographic characteristics and took out systematically different contracts than those who sought credit with different lenders. In particular, steered borrowers are more likely to be female (primary borrower), Hispanic, have no co-signers, and reside in low-to-moderate income areas. These groups of borrowers have been shown to have lower levels of financial literacy (e.g., Lusardi and Mitchell, 2014) and are thus potentially prone to manipulation by unscrupulous lenders.[2] The effects are well-identified and are economically significant. Each demographic characteristic listed above is associated with a 5- to 10-percentage-point higher likelihood of being steered.

We also find that steered borrowers took out mortgage products that delivered high profit margins to lenders. We document that relative to the overall sample mean, steered borrowers were more than twice as likely to take option adjustable-rate mortgages (ARMs) or mortgages with prepayment penalties, 85% more likely to have interest-only mortgages, and 20% more likely to have no- or low-documentation mortgages. Consistent with the idea that originators capitalize on the high margins offered for these products in the secondary market, we report that mortgages of steered borrowers were 47% more likely to be sold to private securitizers.[3] Even more directly, after controlling for various borrower and loan characteristics, we document that steered loans have an annual percentage rate (APR) that is 35–72 basis points higher than that of non-steered loans, which, given the sample average APR of 6.8%, is economically significant. We note that this pattern is observed only for a narrow group of originators, suggesting that a few bad actors practiced this form of predatory lending rather than it being a standard industry practice.

[2] Indeed, Berndt, Hollifield, and Sandås (2016) show that such borrowers paid higher fees for the same loans than their better-educated counterparts. Buchak and Jørring (2021) also find that lender concentration leads to higher upfront fees, with the strongest effects among minority applicants.

[3] Several legal studies argue that the originate-to-distribute model was a prime factor that led lenders to engage in predatory lending (e.g., Engel and McCoy, 2001, 2006; Eggert, 2001; Azmy, 2005). Their basic claim is that strong demand for mortgages from investors (through securitization) incentivized mortgage originators to push for mortgages that generate high origination fees. During our sample period, private-label securitizers paid handsome fees for mortgages with high interest rates and exotic features (e.g., teaser rates and no/flexible amortization).

These differences in contract terms may appear inconsequential, with features that defer debt amortization improving near-term affordability. However, we find marked differences in the relative dynamics of mortgage performance of the steered and non-steered borrowers that reveal the consequences of this predatory lending practice. In a nutshell, steered borrowers refinanced their mortgages much more frequently during the boom years and defaulted much more often in the bust years. This finding is apparent in graphs showing conditional refinancing and default rates for steered and non-steered groups over time (Figure 1A and 1B). During the boom part of our sample—2004 through early 2007— the conditional quarterly refinancing rates of steered borrowers were about 2 percentage points higher, on average (relative to the mean refinancing rate of 3.2% for non-steered borrowers). This difference in the likelihood of refinancing collapsed once the real estate market stalled and the bust began.

Default rates exhibited the reverse pattern (Figure 1B). In the boom part of the sample, steered borrowers defaulted less frequently, but in later years, their quarterly default rates were 2 percentage points above that of the non-steered loans. This is similar in magnitude to the effect of predatory lending on default documented by Agarwal, Amromin, Ben-David, Chomsisengphet, and Evanoff (2014). This reversal in fortune coincided almost perfectly with the disappearance of higher refinancing rates among steered borrowers.[4]

Our results about the refinancing and default patterns over the cycle offer a new perspective on the costs of predatory lending. From the borrowers' viewpoint, exotic mortgage features appear appealing at first because they allow lower mortgage payments in the short

[4]As we argue in Section 4.4, the contrast with findings of *lower* refinancing rates by unsophisticated borrowers in Keys, Pope, and Pope (2016) and Jørring (2024) is largely due to the timing of our sample.

run, and thus, borrowers perform better on average. These very features encourage borrowers to refinance their mortgages (and thus allow lenders to target them a second time to collect origination fees) when house values increase. However, when market prices stall, borrowers can no longer refinance and are trapped in contracts with rising payments and lower equity values, leading to default. Our results thus mirror those of Gennaioli, Shleifer, and Vishny (2012), who argue that financial innovation introduces hidden risks that are exposed during a crisis. The main message of our study is that predatory lending practices may appear innocuous during good times but reveal their true costs when the market trends downward.

Our study directly adds to the literature about predatory lending, mortgage fraud, and financial literacy. Most of this work discusses the extent of the phenomena and hypothesizes about its potential sources (e.g., Eggert, 2001; Engel and McCoy, 2006; Reiss, 2005). Several studies examine the effects of anti-predatory laws on the supply of credit and on mortgage performance (e.g., Elliehausen and Staten, 2004; Harvey and Nigro, 2004; Ho and Pennington-Cross, 2006; Bostic, Engel, McCoy, Pennington-Cross, and Wachter, 2008; Mayer, Pence, and Sherlund, 2009; Bostic, Chomsisengphet, Engel, McCoy, Pennington-Cross, and Wachter, 2012; Agarwal et al., 2014; Di Maggio, Kermani, and Korgaonkar, 2019). A closely related set of work assesses which groups are more susceptible to mortgages with predatory loan terms (see Immergluck and Smith, 2003; Bocian, Ernst, and Li, 2008; Gurun, Matvos, and Seru, 2016; Agarwal, Ambrose, and Yao, 2020a).

Predatory lending is part of a broader set of mortgage fraud practices that flourished during the boom years. Ben-David (2011) documents that borrowers inflated home prices to borrow larger sums from lenders. Garmaise (2015), Jiang, Nelson, and Vytlacil (2014), Piskorski, Seru, and Witkin (2015), and Griffin and Maturana (2016) find systematic misreporting in mortgage applications. In addition, several studies focus on the importance of financial literacy and financial advice in borrower decision-making. Agarwal, Ben-David, and Yao (2017) show that borrowers' decisions regarding mortgage features (mortgage points) are almost arbitrary, likely because of poor financial literacy. Agarwal, Amromin, Ben-David, Chomsisengphet, and Evanoff (2020b) find that providing one-off counseling sessions attempting to warn borrowers about risky mortgages or predatory lending does not change their choice. However, Agarwal, Amromin, Ben-David, Chomsisengphet, and Evanoff (2010) find that *long-term* financial education programs help households make better financial decisions and perform better on loans.

More broadly, our paper contributes to the growing literature that finds evidence linking the real estate bubble in the early 2000s to misaligned incentives of intermediaries. Keys, Mukherjee, Seru, and Vig (2010) show that securitization led to lax screening by lenders, and Agarwal, Ben-David, and Yao (2015) find that appraisers caved to pressures from borrowers and lenders and inflated home prices. Agarwal and Ben-David (2018) find that volume-based incentives to intermediaries worsen the information asymmetry in lending.

2 Background, Hypothesis Development, and Empirical Design

2.1 Background: What Is Mortgage Steering?

Steering is a well-known term in the mortgage industry that refers to an intermediary or a seller pushing a particular product that may or may not be optimal for the customer.

Traditionally, in the real estate world, regulators focused on market steering by realtors, who might restrict neighborhoods shown to certain potential home buyers. Such behavior can result in taste-based or statistical discrimination and distort the spatial patterns of housing demand by white and minority homebuyers in a way that perpetuates neighborhood segregation (Ondrich, Ross, and Yinger, 2003). Such practices are illegal based on the Fair Housing Amendments Act of 1988 and numerous state laws.[5]

During the housing boom of the 2000s, a different form of steering in housing markets emerged, namely, credit steering. Here, the borrowers would be encouraged to obtain credit from a particular lender or through a particular type of mortgage contract. Engel and McCoy (2001) discuss how lenders may steer prime borrowers into high-cost mortgages. Also, Freddie Mac (1996) finds that in the early 1990s, 10% to 35% of subprime borrowers had credentials that should have qualified them for prime loans, and Barr (2005) argues that some subprime borrowers "may have been steered to higher cost lenders." Such behavior could be helpful for borrowers if it makes it possible to obtain credit they may not otherwise receive and if that credit is accurately priced based on their credentials. However, credit steering could also be a predatory lending strategy. The concern is that the lender may not have the borrower's best interest in mind and may "gouge" them—whether through higher interest rates, excess fees, or contract features that increase the value of the loan to the originator but that may be unnecessary or non-transparent to the borrower.[6] In our empirical analysis, we impose no ex-ante value judgment on the value of customer steering and let the data speak.

[5]Steering practices also exist in other domains, e.g., brokers pushing consumers into high-fee mutual funds (Egan, 2019).

[6]Renuart (2004) argues that steering may have played a larger role in mortgage rate determination than did borrower risk.

2.2 Hypotheses Development

Mortgage steering is likely to occur at a potential client's first application. However, it is difficult for an outside observer to identify mortgage choices resulting from steering because of two major hurdles. First, one needs to separate cases in which lenders steered borrowers into a product from cases in which borrowers expressed demand for the product. Second, assessing the optimality of a selected product is problematic in itself, as the econometrician does not observe the complete set of borrower characteristics and constraints. An ideal empirical setting to detect steering activity would be to observe borrowers demanding one product and measure whether lenders concur or try to market a different product with unambiguously inferior features for the borrower.

