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ABSTRACT

We present evidence of a particular type of loan steering in which lenders lead borrowers to take out high margin mortgage products. We identify this activity by comparing borrowers who were rejected by lenders but were subsequently approved by their affiliates (steered borrowers) to other initially rejected borrowers who obtained loans elsewhere. Although steered borrowers default less, they pay significantly higher interest rates and are more likely to borrow through contracts with unconventional features, such as negative amortization or prepayment penalties. Female borrowers, single borrowers with no co-signers, and borrowers in low-income locations are more likely to be steered.

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1 Introduction

At the height of the housing market boom of the 2000s, accusations of unscrupulous lender behavior abounded. Examples included excessive fees, high interest rates, obscured prepayment penalties, and clauses barring borrowers from seeking judicial redress for predatory behavior by lenders (Engel and McCoy, 2002). Yet, the vast majority of the evidence to date has been anecdotal in nature or came from select examples of regulatory enforcement actions or isolated lawsuits. Some research was undertaken to evaluate whether particular groups were targeted with predatory loan terms (Goldstein, 2002; Staten and Elliehausen, 2001; Immergluck and Smith, 2003; Bocian, Ernst, and Li, 2008). However, there has not been a comprehensive, methodical evaluation of whether lenders engaged in business practices—broadly referred to as steering—that led households to mortgage products that were too expensive or contained hidden risks. Conducting such evaluations is difficult since identifying instances of steering in the data requires overcoming two major hurdles. First, one needs to separate cases in which lenders steered borrowers into a product from cases in which borrowers themselves expressed demand for the product. Second, assessing the optimality of a selected product is problematic in itself as the econometrician does not observe the full 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 features that are unambiguously inferior to the borrower.

In the absence of transaction-level negotiation data, we develop a methodology to identify steered loans. We do this by contrasting the outcomes of two observationally equivalent groups of borrowers whose mortgage applications were rejected by one lender, but subsequently approved by another. Borrowers in one group had their applications approved by an *affiliate* of the original lender, while others were approved by unaffiliated entities. We contend that borrowers in the former group are more likely to have been steered.

The identification strategy behind this approach can be illustrated with the following thought experiment, summarized in Figure 1. A borrower enters a lending institution seeking a mortgage and their loan application is evaluated. If they are judged to be a poor credit risk, their application is rejected outright. However, if their credit risk is acceptable they might still be told that they do not qualify for the specific loan applied for, but would qualify for another mortgage product from an affiliate of the organization. The applicant is thus ‘steered’ to an affiliate, which approves the new loan product. In making this decision, the original lender takes the risk that the rejected applicant will apply for a loan with a competitor. To lessen this risk, the lender may choose to deploy this strategy with borrowers more likely to follow the referral, i.e., those that are perceived to be less financially sophisticated. All rejected applicants retain the option of pursuing their loan applications elsewhere, i.e., with a lender unaffiliated with the original entity, and some of them will be successful in obtaining mortgage credit. These are the applicants that we consider to be 'non-steered'.[1] If the initial rejection of the 'steered' applicants was based on reasons largely unrelated to credit quality, we would expect the 'steered' group to be systematically different from the 'non-steered' group in terms of their subsequent loan performance. Moreover, if the initial rejection was motivated by the possibility of guiding the applicants towards a different set of mortgage products (possibly those that are more profitable to the lender), we would also expect the two groups to differ in terms of eventual contract outcomes. Finally, if the likelihood of successful steering was a function of borrower financial sophistication, we would expect the 'steered' group to contain a higher share of individuals with characteristics associated with lower levels of financial literacy.

The focus on borrowers whose original applications were rejected allows us to deal with the first empirical hurdle of not observing the borrower's demand function. All borrowers in our sample are rejected on their original attempt, whose latent parameters presumably reflect the borrowers' most desired outcome. The eventual contract captures the differences that lender paths have on observed outcomes (e.g., mortgage characteristics) rather than borrower's own demand for these features. Closely matching borrower characteristics in the two groups further allows us to ascribe the difference in outcomes to lender behavior rather than differences in the underlying borrower preferences. Put differently, the sample is designed in a way that makes it plausible to assume that desired (and rejected) contract choices are similar between the steered and non-steered groups. Lender actions then become the focal point for analyzing differences in the actual observed outcomes.

To implement this strategy, we focus on a subset of lenders who are organized under bank holding companies (BHCs), and thus are likely to be more closely affiliated with each

[1] Strictly speaking, observing a loan being originated by an affiliate of the lender that rejected the original application only implies the possibility of steering. For ease of exposition, we will be using the term "steered borrowers" rather than "potentially steered borrowers" throughout the paper.

other. For these lenders we can observe the original borrower demand in the form of a mortgage application. Since we cannot identify the steered borrowers directly 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 time period by a different lender.[2] Instances in which the approving lender and the rejecting lender are *affiliates* of the same bank holding company are tagged as 'steered'. These borrowers form our treatment group. The borrowers that were 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 in terms of a wide array of observable borrower characteristics.[3]

Steering potential borrowers is not necessarily nefarious. In fact, this lending behavior could enhance welfare if it enabled borrowers with somewhat blemished credentials to access credit that would otherwise be unavailable to them.[4] However, it could have adverse effects if the borrowers are steered toward loan products for which they are overqualified—a practice consistent with predatory lending behavior. We test for evidence of such practices.

We use data from several sources using the sample period that covers loans originated during calendar years 1998 through 2006. We primarily rely on the Home Mortgage Disclosure Act (HMDA) database to identify applications and their outcomes. We use BHC Structure files from Call Reports to link lenders that are affiliated with the same bank holding company. We also use McDash Analytics mortgage servicing database for detailed information on mortgage contract features and performance.

Our study has three parts. We begin by exploring the credit quality of steered borrowers relative to the control group. We find that although the two groups are closely matched in terms of their FICO scores at origination, the steered customers perform better on their mortgages—consistent with them being lower-risk, better-qualified borrowers than those normally associated

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[2] As described in Section 3.3, we attempt to ensure that these pairs of applications are by the same applicants and are backed by the same property by requiring very tight matches on a set of applicant, loan, and property characteristics.

[3] The comparability of these two groups is further enhanced by the requirement that both of them are comprised of rejected applications that are approved within a short time period thereafter.

[4] In some of the mortgage literature, 'steering' by definition means that the customer is *inappropriately* guided toward a particular loan product. We are taking a broader view at the outset and evaluate whether the form of steering described here can somehow be viewed as inappropriate.

with their eventual loan products. Specifically, we find that the probability of steered loans being delinquent is 1.2–3.0 percentage points lower than that of non-steered loans. Again, given the average delinquency rate of 7.0% in our sample, this differential is also an economically significant result.

In the second part, we explore the characteristics of mortgages that steered borrowers take. We document that steered loans have an annual percentage rate (APR) that is 35–72 basis points higher than that of non-steered loans after controlling for various borrower and loan characteristics. Given the sample average APR of 6.8%, a rate differential of 35–72 basis points is economically significant.[5]

Furthermore, steered borrowers take products that are considered to have high profit margins in the mortgage industry. We document that relative to the overall sample mean, steered borrowers are 58% more likely to take interest only (IO) mortgages, 81% more likely to take option ARM mortgages, 88% more likely to take mortgages with prepayment penalty, and 17% more likely to take low or no documentation mortgages. Consistent with the idea that lenders capitalize on the high margin offered for these products in the secondary market, we report that mortgages of steered borrowers are more likely to be sold to private securitizers. These pieces of evidence are consistent with steered borrowers being exploited in the lending process.

In the final part of the study, we explore characteristics of the borrowers that make them susceptible to steering. Our analysis shows that in our sample steered borrowers are more likely to be female (primary borrower), 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 (see e.g., Lusardi and Mitchell, 2014) and are thus potentially prone to manipulation by unscrupulous lenders.[6] The effects are well-identified and are economically large. Each of the demographic characteristics listed above is associated with a 5 to 10 percentage points higher likelihood of being steered.

Overall, our study presents evidence that steering took place in the mortgage market during the boom period of the early 2000s. We show that despite little difference in observable

[5] For example, Agarwal, Rosen and Yao (2012) find that a significant fraction of consumers refinance their mortgage at an interest rate differential of 40 basis points.

[6] Indeed, Berndt, Hollifield, and Sandas (2014) show that such borrowers paid higher fees for the same loans than their better-educated counterparts.

credit quality relative to the control group, steered borrowers paid higher interest rates and were more likely to end up with complex and more expensive mortgages, while experiencing lower default rates. Steering was more prevalent among demographic groups with potentially lower financial literacy.

Our paper directly contributes to the growing literature that finds evidence linking the real estate bubble in the early 2000s to misaligned incentives of intermediaries—e.g., Keys, Mukherjee, Seru, and Vig (2010, 2012), Ben-David (2011, 2012), Berndt, Hollifield, and Sandas (2014), Agarwal, Ben-David, and Yao (2015), Agarwal and Ben-David (2012), and Jiang, Nelson, and Vytlacil (2014).