Given the absence of transaction-level negotiation data, we develop a novel methodology to identify loans that were likely steered. Specifically, we argue that borrowers whose mortgage applications were rejected by a lender but were approved shortly thereafter without any meaningful changes in terms by the same lender or its close affiliate are more likely to have been steered into a suboptimal mortgage product. We test our conjecture by comparing this group of borrowers to a group of observationally similar borrowers whose application was initially rejected but whose subsequent application was approved by a lender unaffiliated with the original lender.[7]

As an illustrative example, suppose a borrower enters a lending institution seeking a mortgage, and their loan application is evaluated. Their application is rejected outright if

[7] Withdrawn applications may offer another path to steering. In the current version of the paper, we do not analyze this possibility because the "applications withdrawn" reporting code in HMDA data is notoriously inconsistent. For instance, the borrower has to expressly request a withdrawal before a credit decision is made. Simply stopping communications does not qualify as withdrawal, yet some lenders report it as such.

judged to be a poor credit risk. However, if their credit risk is acceptable, they might be told that they do not qualify for the specific loan they applied for but could qualify for another mortgage product. If steering occurs, it would be initiated once the lender has determined that the loan applicant is an acceptable credit risk.

In such cases, a loan officer's job is to determine whether a borrower can be convinced to take an alternative loan product—one that is more profitable for the lender and/or enhances the loan officer's compensation. In making this decision, the officer has to consider the risk of the borrower rejecting an alternative offer and seeking credit elsewhere. Consequently, this decision would be influenced by the perceived financial sophistication of the loan applicant.[8] The likelihood of rejecting an alternative offer might also be affected by how quickly that offer is presented to the applicant following the initial rejection.

This example relates to anecdotal evidence we gathered in written and verbal correspondence with mortgage loan officers active during the pre-GFC housing boom. At least some mortgage originators actively managed the type of contracts for which their clients would be approved, whether or not they applied for those contracts in the first place. These originators engaged in extensive manual exceptions and strategically timed the presentation of alternative offers.

The above description can be used to develop our hypotheses. First, steered borrowers are likely to be less financially sophisticated, e.g., come from socioeconomic groups with weaker financial literacy backgrounds. Second, steered borrowers take loan products that

[8]For most mortgage loans, not just steered loans, the lender would have asymmetric information advantages. The lender operates daily in the mortgage markets and is closely aware of the matching of customer credit qualifications and alternative mortgage products. Many borrowers do not follow the mortgage markets nearly as closely nor do they understand the credit-qualification-to-product matches. However, the lending officer who intends to steer the applicant inappropriately would be looking for applicants with a below-average level of financial sophistication.

are considered to have high profit margins for mortgage lenders (e.g., prepayment penalty, option ARM) and carry higher interest rates than non-steered loans. Third, steered loans are sold to private-label securitizers, who pay a high fee for exotic loan products with said features to monetize these margins. Finally, if steered loans maximize originator profits instead of fitting borrower credit needs, we anticipate their performance will differ.

2.3 Research Design

To implement the identification strategy, we focus on a subset of lenders who are organized under bank holding companies (BHCs) and are thus likely to be more closely affiliated with each other. For these lenders, we can observe the original borrower demand in the form of a mortgage application. Because we cannot directly identify the steered borrowers in the data, we develop an algorithm to detect steering. To do this, we consider mortgage loan applications that are denied by one lender only to be approved within a relatively short period without material changes in the key observable loan application variables.Instances in which the approving and rejecting lenders are the same bank (or its close affiliate) are tagged as "steered." These borrowers form our steered group. The borrowers originally rejected but later approved by an unaffiliated lender fall into the group of potential controls. To make these two groups comparable, we use several approaches to construct matched samples that achieve tight covariate balance on a wide array of observable borrower characteristics, described in Section 3.2.The requirement that both groups comprise rejected applications approved shortly thereafter further enhances their comparability.

Next, we evaluate observed demographic characteristics (not used in sample construction) in these two groups to gauge whether specific borrowers were more likely to have been successfully retained by the original rejecting lender. Finally, we explore whether there are meaningful differences in outcomes between the two groups. In this analysis, we look at APR on the mortgage, the type of mortgage and various mortgage characteristics granted, and mortgage performance as captured by the refinancing propensity and delinquency rate.

We emphasize that we are not attempting to identify all instances of credit steering. The focus here is on one specific practice and one specific group of mortgage applicants. All of them get turned down for credit but are approved shortly thereafter, strongly suggesting that their credit profile at the time of the original application was not disqualifying.

Next, we describe our data and methodology in more detail.

3 Data, Coverage across Data Sets, and Descriptive Statistics

3.1 Data Sources

We identify steered and non-steered loan samples based on the Home Mortgage Disclosure Act (HMDA) data. This source provides the loan application date, the date that a decision is made on the application, and the type of decision made (e.g., accept or reject the loan application). The HMDA dataset provides limited information on affiliation structure, the qualifications of the borrower, or (if a loan originated) the characteristics of the loan. Therefore, we obtain additional information from mortgage servicing sources, the Bank Holding Company Structure files, and Bank Call Reports.

McDash Analytics (McDash) provides loan-level information collected from residential mortgage servicers on loans packaged into government agency and non-agency mortgage-backed securities and loans held in lenders' portfolios. The McDash data provide extensive information about the loan, property, and borrower characteristics at the time of mortgage origination. Property-related variables include appraisal amount, geographic location, and property type (single-family residence, condominium, or other type of property). Loan characteristics include origination amount, term to maturity, lien position, loan type (i.e., whether the loan is conventional), loan purpose (purchase or refinance), and the coupon rate on the mortgage. Credit-risk-related variables include the borrower's debt-to-income ratio, FICO credit score, loan-to-value (LTV) ratio at origination, and the level of documentation provided. The McDash data coverage has grown over time, including nine of the top 10 mortgage servicers by 2003. Since servicers only provide information on active loans when they start reporting data to McDash, the McDash database includes relatively few loans that originated in the late 1990s and the early 2000s.

We note two caveats. First, due to data limitations (McDash), we only consider banks and ignore potential steering to and from credit unions, savings and loan institutions, and mortgage companies.[9] Second, McDash Analytics data contain a smaller share of subprime loans; hence, the effects we document exist in the prime market and among highly regulated lenders. These results are likely to represent conservative estimates of the consequences of steering behavior.

Beyond the McDash information available at origination, the dataset also contains dy-

[9]Demyanyk and Loutskina (2016) emphasize the importance of mortgage companies in originating riskier mortgages during this period under HMDA. Mortgage reporting may be done by the mortgage company or the money-center bank that acquires the loan, often under a standing contract. We might capture the latter type of transaction as "steered" but will likely miss the former.

namically updated loan information, enabling one to monitor refinancing activity and loan performance. Variables of interest include interest rates (which change for adjustable-rate mortgages (ARMs) and have the potential to change with loan modifications), delinquency status (current, 31–60 days delinquent, 61–90 days delinquent, 91 or more days delinquent, foreclosure, real estate owned by the lender (REO), or paid off), investor type (held in portfolio, private securitization, or "public" securitization via the housing government-sponsored entities (GSEs)),and the actual unpaid principal balance as well as the scheduled principal balance if the borrower pays according to the original terms of the loan.

3.2 Sample Construction

To identify the set of loans to study, we start with HMDA loan application data for 1998–2006. The HMDA data encompass nearly all mortgage lending activity each year, with some exceptions for small and rural institutions that do not fall under the mandatory filing requirements. Since the HMDA dataset includes the exact action taken and the date of that action for each application, we can determine whether a withdrawal or denial precedes the origination of a nearly identical loan by either the same or a different lender in the same U.S. Census tract. To develop our sample, we impose rather strict criteria on pairs of applications. These applications are allowed a difference in action date of no more than 60 days. They are required to match on applicant race, applicant sex, loan type (conventional or backed by the Federal Housing Administration (FHA) or administered by the U.S. Department of Veterans Affairs (VA)), loan purpose, Census tract, and occupancy type. We also match iteratively on the loan amount and applicant income, identifying and removing the sample pairs with no difference in amount or income and then increasing the window by $1,000 and matching again. We continue this process up to a maximum differential of $5,000.This matching process produces approximately 3.4 million unique pairs of loan applications. Each is denied at first, but is subsequently approved within a short time window and without substantial changes in application data.

To determine whether a relationship exists between the original (rejecting) and ultimate (approving) lenders, we match the HMDA lender identifier for each application to its highest holder (i.e., the highest bank holding company) in the BHC Structure data and Call Reports. Following this merge, the sample size declines to 1.35 million records, of which 244,621 are loans originated by the original rejecting institution or lenders affiliated with it (i.e., "steered").[10]

Because HMDA data do not include information on key risk characteristics of the borrower (such as the FICO score), loan terms, or loan performance, we match the originated loan in each pair of applications to mortgage-level data from McDash, which collect loan characteristics at origination from mortgage servicers. We then track the performance of these loans over time. The approved HMDA loan applications in our sample are matched to the mortgage-level data on the origination date, zip code, loan amount, loan type, loan purpose, occupancy type, and lien. This step substantially reduces the sample size, as McDash data do not have universal coverage, and mortgage servicer data (particularly information on loan origination dates) may not coincide with the regulator-collected data. Moreover, as the servicer data are concentrated in the latter part of our HMDA sample, the merged dataset

[10]Due to proprietary data restrictions, the process of merging HMDA and mortgage servicers' data requires replacing lender identifiers with randomly generated numbers. Thus, while the resulting analysis can incorporate lender-fixed effects, including lender-specific characteristics is not feasible.

becomes heavily weighted toward the 2003–2006 period (over 98% of all observations). We end up with 303,368 unique loan originations, of which 90,349 fit the definition of a "steered" transaction.

Next, we create two control samples (our non-steered sample). Both control groups consist of borrowers whose applications were also initially denied (potentially in an attempt to steer) but then approved within a short time by another lender not affiliated with the holding company that originally denied the loan. The samples differ in the technique used to match them to the steered sample.