The paper also contributes to the broader literature on the mortgage crisis that addresses a number of issues. One group of studies explores factors explaining potential causes of the mortgage crisis—e.g., Mian and Sufi (2009), Mayer, Pence, and Sherlund (2009), and Agarwal, Chang and Yavas (2012). Also included in this group are studies of predatory lending and concerns that mortgage activity may have become excessive during the run-up to the crisis—e.g., Engel and McCoy (2002), Federal Deposit Insurance Corporation (2006), Garver (2001), Financial Crisis Inquiry Commission (2010) and Gilreath (1999), and Agarwal et al. (2014).[7]

2 Hypothesis Development and Empirical Design

2.1 What is Mortgage Steering?

Steering is a well-known term in the real estate world. Market steering typically involves realtors restricting the neighborhoods shown to certain potential home buyers. Such behavior can result in taste-based discrimination or statistical discrimination and distort the spatial patterns of housing demand by white and minority homebuyers in such a way as to perpetuate neighborhood segregation—see Ondrich, Ross, and Yinger (2003). Such practices are illegal based on the Fair Housing Amendments Act of 1988 and numerous state laws.

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[7] Related studies evaluate the role of the Community Reinvestment Act (Dahl, Evanoff, and Spivey, 2010; Litan, Retsinas, Belsky and Haag, 2000), redlining on credit access (Cohen-Cole 2011; Brevoort 2011), less traditional means of accessing credit (Morgan, Strain, and Seblani, 2012; Morse, 2011), and political influence in mortgage markets (Mian, Sufi, and Trebbi, 2010a, 2013; Igan, Mishra, and Tressel, 2009; and Agarwal, Amromin, Ben-David, and Dinc, 2012).

Leading up to the recent housing bust, a different form of steering in housing markets—namely, credit steering—emerged. Here, the real estate professional encourages the home buyer to access credit from a particular lender. Such behavior may be helpful for borrowers because they may have limited knowledge of credit alternatives and could be steered toward viable alternative credit options. In fact, we impose no ex ante value judgment on customer steering. It could be beneficial if borrowers are able to access credit they may not have otherwise received and if that credit is accurately priced based on their credentials. Additionally, lenders could be "carrying" customers in a manner consistent with the Petersen and Rajan (1994) relationship banking model.[8]

However, credit steering could also be associated with predatory lending. 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.[9] While there were significant claims about credit steering during the run-up to the financial crisis, little empirical analysis of such behavior has been completed.[10] The research most closely associated with credit steering analyzes qualifications of subprime borrowers and finds evidence suggesting that between 10%–35% of these borrowers had credentials that should have qualified them for prime loans (Freddie Mac 1996). Barr (2005) argues that some of these borrowers "may have been steered to higher cost lenders."

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[8] However, we typically think that mortgage finance is more of a production process that emphasizes "hard" information (i.e., quantitative information that is easy to store and transmit in impersonal ways such as credit model scores based on income and other verifiable factors) rather than "soft" information (i.e., information accessible to loan originators, but difficult to completely summarize in a numeric score) to determine if the applicant qualifies for the loan. Soft information, however, has been found to play a large role in small business loans as opposed to mortgage loans—see Agarwal and Hauswald (2010) and Berger and Udell (2002).

[9] Renuart (2004) argues that steering may have played a larger role in mortgage rate determination than did borrower risk. For examples of excessive terms see www.justice.gov/opa/pr/2012/May/12-crt-695.html and www.federalreserve.gov/newsevents/press/enforcement/20110720a.htm. Restrictions on mortgage compensation schemes to address the steering of customers into higher-priced loans (yield spread premiums) were introduced in 2011 through new Federal Reserve rules instituted under its authority to enforce the Truth in Lending Act. Restrictions were also imposed in the Dodd–Frank Wall Street Reform and Consumer Protection Act.

[10] Predatory lending practices figured prominently in a number of high-profile analyses both before and after the financial crisis. See, for instance, FDIC (2006) and the Financial Crisis Inquiry Commission Report (2010).

2.2 Steering to an Affiliate Lender

Mortgage steering is likely to take place at the first application that a potential borrower makes. Yet, without a complete information set about the financial situation of the applicant it is impossible to determine whether the mortgage product was demanded by the applicant or the lender steered the borrower into a suboptimal product. Our identification strategy is based on the idea that some mortgage lenders are affiliated under the same bank holding company. In these cases, steering can occur between affiliated companies.

The steering process that we consider can be summarized by Figure 1. The mortgage applicant files the requested loan documentation and the lender evaluates their credentials to determine if the applicant satisfies the risk criteria established for a particular loan product. That is, the lender (say, Bank A) determines whether the applicant is an 'acceptable' or 'unacceptable' credit risk. This is the standard process for any loan application and the lender would typically either accept the loan application and originate the loan, or deny the loan application. If steering is to occur, it would be initiated *once the lender has determined* that the loan applicant is an acceptable credit risk.

For illustrative purposes, imagine that borrower's creditworthiness has been determined and the loan officer is sitting at a table with the applicant and discussing loan options. The loan officer realizes that the applicant qualifies for a plain vanilla loan, but may evaluate the applicant to determine if they can be convinced to take an alternative loan product—one that either enhances the loan officer's compensation and/or the risk-adjusted profitability of the organization. Thus the loan officer has two options: they can approve the loan that the applicant qualified for or they can consider steering the applicant toward an alternative loan product with less desirable characteristics—higher APR, prepayment penalties, higher up-front fees, etc. If the loan officer decides to steer the applicant they would inform them that they are not qualified for the original mortgage applied for, but that there were alternative products within the organization for which they would be qualified; a loan which would be generated by Bank B, an affiliate firm within the same holding company organization as Bank A. Again, this would be providing the relatively high qualified applicant with an inferior mortgage product for which they are over-qualified. Note that the applicant is not tied to this particular lender (Bank A) or the affiliate they are steered toward (Bank B). If they are told they do not qualify for the product they initially applied for, they can turn down the offer of an alternative mortgage through the affiliate and simply look elsewhere. This is the worst-case scenario for the lending officer; they lose a qualified customer. Hence, the loan officer evaluates potential benefits from steering the applicant—additional compensation, profitability—relative to potential cost of losing the applicant. Thus, the decision would likely be based on the perceived financial sophistication of the loan applicant.[11]

The above description can be used to develop our hypotheses. First, we anticipate that borrowers who are rejected from Bank A and approved by affiliate Bank B (steered loans) have better performance than similar rejected borrowers who took out loans from unaffiliated lenders.[12] Second, if the steering was inappropriate, the steered loans can be expected to carry higher interest rate than non-steered loans. Third, steered borrowers end up taking loan products that are considered to have high-profit margins for mortgage lenders (e.g., prepayment penalty, option ARM). Fourth, steered loans are sold to private originators, who pay a premium for structured loan products with said features. Finally, steered borrowers are likely to be less financially sophisticated, e.g., lack financial education.

One may question why lenders would steer a mortgage customer to an affiliate instead of independently acting on the application. The originally approached lender (Bank A in the above description) could simply steer them toward in-house products. This could certainly happen, but will be unobservable to the econometrician unless Bank A took the effort to formally reject the application first. Still, there may be a number of reasons to steer these applications to an affiliate. First, management may believe that there are efficiencies involved with concentrating certain mortgage contracts (e.g., option ARMs) into one subsidiary firm. For example, there could be efficiencies from expertise in analyzing non-traditional applicants with irregular income streams. Second, isolating non-traditional loans with a particular affiliate could insulate other affiliates from reputational risk associated with such lending. Indeed, use of a holding company affiliate (instead of the bank) for non-prime lending appears to have been relatively commonplace; see

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

[12] In additional tests, we also compare the performance of steered borrowers to those whose *original* applications were *approved* by Bank A, and to those whose original applications were approved by Bank B.

Stein and Libby (2001), Litan, Retsinas, Belsky, and Haag (2000).[13] Finally, individual loan officer reluctance to send an applicant elsewhere in the organization can be overcome by modifying organization-level compensation structure.[14]

2.3 Empirical Design

To analyze the potential for, as well as the impact of, steering mortgage applicants, we take a three-step approach. We first identify loan applicants for which there is evidence consistent with them being steered. Since we do not have the identity of borrowers in the loan data, we develop a methodology to indirectly identify them. We do this by finding mortgage applicants that were denied credit at one lending institution and matching them (using rather strict criteria) to a mortgage applicant with similar characteristics who soon thereafter received a loan at another lending institution. Based on the similarities for borrowers, loan, and property characteristics, we assume these are the same applicants successfully obtaining a loan for the same property. We consider them to be in our steered (treatment) sample if the approving institution is affiliated with the lending institution that originally denied their loan application. It is this cross-organizational steering that we are trying to capture. Our second step is to use all other rejected but not steered loans to generate a control sample with similar characteristics to those of the steered sample for purposes of comparison.[15] Finally, we analyze the resulting sample to see if there is are meaningful differences in outcomes between the two groups; these include APR on the mortgage, the type of mortgage and various mortgage characteristics granted, as well as the performance of the mortgage captured by the delinquency rate.

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[13] For a discussion of how mortgage company subsidiaries may have been used to avoid regulatory burden during the run up in the housing market see Demyanyk and Loutskina (2012). Evanoff and Moeller (2014) discuss the regulatory and legislative response to these practices.

[14] If the objective of the firm is to increase the volume of highest profit margin loans, adjustments may be made to commission schemes that preclude some/all of the lost commissions by loan officers evaluating the original application (Financial Crisis Inquiry Commission Report (2010), Chapter 7, offers some example of product-focused compensation practices). Conversations with bank examiners suggest that during the run up to the housing crisis, certain banking organizations had procedures in place to encourage loan officers to keep loans in the organization if applicants were over/under qualified for their array of mortgage products.

[15] We elaborate on mechanics of constructing matched control samples in Section 3.2. In Section 4.5, we also study comparisons between the loans successfully steered by a lender to its affiliate and loans approved by that lender itself.

It is important to emphasize that we are not attempting to identify all instances of credit steering. Steering could take numerous forms—including in-house steering, where the lender would recommend inappropriate mortgage products—beyond what we evaluate. Rather, we test for the presence of one form where the applicant is steered within a banking organization, and we then test for evidence that the affiliate provides inferior loan terms relative to what the applicant appears to qualify for. 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 loans, and develop some of our control 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 kind of decision made (e.g., deny or accept the loan application). However, the HMDA data provide limited information on affiliation structure, the qualifications of the borrower or (if a loan is originated) the characteristics of the loan. We obtain this 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 as well as loans held in portfolio. The McDash data provides 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, condo, or other type of property). Loan characteristics include origination amount, term to maturity, lien position, loan type (i.e., whether or not 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 9 of the top 10 mortgage servicers by 2003. Since servicers only provide information on loans that are active at the time they start reporting data to McDash, the McDash database includes relatively few loans originated in the late 1990s and the early 2000s.

Beyond the McDash information available at origination, the dataset also contains dynamically updated loan information, enabling one to monitor loan performance. Variables of interest include coupon 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, over 91 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 GSEs),[16] 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 steered loans (which form our *treatment sample*), we start with HMDA loan application data for the 1998–2006 period. The HMDA data encompass nearly all mortgage lending activity in each year, with some exceptions for small and rural institutions that do not fall under the mandatory filing requirements. Since the HMDA data include 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 a different, but affiliated lender in the same U.S. Census tract. To develop our steered group, we impose rather strict criteria on pairs of applications. These applications are allowed a difference in action date of no more than 60 days and 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.[17] We also match iteratively on loan amount and applicant income—by first 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.[18] This matching process produces approximately 3.4 million unique pairs of loan applications. In order to determine whether a relationship exists between the two lenders, we match the HMDA lender identifier for

[16]The public securitizations can be through Government National Mortgage Association (Ginnie Mae), Federal National Mortgage Association (Fannie Mae), Federal Home Loan Mortgage Corporation (Freddie Mac), Ginnie Mae via buyout loans, Local Housing Authority, or Federal Home Loan Banks).

[17] Results were robust when a slightly shorter or longer timeframe was used.

[18] The thought is that the borrower may receive a slightly different loan amount or report a marginally different income based on the interaction with the initial lender.

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 lenders affiliated with the original rejecting institution (i.e., 'steered').

Since 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 and 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 becomes heavily weighted towards the 2003-2006 period. We end up with 303,368 unique loan originations, of which 90,349 fit the definition of a 'steered' transaction.[19]

Next, we create two *control samples*. Both control groups consist of borrowers whose applications were also initially denied, but then approved within a short time period by another lender *not* affiliated with the holding company that originally denied the loan. The samples differ from each other in the technique used to match them to the treatment sample.

The first control sample (labeled Design 1) is based on a propensity score matching procedure. Specifically, we perform a nearest neighbor propensity score match (PSM), 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 loan-to-value (LTV) at origination. We require the potential control 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

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

steered loan. From the resulting sample of potential controls, we choose a loan with the smallest difference in the propensity score, subject to an absolute threshold of 0.05. The resulting propensity-matched sample contains 71,682 steered loans and an equivalent number of control loans.

The second control group (labeled Design 2) is based on strict matching of *each* characteristic. 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 applicant income and loan amount be within 25%, FICO score within 25 points, LTV ratio within 5 percentage points and origination date within 90 days. Not surprisingly, this approach results in a smaller final sample of 13,252 steered loans and 13,252 non-steered loans. [20]

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 not available, 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 that fall in the low-to-moderate income (LMI) category and to obtain the share of area population with at least some college education.[21]

3.3 Descriptive Statistics

Table 1 presents summary statistics for the resulting pair of treatment and control samples. The left-hand panel presents characteristics of the propensity score matching approach (Design 1), and the right-hand panel is based on the strict matching approach (Design 2).

Note that by construction, the propensity-matched sample minimizes the *joint* differences on key observable characteristics. Yet, the summary statistics for the propensity-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 treatment and control samples.

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[20] The more lenient PSM approach generates a larger sample but also increases the possibility of pairwise mismatches in treated and control loans.

[21] LMI areas are defined as those census tracts in which the median family income is less than 80 percent of the area median income.

It is worth noting that the average FICO scores in our sample are around 710 and the average first-lien LTV ratios at origination are under 70 percent. In other words, the borrowers in our sample do not match the profile of a subprime borrower purchasing (or refinancing) their house with the minimum amount of equity possible. More than 80 percent of loans in the PSM sample are owner-occupied, and most (59 percent) are used for home purchases.

In addition to means summarized in Table 1, Figure 2 displays kernel densities for the main continuous variables: loan applicant income, loan amount, FICO score, and the LTV ratio for each of the sample designs. The figure shows that in both designs, the distribution of key covariates in control and treatment samples is very close to each other.

However, achieving tight covariate balance in observables through matching still produces a considerable amount of variation in the means of the *outcome* variables, listed in the lower panel of Table 1. The steering hypothesis suggests that the 'steered' group is charged 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% vs. 6.59%), while experiencing lower unconditional average rates of default (6.3% vs. 7.7%).[22] These differences are statistically as well as economically significant. Furthermore, we also observe sizable differences in propensities to originate loans with certain contract features between the two groups. A much higher fraction of the steered group loans are option ARM (38% vs. 16%) or interest only mortgages (32% vs. 16%), and carry prepayment penalties (41% vs. 20%).

For the strict-matching sample (Design 2), the results are fairly similar, although the resulting sample is much smaller. As with Design 1, the key covariates are closely matched between the treatment and control samples. This is true both for the means and the entire distribution (Figure 2). The comparison of outcome variables between the groups is also similar to that in Design 1. The treatment group has higher average interest rate, lower realized delinquency rates, and higher rates of incidence of high-margin mortgage products (option ARMs, IO loans, and loans with pre-payment penalties). It is worth noting that relying on the strict-matching procedure generates a sample that contains a smaller fraction of non-amortizing mortgage contracts, such as IOs or option ARMs. Amromin et al. (2015) show that such

[22] The initial or first observed APR is the interest rate reported six months after the loan was originated. This allows us to avoid capturing initial teaser rates that were commonly offered on certain loan contracts but typically lasted only for one month.

contracts were common among relatively high-income borrowers purchasing more expensive homes that ended up defaulting at high rates. The difference in relative preponderance 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.

While these comparisons of unconditional means are generally consistent with our hypothesis, the subsequent analysis investigates these differences in a fully specified regression framework. The propensity-score matched sample forms the basis for our regression analysis. However, for completeness, we also report all of the regression results for the strict matching approach in the Appendix.