The first control sample is a propensity-score matched (PSM) sample. Specifically, we perform a nearest-neighbor propensity score match, with each loan in the steered sample cutoff matched with replacement to a similar non-steered loan. The match criterion is the conditional treatment probability from a logit model, where the independent variables include the log income, the log home value, FICO score at origination, and the loan-to-value (LTV) ratio at origination. We require the potential non-steered loans to be in the same state, originated within 90 days, be issued for the same purpose (purchase or refi), have the same occupancy status (owner or investor), and be of the same type (conventional or FHA) as a given steered loan. From the resulting sample of potential controls, we choose the loan with the smallest difference in the propensity score, subject to an absolute threshold of 0.05. The resulting PSM sample contains 71,682 steered loans and an equivalent number of non-steered loans.[11]

The second control group is a strict-matched (SM) sample based on each characteristic.

[11]The more lenient PSM approach generates a larger sample but also increases the possibility of pairwise mismatches in steered and non-steered loans.

That is, for each steered loan, we find a non-steered counterpart that is very close in each of the following: applicant income, loan amount, FICO score, LTV ratio, and origination date, while matching exactly on loan purpose, loan type, occupancy type, and state. We require that the applicant's income and loan amount be within 25%, the FICO score to be within 25 points, the LTV ratio to be within 5 percentage points, and the origination date to be within 90 days. Not surprisingly, this approach results in a smaller final sample of 13,252 steered loans and 13,252 non-steered loans.

In Table 1, we also present t-tests for differences in means between groups. Ideally, we would have non-significant t-statistics for differences of each variable used in matching (the first seven variables). However, some differences are significant. In the propensity-score matched sample, FICO, LTV, and loan amounts are higher for the steered group. In the strict-matched sample, steered borrowers have higher incomes and loan amounts. While these differences are statistically significant and point to less-than-perfect matching, there are some mitigating aspects. First, some of the significant differences (e.g., FICO score) are economically negligible. Second, the steered and non-steered groups are different along different dimensions across the two matching techniques, yet the empirical results shown later are very similar. Third, the direction of the biases varies; for some variables, the steered borrowers are more leveraged or borrow larger amounts, while other variables indicate that they may be more financially stable, e.g., have higher income.

In addition to the data sources discussed above, we use the CoreLogic Home Price Index (HPI) to compute local changes in home prices. HPI data are available at the zip code level for 57.3% of the U.S. population. For observations for which zip-code-level data are unavailable, we use data at the core-based statistical area (CBSA) level, which are available for 83.9% of the U.S. population. Finally, we use the 2000 Census to identify census tracts in the low-to-moderate income (LMI) category, defined as those tracts in which the median family income is less than 80% of the area median income.

3.3 Descriptive Statistics

Table 1 presents summary statistics for the resulting pairs of steered and non-steered samples. The left-hand panel presents characteristics of the propensity score matching approach, and the right-hand panel is based on the strict matching approach.

The summary statistics show that the propensity-score matching procedure matched steered and non-steered observations well. By construction, this sample is designed to minimize the joint differences on a limited set of observable characteristics. Yet, the summary statistics for the propensity-score matched sample displayed in the upper left-hand panel of Table 1 suggest that the means and standard deviations of each continuous variable used in PSM are very similar for the steered and non-steered samples. We note that the average FICO score in our sample is around 710, and the average first-lien LTV ratio at origination is under 70%. In other words, the borrowers in our sample do not match the profile of a subprime borrower purchasing (or refinancing) their home with the minimum amount of equity possible. Over 80% of mortgages in the PSM sample are for owner-occupied properties, and most (59%) are used for home purchases.

However, achieving a tight covariate balance in observables through matching still produces considerable variation in the means of the outcome variables, listed in the middle panel of Table 1. The steering hypothesis suggests that the "steered" group is charged a

Table 1. Summary Statistics

The table provides summary statistics for the analysis used in the study. The first sample is based on a propensity-matching algorithm, and the second sample is based on strict matching criteria. See Section 3 for details on data sources and sample construction. Data sources: Home Mortgage Disclosure Act (HMDA), 1998–2006; McDash Analytics; CoreLogic. Variable definitions are provided in Appendix A.

	Propensity Score Matching					Strict Matching				
	Steered		Non-Steered			Steered		Non-Steered		
Variables	$N = 71,682$		$N = 71,682$			$N = 13,252$		$N = 13,252$		
	Mean	StDev	Mean	StDev	t-Diff	Mean	StDev	Mean	StDev	t-Diff
<u>Matching variables</u>										
FICO score	711.2	49.0	708.7	59.6	8.7	709.2	51.8	709.0	52.5	0.3
LTV ratio (%)	68.8	21.6	65.8	22.2	26.5	70.7	20.4	70.8	20.3	−0.5
Borrower income ($1,000s)	124.5	97.2	124.8	100.7	−0.7	83.5	74.3	74.7	51.5	11.2
Loan amount ($1,000s)	277.2	205.1	262.7	199.9	13.6	185.1	139.8	177.5	132.2	4.5
I(Refinancing)	0.41	0.49	0.41	0.49	0.0	0.58	0.49	0.58	0.49	0.0
I(Owner-occupied)	0.81	0.39	0.81	0.39	0.0	0.95	0.22	0.95	0.22	0.0
I(Conventional (non-FHA))	1.00	0.07	1.00	0.07	0.0	0.99	0.08	0.99	0.08	0.0
<u>Outcome variables of interest</u>										
Initial interest rate (%)	6.96	1.32	6.59	1.98	42.3	6.73	1.35	6.44	1.58	15.9
90-day delinquency w/ 2 years	0.063	0.243	0.077	0.266	−10.4	0.043	0.202	0.048	0.213	−1.9
I(Interest only)	0.32	0.47	0.16	0.37	69.2	0.27	0.45	0.09	0.29	39.0
I(Option ARM)	0.38	0.49	0.16	0.37	96.3	0.27	0.44	0.08	0.27	40.7
I(Pre-payment penalty)	0.41	0.49	0.20	0.40	89.0	0.28	0.45	0.15	0.36	26.6
I(No/low documentation)	0.82	0.39	0.67	0.47	64.0	0.80	0.40	0.72	0.45	15.3
Fixed rate term (months)	75.7	99.9	204.0	149.9	−149.9	112.5	126.5	241.6	138.7	−79.2
Mortgage maturity (months)	340.1	66.4	339.8	68.9	0.8	333.2	68.4	328.8	72.9	5.1
I(Portfolio loan)	0.01	0.11	0.17	0.38	−109.9	0.04	0.20	0.16	0.36	−31.6
I(GSE securitization)	0.29	0.45	0.38	0.48	−36.6	0.44	0.50	0.54	0.50	−16.4
I(Private-label securitization)	0.70	0.46	0.44	0.50	100.6	0.52	0.50	0.30	0.46	36.8
<u>Other covariates</u>										
ΔHPI 12 months pre-origination	0.140	0.104	0.139	0.106	1.8	0.109	0.096	0.107	0.095	2.2
I(African American)	0.06	0.23	0.06	0.23	1.2	0.06	0.24	0.06	0.25	−1.7
I(Hispanic)	0.17	0.38	0.15	0.36	10.3	0.12	0.33	0.13	0.33	−1.5
I(Female)	0.32	0.47	0.25	0.43	30.8	0.34	0.47	0.26	0.44	13.2
I(No co-signer)	0.68	0.47	0.57	0.50	43.7	0.69	0.46	0.57	0.50	20.9
I(Low/moderate income tract)	0.30	0.46	0.27	0.44	13.9	0.31	0.46	0.30	0.46	3.2

higher interest rate and has better ex-post credit quality than the control group. Indeed, we see that borrowers in this group have higher average interest rates (6.96% versus 6.59%), while experiencing lower unconditional average rates of default (6.3% versus 7.7%).[12] These

[12]The initial or first observed APR is the interest rate reported six months after the loan was originated. This lag allows us to avoid capturing initial teaser rates commonly offered on certain loan contracts, which typically last only one month.

differences are statistically as well as economically significant. Furthermore, we also observe sizable differences between the two groups in propensities to originate loans with certain contract features. A much higher fraction of the steered group loans are option ARM (38% versus 16%) or interest-only mortgages (32% versus 16%) or carry prepayment penalties (41% versus 20%).

For the strict-matched sample, the findings are fairly similar, although the resulting sample is much smaller. As with the propensity-score matched sample, the key covariates are closely matched between the steered and non-steered samples. The comparison of outcome variables between the groups is also similar to that in the strict-matched sample. The steered group has a higher average interest rate, lower realized delinquency rates, and a higher likelihood of high-margin mortgage products (option ARMs, IO loans, and loans with prepayment penalties). We note that relying on the strict-matching procedure generates a sample that contains a smaller fraction of non-amortizing mortgage contracts, such as interest-only loans or option ARMs. Amromin, Huang, Sialm, and Zhong (2018) show that such contracts were common among relatively high-income borrowers purchasing more expensive homes that defaulted at high rates. The difference in the relative performance of such contracts between the two sample design approaches accounts for relative differences in income, loan amount, and default rates in the left and right panels of Table 1. In Section 4.4, we discuss performance patterns in greater detail.

4 Empirical Results

4.1 Who Is Successfully Steered?

We begin the analysis by examining demographic characteristics of borrowers who stayed with the same lender relative to borrowers who obtained their loans from a new lender following the initial rejection. We rely on (partial) demographic information and precise geographic location captured in HMDA to determine which borrowers were more likely to be steered. In particular, we can use data on the borrower's gender, their identification as African American or Hispanic, an indicator of not having a co-applicant, and an indicator of a loan secured by a property in a low- or moderate-income (LMI) census tract.[13] Under the null hypothesis that steered borrowers are taking an inferior product relative to what they can get otherwise, we expect that borrowers who stayed with the original lenders share characteristics linked to lower levels of financial sophistication.