4 Empirical Results

4.1 Regression Specification

Once we develop a sample of borrowers who were steered toward affiliated lenders, we conduct cross-sectional regression analysis evaluating borrower and loan contract characteristics to determine whether that group of borrowers is indeed different from other borrowers. In doing so, we control for an array of factors, including various fixed effects. The regressions used in most tables use the following specification:

$$\begin{aligned} Response_i \;=\; \alpha \;+\; \beta\, Steered\,(0/1)_i \;+\; \delta\, BorrowerControls_i \\ +\, \theta\, MortgageControls_i \;+\; \gamma\, FixedEffects_i \;+\; \varepsilon_i, \end{aligned} \tag{1}$$

where *Response*$_i$ is the loan-level response variable, such as the interest rate on mortgages, default status of loans, etc.; *Steered*$_i$ is a dummy variable that receives the value of one if the loan is identified as a steered loan and zero otherwise; *BorrowerControls*$_i$ are a set of borrower characteristics including: logged borrower income, and the FICO credit score of the borrower (splined into the ranges: 621-660, 661-720, 721-760, and >760). *MortgageControls*$_i$ are a set of loan-specific characteristics, which include the following variables: logged loan amount, LTV ratio at origination (splined into 80%-89%, 90%-99%, and ≥ 100%), binary indicators of various contract types (amortizing ARM, option ARM, IO), refi flag, pre-payment penalty flag, owner-occupier flag, conventional mortgage flag, and low documentation flag.. In addition, we control for the 12-month change in the zip-level house price index. Appendix A provides detailed variable descriptions. *FixedEffects*$_i$ account for one of the following: fixed effects for the state interacted with calendar quarter, fixed effects for the state interacted with calendar quarter of origination and with originating bank dummy, and fixed effects for each pair of matched treatment and control loans. In all regressions we double-cluster standard errors at the state and calendar quarter level.

4.2 Performance of Steered Borrowers

We begin by testing for difference between the *ex post* credit quality of steered borrowers to borrowers in the control group. Recall that borrowers in both groups were rejected by one lender and were accepted by another, and that the credit quality of borrowers at origination is very similar in both groups by construction. The only difference between the groups is that steered borrowers were approved by an affiliated lender, while borrowers in the control group were approved by an unrelated lender.

The test is presented in Table 2. The dependent variable is an indicator for whether the borrower defaulted (experienced 90-day delinquency) within the following two years. The variable of interest is whether the borrower was flagged as steered. We present several specifications. Columns (1) and (2) include fixed effects for state interacted with calendar quarter. Columns (3) and (4) include fixed effects for state interacted with bank and calendar quarter, while columns (5) and (6) include fixed effects for matched loan pairs. Even columns include borrower and mortgage controls, as discussed in Section 4.1, while odd columns include only the steered indicator and the corresponding fixed effects.

The results in most specifications show that borrowers who were steered are *less* likely to experience default. The most parsimonious specification in column (1) suggests that after removing the origination date and location effects, steered loans experienced default rates of 1.2 percentage points lower than their non-steered counterparts. For sizing up the economic significance of this effect, recall that the unconditional default rate in the control group is 7.7%. Adding controls for borrower and loan characteristics substantially amplifies the difference in default rates, as the coefficient on the steered loan indicator increases to -2.8 percent. Further soaking up bank-specific effects in columns (3) and (4) largely preserves these estimates, although statistical significance weakens substantially in specification with additional controls. In the tightest specification (column (6)), where we include matched loan pair fixed effects, the estimated coefficient on steered loans is -3.0 percentage points. Put differently, the default rate of steered borrowers is nearly 40% lower than in the control group. It appears, therefore, that the *ex* *post* credit quality of steered borrowers as measured by loan performance is substantially better than that of the borrowers who obtained their loans from unaffiliated lenders.

4.3 Characteristics of Steered Mortgages

4.3.1 Interest Rate

A central part of the steering hypothesis is that steered borrowers are led to taking mortgage products that are profitable to the originator. The most direct measure of loan profitability is risk-adjusted interest rate. Having established in the previous section that steered borrowers are of better *ex post* credit quality, the null hypothesis of higher profitability of steered loans can be evaluated by whether such borrowers pay interest that is equal or lower than that of the non-steered borrowers. Hence, we first turn to measures of mortgage interest rates.

In Table 3, we report the results of regressing the mortgage APR on the variable of interest—steered flag—as well the other control variables and fixed effects as described in Section 4.1. The regressions show that steered borrowers pay interest rates that are up to 72 basis points higher relative to those by similar but non-steered borrowers.

The most parsimonious specification presented in column (1) indicates an estimated interest rate differential of 39 basis points after soaking up the effects of loan origination date 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. Augmenting the set of time-and-state fixed effects with bank-specific indicators in column (4) compresses the estimated differential for steered loans to 35 basis points. The tightest specification that accounts for pairwise fixed effects in column (6) produces an estimated differential of 69 basis points.

These differentials, especially when coupled with favorable performance, generate large gains for the lender. One way to approximate profits generated by higher interest rates is to use industry multipliers for converting interest flows into capitalized dollar values. The magnitude of the conversion factor depends on expected prepayment probabilities, ability to earn float income, and other technical factors, but it generally varies between 4 and 7 (Fuster et al, 2013). Taking the lower end of the multiplier range, our estimated interest rate differential for steered loans suggest increased profitability to lender of between $2,800 and $5,700 on a $200,000 loan (4*34.8bp*$200,000 and 4*72.1bp*$200,000). Note that the historical profitability of mortgage originations during the 2000-2010 period has averaged between 1 and 2 percentage points, or between $2,000 and $4,000 on a $200,000 loan (Goodman, 2012).

4.3.2 Product Type

Next, we examine the type of mortgages and mortgage characteristics taken by borrowers who are flagged as steered, compared to similar borrowers in the control group. In Table 4, we select several mortgage types that are considered to have high-profit margin in the residential mortgage industry. The mortgage types that we study are: interest only mortgages, option ARMs (adjustable rate mortgages), mortgages with prepayment penalty, and low documentation mortgages. Except for interest only mortgages and option ARMs, these features are not mutually exclusive. Interest only loans are loans in which the borrower does not repay any of the principal amount, for a number of 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, as long as it is equal or above the minimum payment. The minimum payment is typically set 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 when the principal reaches a certain level, e.g., 125% of the original loan amount.[23] Mortgages with prepayment penalty are mortgages in which borrowers pay a penalty if they refinance the loan (repay the principal) earlier than scheduled. Prepayment penalties, when they exist, are typically set between 1 and 5 years. Low documentation mortgages (also called stated-income mortgages) are mortgages in which borrowers need either none or limited documentation for their income.

We learn about the profitability of loan products from conversations with lenders in the industry. The information that these loan types are profitable also appears in written sources. In a practical guide about the mortgage market, Baxi (2015) reports that interest only mortgages are the most profitable for the bank (p. 98). Kennedy (2008) cites the comments of the CEO of

[23] See detailed explanation of the mortgage types at https://www.fdic.gov/consumers/consumer/interest-only/.

Washington Mutual (the largest mortgage originator at the time) from the 2004/Q3 conference call, where he says that the company focuses on high margin mortgage products such as option ARM mortgages. Similar message is echoed in an article about the competition in the mortgage market.[24] Mortgages with prepayment penalties were Countrywide's favorite product since "…investors who bought securities backed by the mortgages were willing to pay more for loans with prepayment penalties…".[25] Steven Krystofiak, President of the Mortgage Brokers Association for Responsible Lending (MBARL), an advocacy group protecting consumers and the loan industry from outlandish and counterproductive loan programs, testified in 2006 in front of the Federal Reserve Board. He argued that banks originated increasing amounts of stated-income (i.e., low doc) mortgages because the strong demand from were selling them to securitizers at profit.[26]

The tests for the mortgage types are provided in Table 4. There are 12 regressions, where the dependent variables are indicators to whether the type of the mortgage is interest only (columns (1)-(3)), option ARM (columns (4)-(6)), have a prepayment penalty (columns (7)-(9)), or low documentation (columns (10)-(12)). As in the previous tables, the specifications vary in their configuration of fixed effects. All specifications include controls for borrower and mortgage characteristics.

The results uniformly show that steered borrowers are more likely to take mortgages that have the features that are considered highly profitable in the mortgage industry. The magnitudes of the effect are very large. When considering the first column in each column triplet, the results show that steered borrowers are 85% more likely to take interest only loans (0.141/0.165) than borrowers in the control group, 136% (0.219/0.161) more likely to take an option ARM mortgage, 134% (0.266/0.198) more likely to take a prepayment penalty mortgage, and 19% (0.129/0.671) more likely to take a low documentation loan.

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

[25] 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

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

4.3.3 Securitization

Most of the mortgage loans in our sample were originated between 2003 and 2006. During this period, lenders increasingly originated mortgages to sell them to investment banks which, in turns, packaged them into private-label mortgage-backed securities (PLS MBS) for capital-market investors (Mayer, Pence, and Sherlund, 2009; Nadauld and Sherlund, 2013). According to the sources cited in Section 4.3.2, lenders originated mortgages with exotic features in order to satisfy the demand from Wall Street: both the investment banks and the ultimate investors. In this section, we explore whether steered mortgages were indeed more likely to be sold to private market securitizers.

In Table 5, 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, as opposed to being held on bank portfolios. The point estimates in columns (1) to (3) show that steered loans are 52% (0.231 / 0.44) more likely to be sold into private-label MBS pool. Columns (7) to (9) suggest that steered loans were equally likely to be sold to GSEs as mortgages in the control sample. (Note that the three funding outlets are mutually-exclusive alternatives, and hence sum up to 1.)

These results demonstrate the motivation for the steering activity. Lenders benefit from steering through originating exotic mortgages to borrowers and selling them to securitizers and investors.

4.4 Characteristics of Steered Borrowers

Our final analysis examines the demographic characteristics of steered borrowers. To answer the question of which borrowers were more likely to be steered, we rely on (partial) demographic information and precise geographic location captured in HMDA. In particular, we are able to make use of data on borrower's gender, identification as African-American or Hispanic, indicator of not having a co-applicant, and indicator of a loan being secured by a property in a low or moderate-income census tract, as well as zip-code share of households with at least some college education.[27] Since steering means that borrowers are taking an inferior product relative to what they can get otherwise, we expect that steered borrowers share characteristics that have been linked to lower levels of financial sophistication.

We start with a set of steered and PSM-matched control loans. By construction, this set is evenly split between steered and non-steered loans. More importantly, its construction ensures that each loan pair is closely matched on a set of key loan and borrower characteristics.[28] For this set of loans, 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 6 (logit models produce similar estimates and are available on request). Starting with the first column, we find that all else equal, African-American applicants had a similar likelihood of being steered while Hispanic applicants had a somewhat higher propensity. Female applicants and applicants that did not have a co-borrower were much more likely to be steered towards more expensive loans. We also found applicants residing in LMI census tracts to be considerably more likely to be steered. The magnitudes of the estimated coefficients are in the order of 0.05 – 0.10, suggesting, for instance, that borrowers with no cosigners are about 20% more likely to be steered. Somewhat counterintuitively, higher shares of educated borrowers in a given zip code are associated with a higher probability of steering. However, in contrast with the other regressors, the education share is much less precise as it is a geographic (not an individual) measure and is time-invariant (set at the 2000 Census level).

These results are closely aligned with existing empirical evidence on which population subgroups display lowest levels of financial literacy. An extensive recent literature survey by

[27] Prior to 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, black, Asian, American Indian and Alaska native, Hawaiian or other Pacific Islander). This 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. 361-62) approach to addressing this issue.

[28] Recall that the PSM algorithm conditions on borrower income, loan amount, FICO score, and LTV at origination. It also requires an exact match loan purpose and type, occupancy status, and state in which the property is located, as well as an application date within 90 days of that of the treated loan.

Lusardi and Mitchell (2014) highlights substantial shortfalls in financial literacy among certain groups. In particular, the young and the old households, women, minorities, those who are least educated and those with lower incomes all display markedly lower levels of financial sophistication. By and large, these also happen to be the groups identified as more likely to be steered by their mortgage lender.

Column (2) presents the specification in which state-quarter fixed effects are further interacted with dummy variables for rejecting Bank Holding Companies (BHCs). Recall that each of the loans in this sample had been rejected initially by some bank. Adding bank fixed effects to the set of controls allows us to check whether demographic factors retain their predictive power within rejecting BHCs in a given state and calendar quarter. The results in column (2) suggest that they largely do, albeit with somewhat lower magnitudes. In the final column, we introduce a dummy variable for each matched pair. All of the demographic variables appear as strong predictors of the likelihood of being steered.

Overall, the results suggest that female borrowers, borrowers with no co-signers and borrowers residing in low- and moderate-income areas were the ones most likely to have gotten steered towards more expensive loans. This result feeds back and supports 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 and thus might be more likely to be vulnerable to lender steering practices (Berndt, Hollifield, Sandas, 2014).

4.5 Alternative control samples

Throughout our analysis, we have been comparing two groups of borrowers whose initial mortgage applications were rejected. The steered group obtained a loan from an affiliate of the original rejecting lender, while the control group was successful in securing a mortgage through a lender unaffiliated with the original one. These are the two borrower groups at the bottom of Figure 1.

However, the study can also benefit from analyzing differences between steered borrowers and borrowers whose mortgage applications were approved on the first attempt. Since each of the steered loans has a record with the rejecting lender (Bank A) and the lender that approved the subsequent application (Bank B), the alternative control samples can be drawn from two sources: borrowers approved by Bank A and borrowers approved by Bank B. In the former case, we compare borrowers who were approved by the original lender with those that were *successfully* steered to an affiliate. In terms of Figure 1, the control group is that on the far right branch of the diagram and captures borrowers that the lender might have considered to be too risky to steer for fear of losing them to competitors. In the latter case, we compare borrowers who went directly to an affiliate with those who found their way there after being turned down by the original lender. This control group may be expected to consist of riskier borrowers who would find the product mix offered by Bank B appealing (see results in 4.3.2, as well as Amromin et al., 2014).

These alternative control groups can be used to analyze each of the outcomes studied in Tables 2 through 6. We choose to focus on realized performance as it encapsulates the underlying credit quality of the applicants. As done elsewhere in the paper, each of the control groups is constructed to make it have the same covariate balance as the treated group (the steered borrowers). That is, we use propensity-matched scoring to create a control group of Bank A-approved (or Bank B-approved) borrowers that are observationally equivalent to the steered borrowers. For example, for a steered borrower rejected at Bank A and later approved by Bank A's affiliate, we choose a similar borrower that was approved right away by Bank A. The restriction of only looking for similar borrowers approved by a given institution produces smaller control and treatment samples. The Bank A control group consists of 9,374 borrowers (matched to 9,374 steered borrowers) and Bank B control group consists of 11,111 borrowers (matched to the same number of steered borrowers).

Based on our discussion of the potential steering process, one can hypothesize that the steered borrowers would have comparable performance with the successful Bank A borrowers – they could have been approved by the original lender but ended up with the affiliate's more expensive products. We would also expect that the borrowers steered to Bank B would perform *better* than the borrowers who went to Bank B's product mix directly. The results presented in Table 7 are consistent with these hypotheses.

We find that borrowers rejected by Bank A and steered towards its affiliate have effectively the same realized default rates as borrowers that were approved by Bank A (Panel A, column (1)). This result survives the addition of lagged HPI growth, and borrower and loan characteristics (column (2)), as well as the addition of bank holding company fixed effects interacted with the state and calendar quarter of origination (columns (3)-(4)). In contrast, the results in Panel B suggest that borrowers steered to Bank B performed better than borrowers whose original application to Bank B was approved immediately. The performance differential among the steered borrowers is sizable as their realized default rates are nearly 30 percent lower. This result is also consistent with the notion that borrowers steered to costlier products at Bank B were overqualified compared to Bank B's clientele, but could have been approved (and benefitted from) Bank A's product offerings.

5 Conclusion

During the housing boom of the 2000s, there were frequent accusations of unscrupulous lender behavior. However, there has been little research that has methodically evaluated the housing market data to find systematic evidence of such behavior. We attempt to fill some of this research void. We look for evidence that some lenders may have steered borrowers to an affiliate that charged higher rates and provided more expensive mortgage products than what the borrower could have obtained had they gone to an unaffiliated lender instead.

Our evidence shows that borrowers who are flagged as steered are performing at least as well, if not better, compared with borrowers in the control group. Nevertheless, steered borrowers pay significantly higher interest rates and are more likely to take mortgages that are considered high-profit margin products. These loans are also more likely to be securitized by lenders through private-label mortgage pools. We conduct analysis on the determinants of being steered and find the applicants most likely to be steered are single, female borrowers residing in low- and moderate-income areas.

Thus, in general, the findings are consistent with a particular form of loan product steering during the formative years of the housing bubble. While lending terms have tightened significantly following the collapse of the housing market, once markets recover, there may be a tendency for such practices to creep back into the lending mix. Improvements in financial literacy of the borrowers as well as monitoring of lender practices could be effective approaches to remedying the problem.

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Table 1. Summary Statistics

The table provides summary statistics for the analysis used in the study. The first sample (Design 1) is based on propensity matching algorithm of loans that were rejected from one lender and was eventually approved by an affiliate. The second sample (Design 2) is based on exact matching criteria. See Sections 3.1 and 3.2 in text for details on data sources and sample construction.