The regressions in this subsection use the following specification:

$$\begin{aligned} I(SteeredBorrower)_i &= \alpha + \beta Demographics_i + \delta MortgageControls_i \\ &\quad + \theta MarketControls_i + \gamma FixedEffects_i + \varepsilon_i. \end{aligned} \tag{1}$$

We start with a set of steered and PSM-matched non-steered loans. By construction, this set is evenly split, and each loan pair is closely matched on key loan and borrower

[13] Before 2004, HMDA required respondents to choose among six racial or ethnic classifications. In 2004, the reporting rules separated questions on ethnicity (Hispanic or non-Hispanic) and race (white, African American, Asian, American Indian and Alaska Native, Hawaiian or other Pacific Islander). This reporting change creates potential problems with making race and ethnicity classifications consistent over the two periods. A related problem arises with determining race and ethnicity in records where either of the two fields is missing. We follow the (Avery, Brevoort, and Canner, 2007, pp. 361–362) approach to addressing this issue.

characteristics. We estimate the likelihood of being steered as a function of HMDA variables, absorbing a set of fixed effects as in the earlier tables. Our preferred method employs the linear probability model, given the large number of fixed effects in some specifications.

The OLS results are shown in Table 2. Starting with Panel A, Column 1, we find that all else equal, Hispanic applicants had a somewhat higher propensity to be steered (with no apparent effect for African American applicants). Female applicants and applicants who did not have a co-borrower were much more likely to be steered toward more expensive loans. The magnitudes of the estimated coefficients are on the order of 0.03–0.10, suggesting, for instance, that borrowers with no co-signers are up to 10% more likely to be steered. Column 2 introduces controls for key mortgage characteristics observable at the time of application: FICO score and estimated LTV bins, and an indicator of whether a loan is a refinancing of an existing mortgage. The introduction of mortgage controls preserves the magnitudes and statistical significance of demographic variables while also amplifying the estimated effect of the indicator of the property being in a low to moderate income (LMI) Census tract and making it statistically significant at the 10% level (p-value of 0.066).

In Column 3, we introduce a control for recent home price appreciation, measured as price change at the zip code (where available) or CBSA level over the preceding 12 months. Past price growth does not appear to affect the likelihood of steering. Finally, Column 4 introduces a measure of lender concentration as an additional control. This measure, the share of loans held by the top four lenders within a county (i.e., county-level top-4 lender share), follows the insight of Buchak and Jørring (2021) that in areas with higher lender concentration, borrowers face stricter lending standards (e.g., higher rejection rates) and higher upfront fees. We similarly find that mortgages originated in less competitive locales are substantially more likely (p-value of 0.054) to end up in the steered group. This result is consistent with the hypothesis that fewer outside options gives the original lender greater power to steer borrowers into more profitable contracts.

In Panel B of Table 2, we present the results from the strict-matching procedure. Here, the results on the dummies for female applicants, no co-signer, and low/moderate income Census tracts are as before. However, the results for minorities are different: we find no significant results for Hispanic or African American applicants.

These results broadly align with existing empirical evidence on which population subgroups display the lowest levels of financial literacy. A literature survey by Lusardi and Mitchell (2014) highlights substantial shortfalls in financial literacy among the young and the old, women, minorities, the least educated, and those with lower incomes. Consistent with these results, a recent study by the Urban Institute finds that mortgage applications by single women are more likely to be denied.[14] These results also resonate with findings from Morton, Zettelmeyer, and Silva-Risso (2003) that women, minorities, and the elderly pay more, on average, for cars. By and large, these are the groups identified as more likely to be steered by their mortgage lender.

Overall, the results in Table 2 support the mechanism we proposed earlier in Section 2.2. Specifically, lenders are more likely to steer applicants with lower levels of financial sophistication to minimize the risk that rejected but qualified borrowers shop around and end up with a different lender. Furthermore, existing research suggests that these populations might be less informed about credit markets in general, making them potentially vulnerable

[14]Goodman, Laurie, Jun Zhu, and Bing Bai, We're Still Shortchanging Women When It Comes to Mortgages, *Urban Wire*, 8 September 2016.

Table 2. Borrower Characteristics and Likelihood of Steering

The table presents regressions of the same lender indicator on borrower personal and area characteristics and various fixed effects described in the text. The sample is constructed using propensity-score matching (Panel A) and a strict-matching algorithm (Panel B). All regressions are OLS regressions. Standard errors are double-clustered by calendar quarter and state of origination. Data sources: Home Mortgage Disclosure Act (HMDA), 1998–2006; U.S. Census. t-statistics are reported in brackets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. See Section 3 for details on data sources and sample construction. Variable definitions are provided in Appendix A.

Panel A. Propensity-Score Matched Sample

Dependent variable:	Borrower Steered (0/1)			
	(1)	(2)	(3)	(4)
African American	−0.009	−0.003	−0.004	−0.002
	[−0.53]	[−0.16]	[−0.26]	[−0.13]
Hispanic	0.031**	0.035***	0.035***	0.035***
	[2.56]	[2.88]	[2.77]	[2.80]
Female	0.062***	0.062***	0.063***	0.061***
	[11.12]	[11.89]	[12.84]	[12.33]
No co-signer	0.102***	0.102***	0.104***	0.105***
	[12.08]	[10.75]	[10.02]	[9.69]
Low/moderate income tract	0.013	0.019*	0.018*	0.019*
	[1.40]	[1.88]	[1.72]	[1.76]
Refinancing		0.022***	0.022***	0.022***
		[5.58]	[6.20]	[6.42]
HPI growth previous year			−0.066	−0.051
			[−1.34]	[−1.08]
Top 4 share				0.179*
				[1.97]
Mortgage characteristics	No	Yes	Yes	Yes
State × Qtr fixed effects	Yes	Yes	Yes	Yes
No. of obs.	133,756	133,756	127,260	124,363
Adj. R^2	0.024	0.031	0.032	0.034

to lender steering practices (Berndt et al., 2016).

Table 2. Borrower Characteristics and Likelihood of Steering (Cont.)

Panel B. Strict-Matched Sample

Dependent variable:	I(Steered Borrower)			
	(1)	(2)	(3)	(4)
I(African American)	−0.054**	−0.049***	−0.018	−0.110*
	[−2.22]	[−2.80]	[−1.28]	[−1.70]
I(Hispanic)	−0.011	−0.016	0.010	−0.034
	[−0.60]	[−0.64]	[0.81]	[−0.50]
I(Female)	0.051***	0.031***	0.018***	0.041
	[14.49]	[4.73]	[3.58]	[1.47]
I(No co-signer)	0.122***	0.046***	−0.007	0.083***
	[8.86]	[5.26]	[−0.69]	[4.28]
I(Low/moderate income)	0.043***	0.019*	−0.001	0.047
	[4.27]	[1.84]	[−0.12]	[1.40]
Borrower characteristics	No	Yes	Yes	Yes
Mortgage characteristics	No	Yes	Yes	Yes
State × Qtr fixed effects	No	No	Yes	No
Matched pair fixed effects	No	No	No	Yes
No. of obs.	24,047	17,618	17,618	17,618
Adj. R^2	0.021	0.027	0.066	−0.131

4.2 Regression Specification

Once we identify a sample of steered borrowers (i.e., those whose application is approved by the original lender or its affiliate), we conduct a cross-sectional regression analysis evaluating borrower and loan contract characteristics to determine whether that group of borrowers differs from the control group. In this analysis, we control for a number of factors, including various fixed effects. The regression results reported in most tables are based on the following specification:

$$\begin{aligned} Response_i \quad &= \quad \alpha + \beta I(SteeredBorrower)_i + \delta BorrowerControls_i \\ &\quad + \theta MortgageControls_i + \gamma FixedEffects_i + \varepsilon_i, \end{aligned} \tag{2}$$

where $Response$ is the loan-level response variable, such as the interest rate on mortgages, default status of loans, etc.; $I(SteeredBorrower)$ is an indicator variable for whether a loan was steered (or, equivalently, whether the eventual lender is the same as the original one); $BorrowerControls$ are a set of borrower characteristics, including logged borrower income and the FICO credit score of the borrower (splined into four ranges: 621–660, 661–720, 721–760, and > 760). $MortgageControls$ is a set of loan-specific characteristics that includes the following variables: logged loan amount, LTV ratio at origination (splined into 80%–89%, 90%–99%, and $\geq$ 100%), a refi indicator, a prepayment penalty indicator, and an owner-occupier indicator. In addition, we control for the 12-month change in the zip code–level house price index. Appendix A provides detailed variable descriptions. $FixedEffects_i$ account for either fixed effects for the state interacted with calendar quarter, or fixed effects for each pair of matched steered and non-steered loans. We double-cluster standard errors in all regressions at the state and calendar quarter levels. In most tables, we present the propensity-score matched sample forms in Panel A and the regression results for the strict-matching approach in Panel B.

4.3 Characteristics of Steered Mortgages

To further understand whether steered borrowers took out inferior contracts, we examine characteristics of their mortgage products and compare them to those taken by borrowers who went to new lenders.

4.3.1 Interest Rate

A central part of the steering hypothesis is that steered borrowers are led to mortgage products that are more profitable to the originator. The most direct measure of loan profitability is the risk-adjusted interest rate.

In Table 3, Panel A, we report the results of regressing the mortgage APR on the variable of interest—the steered indicator—as well the other control variables and fixed effects as described in Section 4.2, using the propensity-score matched sample. The regressions show that steered borrowers pay up to 72 basis points higher interest rates than non-steered borrowers.

The most parsimonious specification in Column 1 of Table 3, Panel A, indicates an estimated interest rate differential of 39 basis points after soaking up the effects of loan origination quarter and property location (state). Since mortgages of different contractual forms have substantial variation in their interest rate—owing to the term premium and the frequency of interest rate resets—it is especially important to account for loan characteristics. When we add such controls in Column 2, the estimated interest rate differential nearly doubles to 72 basis points. The magnitude of the effect is large both in absolute terms and relative to the mean interest rate of 6.59% in the control group. Columns 3 and 4 provide a tighter specification that includes pairwise fixed effects and produces an estimated differential of 69 basis points. The results in Panel B, which uses the strict-matched sample, are of similar magnitude (up to 54 basis points) .

Table 3. Interest Rate Paid, by Steered Status

The table presents regressions of the initial interest rate on an indicator of steering, as well as a variety of fixed effects and borrower and mortgage characteristics. Borrower and mortgage controls include logged borrower income, the FICO credit score of the borrower (splined into four ranges: 621–660, 661–720, 721–760, and > 760), the logged loan amount, the LTV ratio at origination (splined into 80%–89%, 90%–99%, and ≥ 100%), a refi indicator, and an owner-occupier indicator. All regressions are OLS regressions. Standard errors are double-clustered by calendar quarter and state of origination. Data sources: Home Mortgage Disclosure Act (HMDA), 1998–2006; U.S. Census. *t*-statistics are reported in brackets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. See Section 3 for details on data sources and sample construction. Variable definitions are provided in Appendix A.

Panel A. Propensity-Score Matched Sample

Dependent variable:	Initial Interest Rate (%)			
Mean of control sample:	6.79			
	1	2	3	4
I(Steered borrower)	0.387***	0.721***	0.376*	0.692***
	[2.60]	[5.07]	[1.84]	[3.47]
Borrower characteristics	No	Yes	No	Yes
Mortgage characteristics	No	Yes	No	Yes
State × Qtr fixed effects	Yes	Yes	No	No
Matched pair fixed effects	No	No	Yes	Yes
No. of obs.	143,364	140,072	143,364	140,072
Adj. R^2	0.165	0.460	0.152	0.447

Panel B. Strict-Matched Sample

Dependent variable:	Initial Interest Rate (%)			
Mean of control sample:	6.44			
	1	2	3	4
I(Steered borrower)	0.288***	0.540***	0.288**	0.496**
	[2.89]	[4.29]	[2.17]	[2.32]
Borrower characteristics	No	Yes	No	Yes
Mortgage characteristics	No	Yes	No	Yes
State × Qtr fixed effects	Yes	Yes	No	No
Matched pair fixed effects	No	No	Yes	Yes
No. of obs.	26,503	19,758	26,503	19,758
Adj. R^2	0.198	0.428	0.405	0.452

4.3.2 Product Type

Next, we examine the type of mortgages and mortgage characteristics taken by the borrowers categorized as steered, compared to similar borrowers in the non-steered group.

During the market run-up period of the early 2000s, many banks moved from a model of originate-to-hold to originate-to-distribute (Purnanandam, 2011; Bord and Santos, 2012). That is, lenders were interested in originating loans that they could sell to Wall Street firms for a fee instead of quality loans that they could hold on their balance sheets (Keys et al., 2010). Thus, lenders had a strong incentive to convince borrowers to take mortgages that generate high fees (Kolb, 2011).

We focus on the following mortgage types known for their high profit margins in the residential mortgage industry (Engel and McCoy, 2001): interest-only mortgages, option ARMs (adjustable rate mortgages), mortgages with prepayment penalties, and no/low documentation mortgages. These features are not mutually exclusive except for interest-only mortgages and option ARMs. These mortgage products were suited to an economic environment in which the common wisdom was that property prices always increase (Shiller, 2017). Therefore, it made sense to take mortgages that offered minimal payment through flexible or no amortization, or mortgages that offered teaser rates in the first few years (for instance, more than 80% of option ARMs in our sample came with very low initial teaser rates). The common strategy to avoid the reset of mortgage rates following the expiration of the teaser rates or onset of regular amortization was to refinance the mortgage,[15] which is, of course, advantageous to lenders who collect origination fees.

Interest-only loans are loans in which the borrower does not repay any of the principal amount for several years, thus lowering the monthly payment for a certain period. Option ARM mortgages are mortgages in which the borrower can decide about the monthly payment, subject to some minimum payment requirement. The minimum payment is typically set

[15] E.g., Damon Darlin, Keep Eyes Fixed on Your Variable-Rate Mortgage, *New York Times*, July 15, 2006.

below the interest servicing requirements, leading to negative amortization, i.e., borrowers accruing principal instead of repaying it. Lenders usually discontinue the optionality of the mortgage after a pre-specified period, typically five years or less. At that point, payments are recalculated to allow full amortization over the remaining term (25 years $= 30 - 5$ in the example above). The optionality may also be terminated when the principal reaches a certain level, typically 110% or 125% of the original loan amount. Borrowers who take out mortgages with prepayment penalties must pay a penalty if they refinance the loan (repay the principal) earlier than scheduled. When they exist, prepayment penalties are typically set between 1 and 5 years. No/low documentation mortgages (also called stated-income mortgages) are mortgages in which borrowers must provide either no or limited documentation of their income.

We learn about the profitability of loan products from conversations with lenders in the industry. Written sources confirm that these loan types are profitable. For example, Bowen, Jollineau, and Lougee (2014) cites the comments of the CEO of Washington Mutual (the largest mortgage originator at the time) from the 2004/Q3 conference call in which he said that the company focused on high-margin mortgage products such as option ARM mortgages. A similar message is echoed in an article about competition in the mortgage market.[16] Mortgages with prepayment penalties were Countrywide's favorite product because "...investors who bought securities backed by the mortgages were willing to pay more for loans with prepayment penalties...."[17] Steven Krystofiak, president of the Mortgage Brokers Association for Responsible Lending, an advocacy group protecting consumers and

[16]Ruth Simon and James R. Hagerty, Countrywide's New Scare, *Wall Street Journal*, October 24, 2007. Available at: http://www.wsj.com/articles/SB119318489086669202.

[17]Gretchen Morgenson, Inside the Countrywide Lending Spree, *New York Times*, August 26, 2007. Available at: http://www.nytimes.com/2007/08/26/business/yourmoney/26country.html.

the loan industry from outlandish and counterproductive loan programs, testified in 2006 to the Federal Reserve Board. He argued that banks originated more stated-income (i.e., no/low documentation) mortgages because they were selling them to securitizers for sizeable profit given the strong demand from Wall Street.[18]

Results from tests for these mortgage types are provided in Table 4. Both Panels A and B show results for eight regressions, where the dependent variables are indicators of whether the type of the mortgage is interest-only (Columns 1–2), is an option ARM (Columns 3–4), has a prepayment penalty (Columns 5–6), or requires no/low documentation (Colums 7–8). As in the previous table, the specifications vary in their configuration of fixed effects. All specifications include controls for borrower and mortgage characteristics. Panel A presents results from the propensity-score matched sample, and Panel B presents results from the strict-matched sample.

The results uniformly show that borrowers from affiliated lenders are more likely to take mortgages with features considered highly profitable for lenders in the mortgage industry. The odd-numbered columns in Panel A include state and quarter fixed effects. The results in these columns indicate that relative to the overall sample mean, steered borrowers are more than twice as likely to take option ARM mortgages or mortgages with prepayment penalties, 85% more likely to have interest-only mortgages (IOs), and 20% more likely to have no- or low-documentation mortgages. The results in the even-numbered columns, which use matched-pair fixed effects, are almost identical. The results in Panel B are even stronger due to the lower base rate.

[18] Available at: `http://www.federalreserve.gov/secrs/2006/august/20060801/op-1253/op-1253_3_1.pdf`.

Table 4. Mortgage Products, by Steered Status

The table presents regressions of indicators of mortgage type (interest-only, option ARM, prepayment penalty, and no/low documentation) on our steering indicator, as well as a variety of fixed effects and borrower and mortgage characteristics. Borrower and mortgage controls include the logged borrower income, the FICO credit score of the borrower (splined into the four ranges: 621–660, 661–720, 721–760, and > 760), the logged loan amount, LTV ratio at origination (splined into 80%–89%, 90%–99%, and $\geq 100\%$), a refi indicator, and an owner-occupier indicator. All regressions are OLS regressions. Standard errors are double-clustered by calendar month and state of origination. Data sources: Home Mortgage Disclosure Act (HMDA), 1998–2006; U.S. Census. t-statistics are reported in brackets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. See Section 3 for details on data sources and sample construction. Variable definitions are provided in Appendix A.

Panel A. Propensity-Score Matched Sample

Dependent variable:	I(Interest Only)		I(Option ARM)		I(Prepayment Penalty)		I(No/Low Doc)	
Mean of control sample:	0.165		0.161		0.198		0.671	
	1	2	3	4	5	6	7	8
I(Steered borrower)	0.141***	0.136***	0.219***	0.221***	0.266***	0.262***	0.129***	0.125***
	[6.13]	[4.11]	[5.30]	[3.99]	[5.60]	[4.03]	[8.70]	[6.15]
Borrower and mortgage characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State × Qtr fixed effects	Yes	No	Yes	No	Yes	No	Yes	No
Matched pair fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
No. of obs.	143,364	143,364	143,364	143,364	143,364	143,364	143,364	143,364
Adj. R^2	0.158	0.144	0.241	0.204	0.263	0.218	0.097	0.085

Panel B. Strict-Matched Sample

Dependent variable:	I(Interest Only)		I(Option ARM)		I(Prepayment Penalty)		I(No/Low Doc)	
Mean of control sample:	0.093		0.082		0.148		0.719	
	1	2	3	4	(5)	6	7	8
I(Steered borrower)	0.174***	0.184***	0.195***	0.195***	0.190***	0.197**	0.135***	0.139***
	[3.82]	[2.55]	[4.36]	[2.87]	[8.14]	[6.05]	[7.41]	[5.39]
Borrower and mortgage characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State × Qtr fixed effects	Yes	No	Yes	No	Yes	No	Yes	No
Matched pair fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
No. of obs.	20,164	20,164	20,164	20,164	20,164	20,164	20,164	20,164
Adj. R^2	0.235	0.182	0.208	0.170	0.163	0.150	0.068	0.037

4.3.3 Securitization

Most mortgage loans in our sample (99%) were originated between 2003 and 2006. During this period, lenders increasingly originated mortgages to sell them to investment banks, which, in turn, packaged them into private-label mortgage-backed securities for capital-market investors (Mayer et al., 2009; Nadauld and Sherlund, 2013). According to the sources cited in Section 4.3.2, mortgages with exotic features satisfied the demand from Wall Street: both the investment banks and the ultimate investors. This section explores whether steered mortgages were more likely to be sold to private market securitizers.