	Design 1 (Propensity Score Matching)				Design 2 (Strict Matching)			
Variables	Steered		Control		Steered		Control	
N	71,682		71,682		13,252		13,252	
Match quality	Mean	StDev	Mean	StDev	Mean	StDev	Mean	StDev
FICO at origination	711.2	49.0	708.7	59.6	709.2	51.8	709.0	52.5
LTV Ratio	68.8	21.6	65.8	22.2	70.7	20.4	70.8	20.3
Income, $1000s	124.5	97.2	124.8	100.7	83.5	74.3	74.7	51.5
Loan amount, $1000s	277.2	205.1	262.7	199.9	185.1	139.8	177.5	132.2
Refi flag	0.41	0.49	0.41	0.49	0.58	0.49	0.58	0.49
Owner-occupied flag	0.81	0.39	0.81	0.39	0.95	0.22	0.95	0.22
Conventional flag	1.00	0.07	1.00	0.07	0.99	0.08	0.99	0.08
Outcome variables of interest								
First observed interest rate (percent)	6.96	1.32	6.59	1.98	6.73	1.35	6.44	1.58
90-day delinquency within 2 years	0.063	0.243	0.077	0.266	0.043	0.202	0.048	0.213
Amortizing ARM	0.11	0.31	0.12	0.32	0.15	0.36	0.13	0.33
Interest Only	0.32	0.47	0.16	0.37	0.27	0.45	0.09	0.29
Option ARM	0.38	0.49	0.16	0.37	0.27	0.44	0.08	0.27
Pre-payment penalty	0.41	0.49	0.20	0.40	0.28	0.45	0.15	0.36
Low documentation	0.82	0.39	0.67	0.47	0.80	0.40	0.72	0.45
Fixed rate term, months	75.7	99.9	204.0	149.9	112.5	126.5	241.6	138.7
Loan amortization period, months	340.1	66.4	339.8	68.9	333.2	68.4	328.8	72.9
Portfolio loan	0.01	0.11	0.17	0.38	0.04	0.20	0.16	0.36
GSE securitization	0.29	0.45	0.38	0.48	0.44	0.50	0.54	0.50
Private-label securitization	0.70	0.46	0.44	0.50	0.52	0.50	0.30	0.46
Other covariates								
Change in HPI 12-mo prior to orig. (%)	0.140	0.104	0.139	0.106	0.109	0.096	0.107	0.095
Change in HPI 12-mo after to orig. (%)	0.045	0.112	0.045	0.113	0.059	0.110	0.059	0.111
Share African-American	0.06	0.23	0.06	0.23	0.06	0.24	0.06	0.25
Share Hispanic	0.17	0.38	0.15	0.36	0.12	0.33	0.13	0.33
Share Female	0.32	0.47	0.25	0.43	0.34	0.47	0.26	0.44
Share with no co-signer	0.68	0.47	0.57	0.50	0.69	0.46	0.57	0.50
Share in Low-Moderate Income tracts	0.30	0.46	0.27	0.44	0.31	0.46	0.30	0.46
Share with some college education	0.59	0.18	0.59	0.18	0.58	0.17	0.56	0.17

Data sources: Home Mortgage Disclosure Act (HMDA), 1998-2006; McDash Analytics; CoreLogic.

Table 2. Credit Quality of Steered Borrowers

The table presents regressions of a 90-day delinquency indicator on steered mortgage flag, as well as a variety of fixed effects and borrower and mortgage characteristics. Borrower and mortgage controls include: logged borrower income, FICO credit score of the borrower (splined into the ranges: 621-660, 661-720, 721-760, and >760), logged loan amount, LTV ratio at origination (splined into 80%-89%, 90%-99%, and ≥ 100%), amortizing ARM flag, interest only flag, refi flag, pre-payment penalty flag, owner-occupier flag, conventional mortgage flag, low documentation flag, and the 12-month lagged change in the house price index. All regressions are OLS regressions. Standard errors are double- clustered by calendar month and state. t-statistics are reported in brackets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. See Sections 3.1 and 3.2 in text for details on data sources and sample construction.

Dependent variable:	90-day delinquency within 2 years					
Mean of control sample:	0.077					
	(1)	(2)	(3)	(4)	(5)	(6)
Steered flag	-0.012*	-0.028***	-0.016**	-0.014	-0.014	-0.030**
	[-1.89]	[-3.58]	[-2.20]	[-1.26]	[-1.41]	[-2.45]
HPI growth, lagged 12 mo		0.018		0.007		-0.027
		[0.55]		[0.21]		[-0.79]
Fixed effects	State x Qtr		State x BHC X Qtr		Matched pair	
Borrower and mortgage characteristics	No	Yes	No	Yes	No	Yes
Observations	143364	136484	143364	136484	143364	136484
Adjusted R^2	0.054	0.102	0.147	0.178	0.055	0.099

Data sources: Home Mortgage Disclosure Act (HMDA), 1998-2006; McDash Analytics; CoreLogic.

Table 3. Interest Rate Paid by Steered Borrowers

The table presents regressions of the initial interest rate on mortgages on steered mortgage flag, as well as a variety of fixed effects and borrower and mortgage characteristics. Borrower and mortgage controls include: logged borrower income, FICO credit score of the borrower (splined into the ranges: 621-660, 661-720, 721-760, and >760), logged loan amount, LTV ratio at origination (splined into 80%-89%, 90%-99%, and ≥ 100%), amortizing ARM flag, interest only flag, refi flag, pre-payment penalty flag, owner-occupier flag, conventional mortgage flag, and low documentation flag. All regressions are OLS regressions. Standard errors are double-clustered by calendar month and state of origination. t-statistics are reported in brackets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. See Sections 3.1 and 3.2 in text for details on data sources and sample construction.

Dependent variable:	Initial interest rate					
Mean of control sample:	6.59					
	(1)	(2)	(3)	(4)	(5)	(6)
Steered flag	0.387***	0.721***	-0.060	0.348***	0.376*	0.692***
	[2.60]	[5.07]	[-0.68]	[8.43]	[1.84]	[3.47]
Borrower characteristics	No	Yes	No	Yes	No	Yes
Mortgage characteristics	No	Yes	No	Yes	No	Yes
State*Qtr fixed effects	Yes	Yes	No	No	No	No
State*BHC*Qtr fixed effects	No	No	Yes	Yes	No	No
Matched pair fixed effects	No	No	No	No	Yes	Yes
Observations	143364	140072	143364	140072	143364	140072
Adjusted R^2	0.165	0.460	0.384	0.591	0.152	0.447

Data sources: Home Mortgage Disclosure Act (HMDA), 1998-2006; McDash Analytics.

Table 4. Mortgage Types Taken by Steered Borrowers

The table presents regressions of indicators of mortgage type (interest only, option ARM, prepayment penalty, and low documentation) on steered mortgage flag, as well as a variety of fixed effects and borrower and mortgage characteristics. Borrower and mortgage controls are as in the previous table. All regressions are OLS regressions. Standard errors are double-clustered by calendar month and state of origination. t-statistics are reported in brackets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. See Sections 3.1 and 3.2 in text for details on data sources and sample construction.

Dependent variable:	Interest Only			Option ARM		
Mean of control sample:	0.165			0.161		
	(1)	(2)	(3)	(4)	(5)	(6)
Steered flag	0.266***	0.186***	0.262***	0.129***	0.046***	0.125***
	[5.60]	[8.80]	[4.03]	[8.70]	[2.98]	[6.15]
State*Qtr fixed effects	Yes	No	No	Yes	No	No
State*Bank*Qtr fixed effects	No	Yes	No	No	Yes	No
Matched pair fixed effects	No	No	Yes	No	No	Yes
Borrower and mortgage characteristic	-------- Yes --------			-------- Yes --------		
Observations	143364	143364	143364	143364	143364	143364
Adjusted R^2	0.158	0.254	0.144	0.241	0.404	0.204

Dependent variable:	Prepayment Penalty			Low documentation		
Mean of control sample:	0.198			0.671		
	(1)	(2)	(3)	(4)	(5)	(6)
Steered flag	0.141***	0.102***	0.136***	0.219***	0.180***	0.221***
	[6.13]	[2.92]	[4.11]	[5.30]	[4.88]	[3.99]
State*Qtr fixed effects	Yes	No	No	Yes	No	No
State*BHC*Qtr fixed effects	No	Yes	No	No	Yes	No
Matched pair fixed effects	No	No	Yes	No	No	Yes
Borrower and mortgage characteristic	-------- Yes --------			-------- Yes --------		
Observations	143364	143364	143364	143364	143364	143364
Adjusted R^2	0.158	0.254	0.144	0.241	0.404	0.204

Data sources: Home Mortgage Disclosure Act (HMDA), 1998-2006; McDash Analytics.

Table 5. Allocation of Steered Mortgages

The table presents regressions of indicators for the allocations of mortgage to banks' portfolios, private securitizations, and public (GSE) securitizations on steered mortgage flag, as well as a variety of fixed effects and borrower and mortgage characteristics. Borrower and mortgage controls are defined as in tables above. All regressions are OLS regressions. Standard errors are double-clustered by calendar month and state of origination. t-statistics are reported in brackets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. See Sections 3.1 and 3.2 in text for details on data sources and sample construction.

Dependent variable:	Portfolio			Private (PLS) securitization			Public (GSE) securitization		
Mean in the control sample:	0.17			0.44			0.38		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Steered flag	-0.231***	-0.200***	-0.230***	0.207***	0.204***	0.203***	0.025	-0.005	0.028
	[-12.32]	[-4.25]	[-8.12]	[6.13]	[4.57]	[4.16]	[0.91]	[-0.22]	[0.76]
State*Qtr fixed effects	Yes	No	No	Yes	No	No	Yes	No	No
State*BHC*Qtr fixed effects	No	Yes	No	No	Yes	No	No	Yes	No
Matched pair fixed effects	No	No	Yes	No	No	Yes	No	No	Yes
Borrower and mortgage characteris	-------- Yes --------			-------- Yes --------			-------- Yes --------		
Observations	134083	134083	134083	134083	134083	134083	134083	134083	134083
Adjusted R^2	0.172	0.418	0.139	0.314	0.439	0.300	0.372	0.471	0.376

Data sources: Home Mortgage Disclosure Act (HMDA), 1998-2006; McDash Analytics.