In Table 5, Panel A, we regress indicators for whether a mortgage was kept as a portfolio loan, securitized by a private market organization, or securitized by one of the government-sponsored entities (GSEs). Our results strongly indicate that the steered loans were much more likely to be funded through private-label securitizations than held on bank portfolios. The point estimates in Columns 1 and 2 show that steered loans are 47% (= 0.207/0.440) more likely to be sold into a private-label mortgage-backed securities pool relative to being held in a bank's own portfolio. The results in Columns 5 and 6 suggest no difference between steered and non-steered loans in their likelihood of being sold to GSEs. (Note that the three funding outlets are mutually exclusive alternatives, summing up to 1.) The results in Panel B (the strict-matched sample) show about half the magnitude compared with Panel A.

These results corroborate our conjecture that generating origination fees from selling mortgages to securitizers was the primary motivation for lenders to steer borrowers into exotic products.

4.4 The Cost of Predatory Lending: An Interplay between Refinancing and Defaulting

To examine the behavior of borrowers from affiliated lenders post-origination, we focus on two actions: refinancing and default. As shown earlier, many of the mortgage types that were sold to borrowers from affiliated lenders seemed affordable in the short term through

Table 5. Mortgage Allocation, by Steered Status

The table presents regressions of indicators for the allocations of mortgages to banks' portfolios, private securitizations, and public (GSE) securitizations on our steering indicator, as well as various fixed effects and borrower and mortgage characteristics. Borrower and mortgage controls include logged borrower income, the FICO credit score of the borrower (splined into four ranges: 621–660, 661–720, 721–760, and > 760), the logged loan amount, the LTV ratio at origination (splined into 80%–89%, 90%–99%, and ≥ 100%), an amortizing ARM indicator, an interest-only indicator, a refi indicator, a prepayment penalty indicator, an owner-occupier indicator, a conventional mortgage indicator, and a no/low-documentation indicator. All regressions are OLS regressions. Standard errors are double-clustered by calendar month and state of origination. Data sources: Home Mortgage Disclosure Act (HMDA), 1998–2006; U.S. Census. *t*-statistics are reported in brackets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. See Section 3 for details on data sources and sample construction. Variable definitions are provided in Appendix A.

Panel A. Propensity-Score Matched Sample

Dependent variable:	I(Portfolio Loan)		I(Private-Label Securitization)		I(GSE Securitization)	
Mean in the control sample:	0.17		0.44		0.38	
	1	2	3	4	5	6
I(Steered borrower)	−0.231***	−0.230***	0.207***	0.203***	0.025	0.028
	[−12.32]	[−8.12]	[6.13]	[4.16]	[0.91]	[0.76]
Borrower and mortgage characteristics	Yes	Yes	Yes	Yes	Yes	Yes
State × Qtr fixed effects	Yes	No	Yes	No	Yes	No
Matched pair fixed effects	No	Yes	No	Yes	No	Yes
No. of obs.	134,083	134,083	134,083	134,083	134,083	134,083
Adj. R^2	0.172	0.139	0.314	0.300	0.372	0.376

Panel B. Strict-Matched Sample

Dependent variable:	I(Portfolio Loan)		I(Private-Label Securitization)		I(GSE Securitization)	
Mean in the control sample:	0.16		0.54		0.30	
	1	2	3	4	5	6
I(Steered borrower)	−0.161***	−0.177***	0.123***	0.117**	0.040	0.063
	[−13.77]	[−7.60]	[4.02]	[2.44]	[1.36]	[1.39]
Borrower and mortgage characteristics	Yes	Yes	Yes	Yes	Yes	Yes
State × Qtr fixed effects	Yes	No	Yes	No	Yes	No
Matched pair fixed effects	No	Yes	No	Yes	No	Yes
No. of obs.	19,199	19,199	19,199	19,199	19,199	19,199
Adj. R^2	0.140	0.031	0.322	0.320	0.350	0.386

teaser rates, flexible payments, and zero or even negative amortization. This affordability, however, came at the potential cost of higher interest rates later, a jump in payments when accelerated amortization kicked in, and higher loan-to-value ratios. The common wisdom during the years we study was that one could always refinance the mortgage and thus avoid the cost of a nontraditional contract later.[19] This was true as long as home prices continued to increase (2002–2006), but became more difficult in 2007 and almost impossible in 2008. On the flip side, once refinancing was not possible during a period of falling house prices, borrowers from affiliated lenders with mortgages experiencing rising payments (e.g., due to the expiration of teaser rates and the onset of amortization) and larger balances relative to house value would be subject to high risk of default.

While contract form contributes to refinancing propensity, there is also a possibility that getting "stuck" with a lender, as is the case for steered originations, has an independent effect as well. We hypothesize that borrowers who are successfully steered remain more likely to be swayed by the same lender to engage in future refinancing transactions, particularly during period of rising home prices that created opportunities for one to cash out home equity.

To summarize, we anticipate that the steered and non-steered groups will behave differently regarding their refinancing and default propensities during the boom and bust phases of the housing cycle. In boom times, we expect refinancing activity to be higher for borrowers from affiliated lenders (i.e., steered borrowers), a difference that will diminish once the crisis hits. The default rate should exhibit the opposite pattern: the likelihood of default should be similar between steered and non-steered borrowers during boom times but should be materially higher during the crisis. The increased default rate during bad times manifests the costs of predatory lending.

[19]Demyanyk and Van Hemert (2011) document that 30% of alternative loan products were paid in full within the first year, and almost all were repaid in 3 years after origination.

We present the results in two ways. First, we discuss the raw data, presented in Figure 1 A and B. Graph 1A shows the quarterly refinancing rate from 2004 through 2011 for steered (solid line) and non-steered (dotted line) loans. The refinancing rates in each calendar quarter are computed relative to a set of mortgages that survived at the beginning of the quarter (i.e., were not refinanced and did not default). We observe a substantially higher propensity of steered loans to refinance from early 2005 through early 2007. Steered loans had about 50% higher quarterly refinancing rates during this period. However, this gap effectively evaporated as the housing bubble burst.

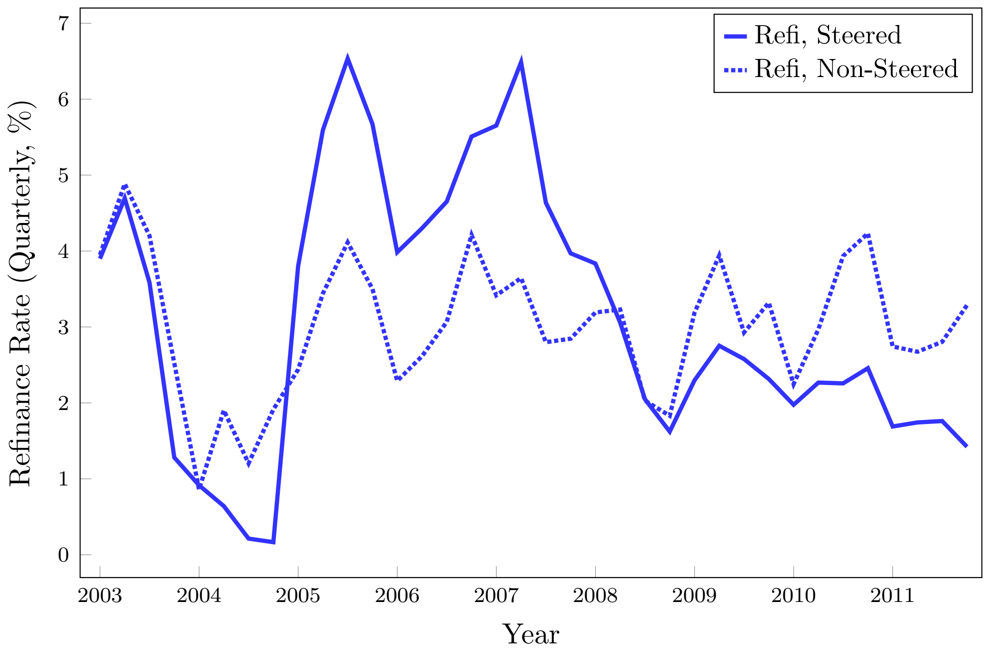
A similar analysis of default rates over time in Graph 1B shows them to be very similar for the two groups until early 2007. At that point—precisely when the propensity to refinance among steered borrowers slows dramatically—their default rates accelerate well past the also rising rates of the borrowers from affiliated lenders. The inverse relationship between the series in these two graphs illustrates the apparent tradeoff between the ability to refinance and mortgage default, which is more pronounced among the nontraditional mortgages of steered borrowers.

An alternative way to evaluate refinancing and default patterns is by focusing on origination cohorts, building on the insights of Demyanyk and Van Hemert (2011). While Figure 1, Graphs A and B display a clear pattern in calendar time, the sample comprises varying numbers of loans originating in different years under different market conditions. Hence, one might worry that secular changes in the prevalence of nontraditional mortgage contracts in different cohorts are driving the difference between the two groups. To check this possibility, we follow the Demyanyk and Van Hemert (2011) approach to show the refinancing and default rates over time for individual origination cohorts. These are broken into eight

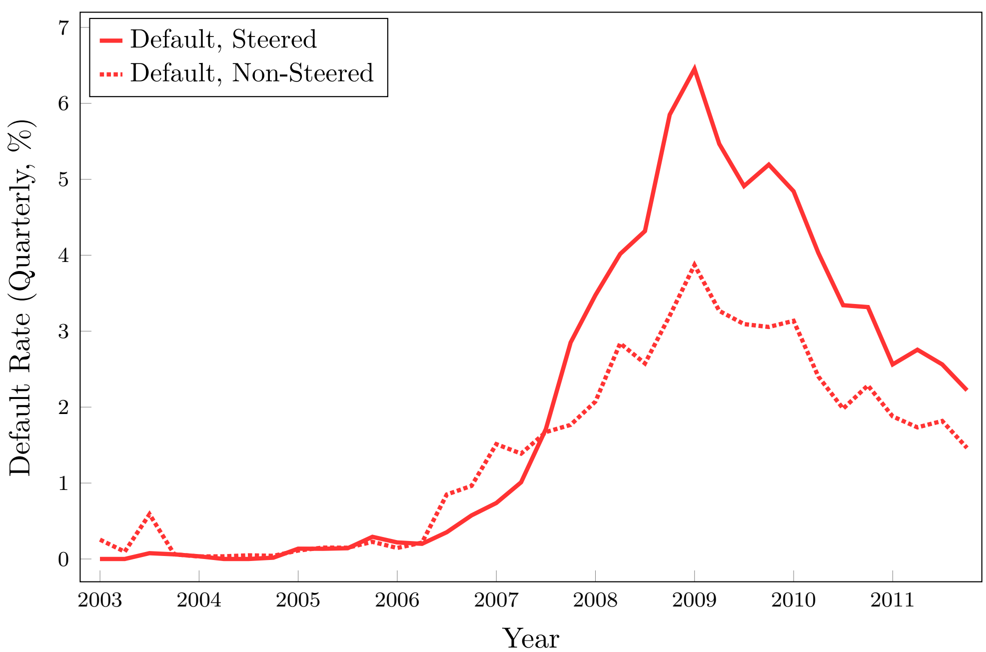
Figure 1. Quarterly Refinancing and Default Rates

This figure shows the quarterly refinancing and default rates from 2004 through 2011 for steered (solid line) and non-steered (dotted line) loans. The refinancing (default) rates in each calendar quarter are computed relative to a set of mortgages that survived at the beginning of the quarter (i.e., were not refinanced and did not default).

Graph A. Refinance Rate



Graph B. Default Rate



groups: steered and non-steered mortgages originated in each of the years 2003–2006. We plot the refinancing (default) rates in each origination cohort as shares of mortgages that survived at the beginning of the year (i.e., were not refinanced and did not default in prior years). Refinancing (default) rates of steered mortgages are presented with solid lines, while non-steered series are shown with dotted lines.

Graph A of Figure 2 shows that for almost all origination cohorts, refinancing activity is stronger for mortgages in the steered group. The gap in the refinancing rates between steered and non-steered groups is exceptionally high for 2005–2006. For instance, 27% of steered loans originating in 2005 that survived their first year were refinanced in 2006, compared to only 14% of non-steered loans. By 2007, however, the refinancing rates on remaining loans shrank dramatically for both groups—to 13% and 9%, respectively, nearly closing the gap.

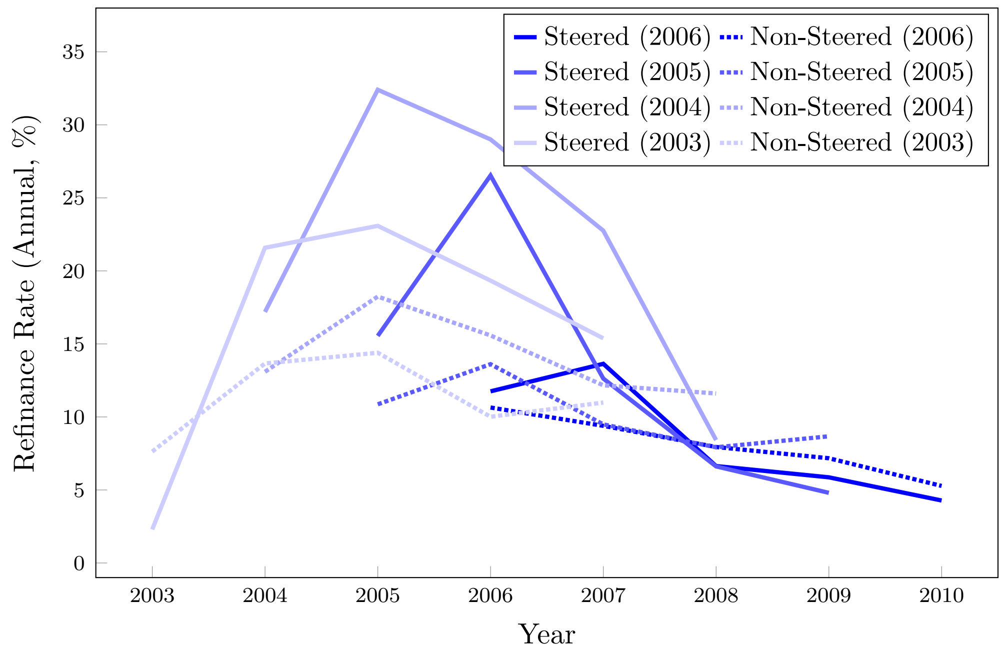
The cohort default rates in Graph B of Figure 2 also display a familiar pattern. Default rates on surviving loans jump dramatically in 2007–2008 for all origination cohorts. Within each cohort, the difference in the default rate between steered and non-steered loans, which was negligible in 2003–2005, starts opening up in 2006 and peaks in 2008, precisely at the same time when steered borrowers cannot refinance their mortgages. These graphs underscore the differences between the steered- and non-steered borrowers from affiliated lenders within each cohort, which became much more amplified during the time of falling home prices.

Finally, we present a similar analysis in a regression framework that accounts for time and cohort effects, as well as contract features. We transform our data to a panel dataset where each observation reflects a borrower–quarter. Borrowers can exit the sample if they defaulted (about 27% of the sample), refinanced (about 49% of the sample), or were transferred to a

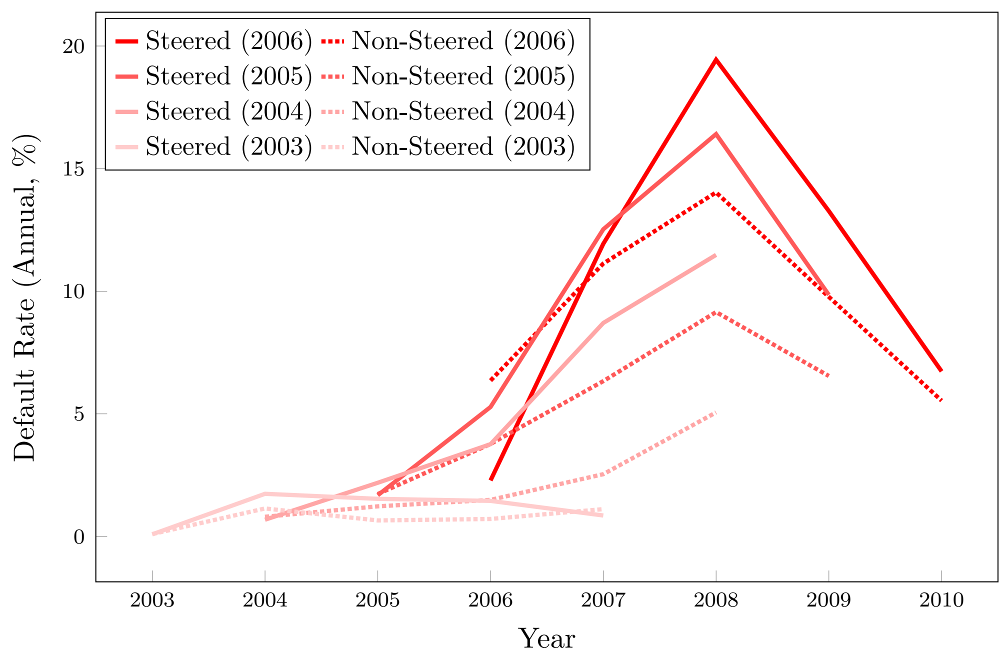
Figure 2. Refinancing and Default Rate, by Origination Cohort

This figure shows the quarterly refinancing and default rates from 2003 through 2011 for steered (solid line) and non-steered (dotted line) loans stratified by their year-of-origination cohort. The refinancing (default) rates in each calendar quarter are computed relative to a set of mortgages that survived at the beginning of the quarter (i.e., were not refinanced and did not default).