Table 6. Characteristics of Steered Borrowers

The table presents regressions of whether mortgages were steered on borrower personal characteristics and area characteristics, as well as well as a variety of fixed effects as described in text. The regression sample is constructed using propensity-score matching on a number of borrower and mortgage characteristics in McDash Analytics data mortgage servicing data. All regressions are OLS regressions. Standard errors are double-clustered by calendar month and state of origination. t-statistics are reported in brackets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. See Sections 3.1 and 3.2 in text for details on data sources and sample construction.

Dependent variable:	Borower Steered (0/1)		
	(1)	(2)	(3)
African-American	-0.013	0.001	-0.020
	[-0.77]	[0.12]	[-0.43]
Hispanic	0.036***	0.001	0.073**
	[3.04]	[0.38]	[2.08]
Female	0.062***	0.019***	0.121***
	[14.43]	[3.43]	[7.11]
No cosigner	0.101***	0.034***	0.205***
	[9.33]	[4.19]	[6.38]
Low/Moderate Income	0.048***	0.027***	0.104***
	[4.77]	[3.56]	[3.60]
Share with some college education or above	0.115***	0.060***	0.207*
	[3.06]	[2.80]	[1.80]
State*Qtr fixed effects	Yes	No	No
State*Rejecting Bank*Qtr fixed effects	No	Yes	No
Matched pair fixed effects	No	No	Yes
Observations	133011	133011	133011
Adjusted R^2	0.026	0.708	-0.928

Data sources: Home Mortgage Disclosure Act (HMDA), 1998-2006; U.S. Census.

Table 7. Credit Quality of Steered Borrowers – Alternative control samples

The table presents regressions of a 90-day delinquency indicator on steered mortgage flag, as well as a variety of fixed effects and borrower and mortgage characteristics. Borrower and mortgage controls include: logged borrower income, FICO credit score of the borrower (splined into the ranges: 621-660, 661-720, 721-760, and >760), logged loan amount, LTV ratio at origination (splined into 80%-89%, 90%-99%, and ≥ 100%), amortizing ARM flag, interest only flag, refi flag, pre-payment penalty flag, owner-occupier flag, conventional mortgage flag, low documentation flag, and the 12-month change in the house price index. All regressions are OLS regressions. Standard errors are double- clustered by calendar month and state. t-statistics are reported in brackets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. See Section 4.5 in text for details on sample construction.

Panel A. Relative to similar loans approved on the first try by Bank A

Dependent variable:	90-day delinquency within 2 years			
Mean of control sample:	0.041			
	(1)	(2)	(3)	(4)
Steered flag	0.006	-0.004	-0.016	-0.021
	[1.40]	[-1.14]	[-0.88]	[-0.90]
HPI growth, lagged 12 mo		-0.036		-0.050
		[-0.82]		[-1.29]
Fixed effects	State x Qtr		State x BHC X Qtr	
Borrower and mortgage characteristics	No	Yes	No	Yes
Observations	18748	17510	18748	17510
Adjusted R^2	0.032	0.054	0.025	0.046

Panel B. Relative to similar loans approved on the first try by Bank B

Dependent variable:	90-day delinquency within 2 years			
Mean of control sample:	0.062			
	(1)	(2)	(3)	(4)
Steered flag	-0.017***	-0.019***	-0.018***	-0.020***
	[-6.86]	[-5.56]	[-6.65]	[-5.48]
HPI growth, lagged 12 mo		-0.010		-0.014
		[-0.23]		[-0.32]
Fixed effects	State x Qtr		State x BHC X Qtr	
Borrower and mortgage characteristics	No	Yes	No	Yes
Observations	22222	20700	22222	20700
Adjusted R^2	0.020	0.058	0.020	0.058

Data sources: Home Mortgage Disclosure Act (HMDA), 1998-2006; McDash Analytics; CoreLogic.

Figure 1. Steering Process

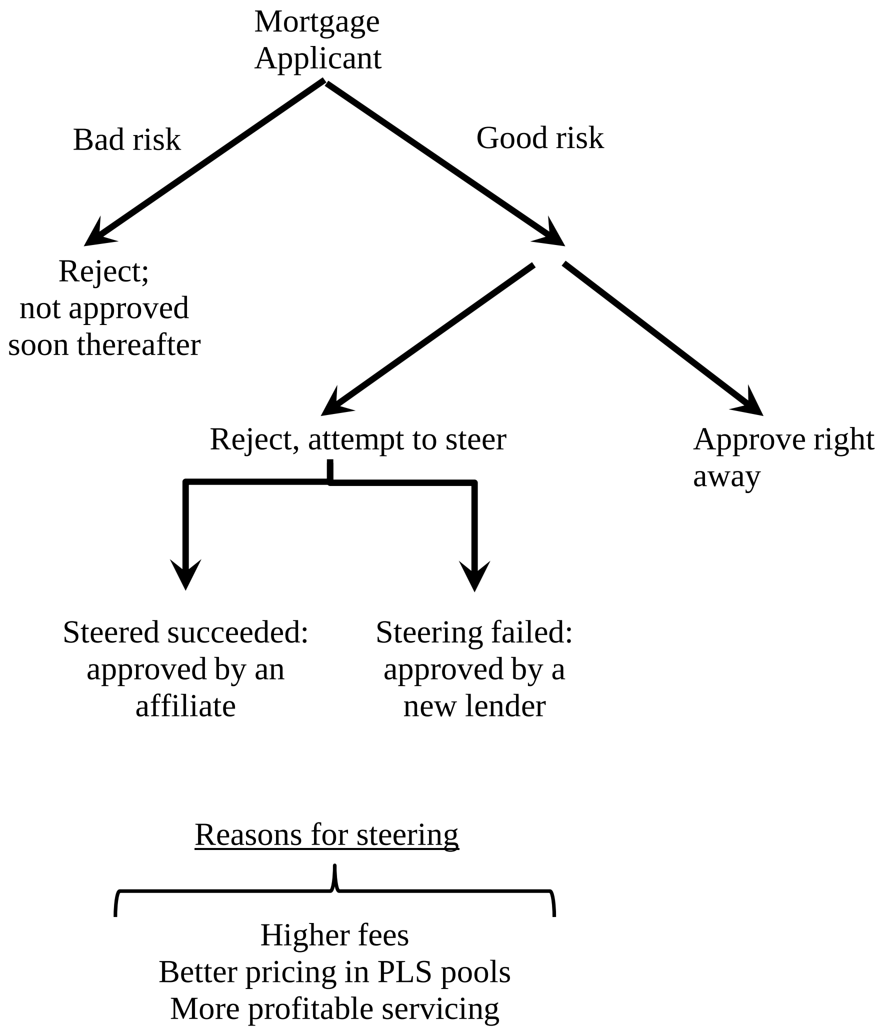


Figure 2. Kernel Densities – Propensity matched sample

This figure shows the kernel density distributions of income, loan amount, FICO score, and LTV ratio at origination of HMDA-McDash loans originated between 1998 and 2006. All originated loans in this sample have been matched to a previous loan application in HMDA that was denied by the lender or withdrawn by the applicant. *Steered flag* is equal to one if the lender that denied the first loan application is affiliated with the lender that ultimately originated the loan. Each loan with *Steered*=1 has been propensity-matched on loan and borrower characteristics to a similar loan with *Steered*=0.