Graph A. Refinance, by Origination Cohort



Graph B. Default, by Origination Cohort



servicer that is not covered by McDash (only 2% of our sample). We are interested in exploring the timing of different exit events. We hypothesize that refinancing was the prevalent exit event when the real estate market boomed and that default was prevalent after house prices stopped increasing. Ferreira and Gyourko (2012) show that housing prices peaked in most neighborhoods between the second half of 2005 and the second half of 2007, with the greatest concentration in 2006. The differential hazard rates of default and refinancing for steered and non-steered groups represent our estimates of the effects of predatory lending. Specifically, we estimate the following econometric model:

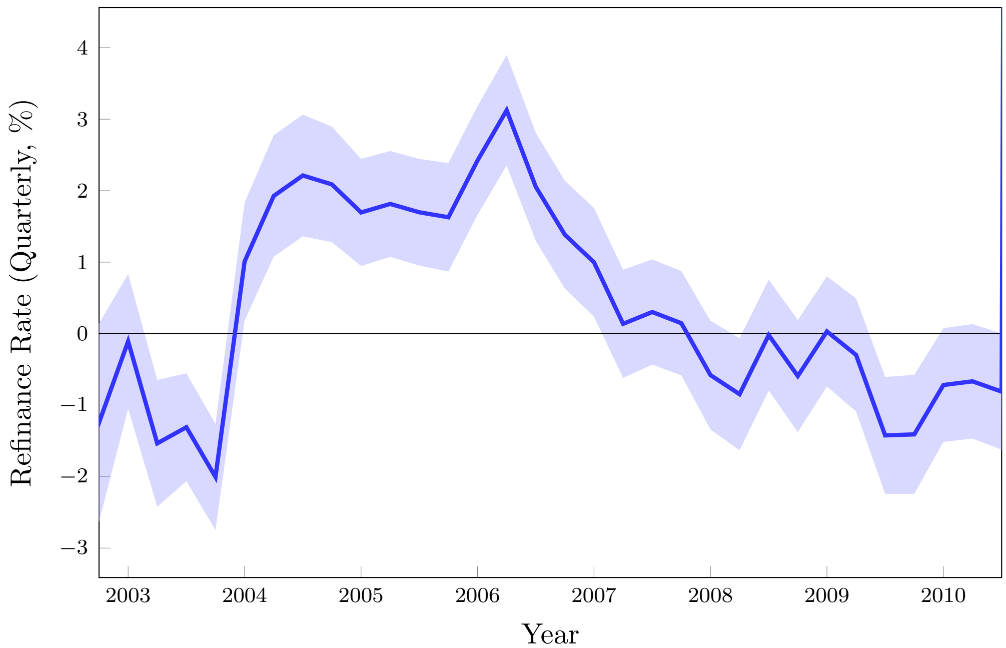
$$\begin{aligned} ExitEvent_{it} &= \alpha + \beta I(SteeredBorrower)_i + \sum_t \tau_t CalendarQuarter_t \\ &\quad + \sum_t \gamma_t I(SteeredBorrower)_i * CalendarQuarter_t \\ &\quad + \delta BorrowerControls_i + \theta MortgageControls_i + StateFE_i + \varepsilon_{it}. \end{aligned} \tag{3}$$

This specification controls for time and state fixed effects and the same array of borrower characteristics used in regressions in Tables 3–5. We further add 12-month zip code–level changes in house prices as they are germane to default and refinancing decisions and add more information to a set of time and state fixed effects. Because we are interested in isolating the effects of product differences and financial sophistication, we also add controls for contract form (i.e., indicators of non-amortizing contract types and prepayment penalties). We are interested in the series of estimated coefficients $(\beta + \gamma_t)$ for both refinancing and default hazards. These series, along with the estimated error bands, are plotted in Figure 3, Graphs A and B.

Figure 3. Refinancing and Default Rate, by Origination Cohort

This figure shows the difference in quarterly refinancing and default rates of steered and non-steered loans obtained from the regression analysis specified in equation (3) in the text. The shaded areas show the 95% confidence interval.

Graph A. Refinance Rate: Steered Minus Non-Steered Borrowers



Graph B. Default Rate: Steered Minus Non-Steered Borrowers

The regression results reaffirm observations using raw data and provide additional information about the magnitude of the effects. During the boom part of our sample, steered borrowers are more likely to refinance their mortgages, with conditional quarterly refinancing rates about two percentage points higher, on average (relative to the mean refinancing rate of 3.2% for non-steered borrowers). Once the real estate market stalls, the difference in the likelihood of refinancing collapses.

Default rates exhibit the reverse pattern. In the first half of the sample (2004 to early 2007), the default likelihood of steered borrowers is somewhat lower than that of non-steered borrowers. In later years, the quarterly default rates of the steered are nearly two percentage points above that of the non-steered group. This is similar in magnitude to the effect of predatory lending on default documented by Agarwal et al. (2014). This reversal in fortune coincides almost perfectly with the disappearance of higher refinancing rates by steered borrowers.

Importantly, these patterns are not informative about optimal refinancing behavior but rather about the constraints faced by steered borrowers during the time period in this study. For instance, Agarwal, Rosen, and Yao (2016), Keys et al. (2016), and Jørring (2024) find that less financially sophisticated borrowers (whom we argue are also more likely to be steered) are *less* likely to refinance when it is optimal for them to do so. However, these papers evaluated borrower behavior during the 2010–2012 period, when housing prices were slowly recovering and mortgage rates were still low. Borrowers were becoming newly eligible for non-HARP refinancing as their LTVs improved, and most transactions had no equity extraction. Thus, borrowers in that time period could decide when to refinance to improve their cash flow.

In contrast, for the borrowers that we study in 2005–2007, refinancing is not an option to improve their cash flow; it is either (a) the *only* way possible to avoid default as payments reset following the expiration of teaser interest rates or onset of amortization, or (b) a way to pump out equity from their (still appreciating) house. Our results also suggest that even after controlling for contract form, the steered borrowers of the boom years were more likely to stay on the refinancing train, presumably to extract equity. But once the refinancing opportunities ran out with house prices dropping, they simply defaulted.

5 Conclusion

The housing boom of the 2000s saw frequent accusations of predatory lending. In this study, we provide micro-level evidence about the process of predatory lending. Our results are consistent with a narrative in which lenders engage in the origination-to-distribute model (Purnanandam, 2011) and thus attempt to steer borrowers into products that yield greater origination fees. While these products appear to be affordable in the short run, they expose the borrowers to risks in the long run.

Aggressive selling practices are generally unobservable to us as they occur at the point of sale: we typically do not know the consumer's true needs or which product the loan officer offers. We only observe the mortgage product that the consumer eventually enters. Therefore, in this study, our focus is on a very specific business practice in which steering activity is potentially visible—when applicants are rejected by a lender but are then quickly approved by either the same or a different lender without any changes in their application.

Our results suggest that borrowers who stayed with the original rejecting lender (or one of its affiliates) appear to have taken mortgages that have features of predatory loans (high interest, no/low documentation, and no/low amortization). Borrowers who were steered to expensive mortgage products tend to come from populations that are considered in the literature to be more vulnerable: females, singles (no co-signers), and people from low-income neighborhoods. We confirm that these loans are likely to be predatory as their characteristics and features match those described by the literature: high interest and exotic features (prepayment penalties, no/low amortization, and no/low documentation). Furthermore, we find that these mortgages were significantly more likely to end up in private securitization pools, consistent with claims of legal scholars that the demand from investors bolstered predatory lending in the early 2000s.

When examining the behavior of borrowers and the performance of mortgages, we document that borrowers stayed for a relatively short time with predatory products. In good years (2003–2006), they were likely to refinance their mortgages (and therefore help lenders generate additional fees). In bad years (post-2006), their default rate was significantly higher, indicating that the mortgage products were not affordable for borrowers.

Overall, our results show that the true costs of predatory lending are revealed when a crisis hits. At that point, borrowers who carry expensive mortgages become fragile and default. The findings resonate with Zingales (2015), questioning the benefit that financial innovation that shrouds certain risks for financially unsophisticated borrowers brings to society.

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Appendix A Variable Definitions

Variable	Description	Source
I(Steered borrower)	1 if the rejected mortgage application is approved soon after by the same lender; 0 if different lender	HMDA, authors' calculations
FICO score	FICO score of the borrower at origination	McDash
LTV ratio	First-lien loan-to-value ratio at origination	McDash
Borrower income	Borrower income at origination, as reported	HMDA
Loan amount	First-lien mortgage amount at origination	McDash
I(Refinancing)	1 if a mortgage is identified as refinancing an existing mortgage	McDash
I(Owner-occupied)	1 if a property is reported to be owner-occupied	McDash
I(Conventional (non-FHA))	1 if a mortgage originated outside of FHA/VA	McDash
Initial interest rate (%)	First recorded interest rate 6 months after origination	McDash
90-day delinquency w/ 2 years	1 if loan enters 90dpd status at any point during the first 2 years since origination	McDash
I(Interest only)	1 if a mortgage calls for interest-only payments for a pre-specified number of years, fixed amortization schedule thereafter	McDash
I(Option ARM)	1 if a mortgage has an adjustable interest rate but required payments may be less than interest charges subject to time and LTV restrictions	McDash
I(Prepayment penalty)	1 if a mortgage contract has a penalty for refinancing before a pre-specified time	McDash
I(No/low documentation)	1 for mortgages that are listed as not being underwritten based on fully documented income and assets	McDash
Fixed rate term	Number of months over which the mortgage interest rate is fixed	McDash
Mortgage maturity	Number of months over which a fixed rate loan amortizes	McDash
I(Portfolio loan)	1 if mortgage is held on the originator's portfolio 6 months after origination	McDash
I(GSE securitization)	1 if mortgage is sold to a GSE by 6 months after origination	McDash
I(Private-label securitization)	1 if mortgage is sold into a PLS pool by 6 months after origination	McDash
ΔHPI 12 months pre-origination	Annual change in zip code or MSA home price index in the 12 months preceding mortgage origination	CoreLogic
I(African American)	Coded using the Avery et al. (2007) approach	HMDA
I(Hispanic)	Coded using the Avery et al. (2007) approach	HMDA
I(Female)	1 if primary applicant is coded as "female"	HMDA
I(No co-signer)	1 if co-applicant fields indicate "no co-applicant"	HMDA
I(Low/moderate income tract)	1 if the tract median income is less than 80% of the CBSA median income	U.S. Census