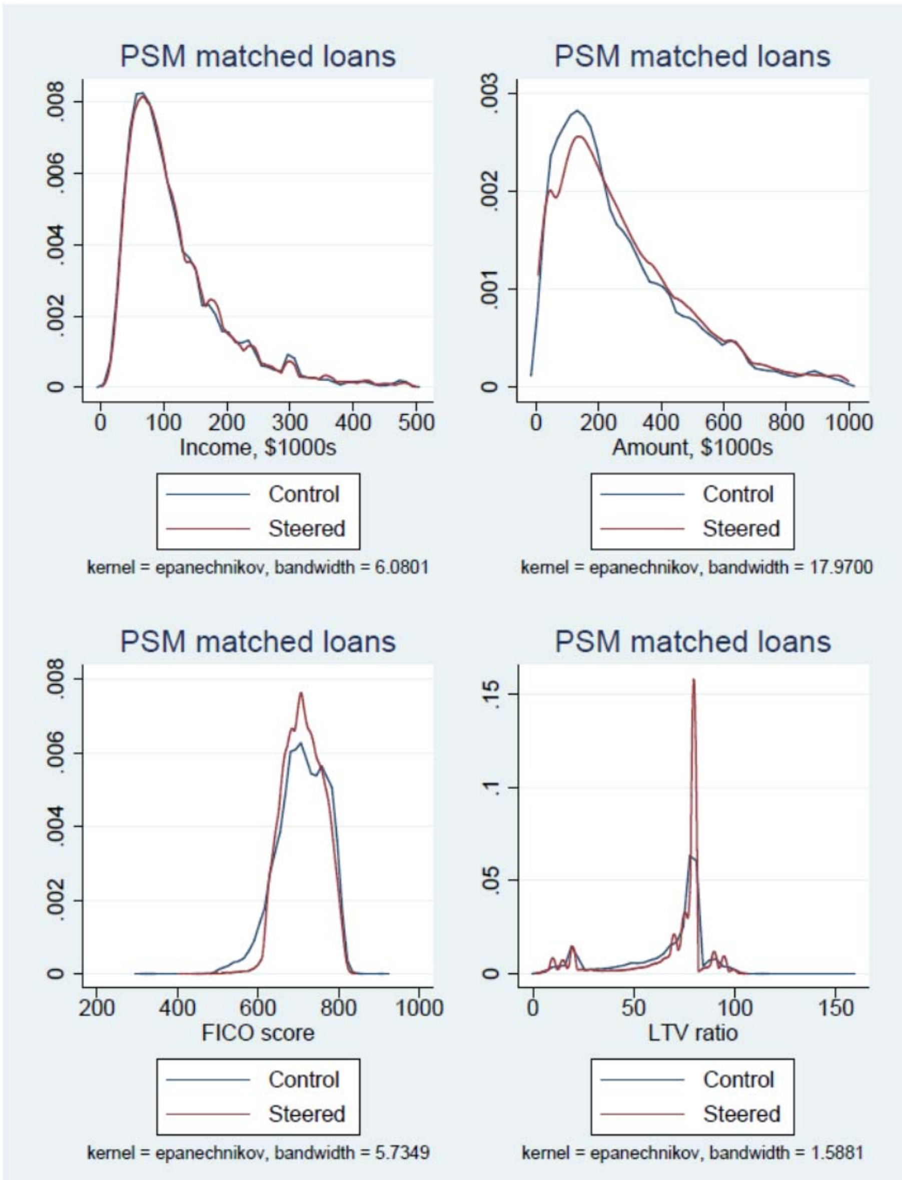
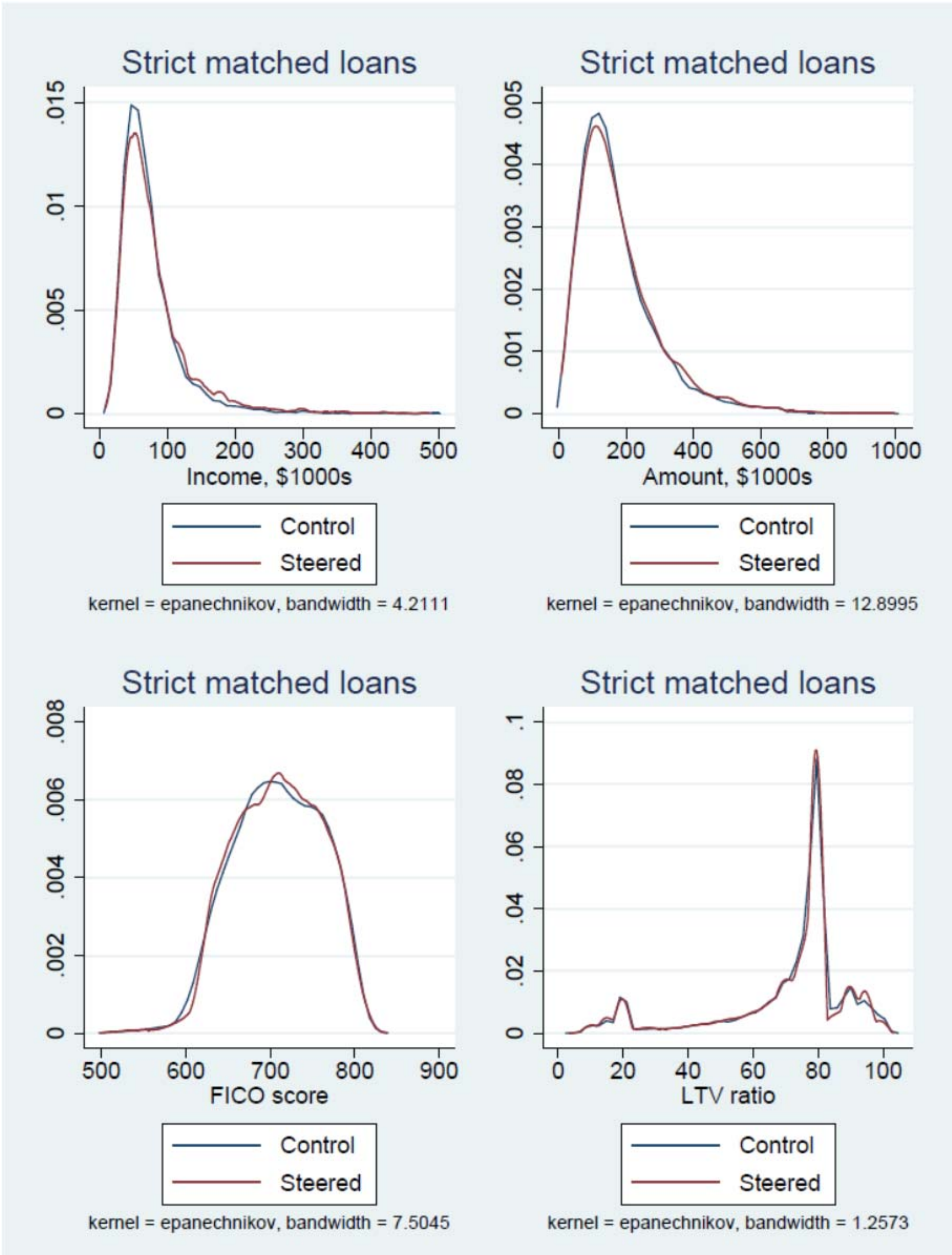


Figure 2 (continued). Kernel Densities – Strictly-matched sample

This figure shows the kernel density distributions of income, loan amount, FICO score, and LTV ratio at origination of HMDA-McDash loans originated between 1998 and 2006. All originated loans in this sample have been matched to a previous loan application in HMDA that was denied by the lender or withdrawn by the applicant. *Steered flag* is equal to one if the lender that denied the first loan application is affiliated with the lender that ultimately originated the loan. Each loan with *Steered*=1 has been strictly matched on each of the loan and borrower characteristics depicted here to a similar loan with *Steered*=0.



Appendix A. Regressions results for Tables 2-6 estimated on the strict-matched sample.

Table A.2. Credit Quality of Steered Borrowers. Strict-matched sample.

The table presents regressions of a 90-day delinquency indicator on steered mortgage flag, as well as a variety of fixed effects and borrower and mortgage characteristics. Borrower and mortgage controls include: logged borrower income, FICO credit score of the borrower (splined into the ranges: 621-660, 661-720, 721-760, and >760), logged loan amount, LTV ratio at origination (splined into 80%-89%, 90%-99%, and ≥ 100%), amortizing ARM flag, interest only flag, refi flag, pre-payment penalty flag, owner-occupier flag, conventional mortgage flag, low documentation flag, and the 12-month change in the house price index. All regressions are OLS regressions. Standard errors are double- clustered by calendar month and state. t-statistics are reported in brackets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. See Sections 3.1 and 3.2 in text for details on data sources and sample construction.

Dependent variable:	90-day delinquency within 2 years					
Mean of control sample:	0.048					
	(1)	(2)	(3)	(4)	(5)	(6)
Steered flag	-0.005	-0.027***	-0.025***	-0.037**	-0.005	-0.031*
	[-0.95]	[-2.71]	[-2.73]	[-2.50]	[-0.70]	[-1.76]
HPI growth, lagged 12 mo		-0.032***		-0.060		-0.083
		[-3.04]		[.]		[-0.67]
Fixed effects	State x Qtr		State x BHC X Qtr		Matched pair	
Borrower and mortgage characteri	No	Yes	No	Yes	No	Yes
Observations	26504	19047	26504	19047	26504	19047
Adjusted R^2	0.029	0.056	-0.016	0.035	0.095	0.045

Table A.3. Interest Rate Paid by Steered Borrowers. Strict-matched sample.

The table presents regressions of the initial interest rate on mortgages on steered mortgage flag, as well as a variety of fixed effects and borrower and mortgage characteristics. Borrower and mortgage controls include: logged borrower income, FICO credit score of the borrower (splined into the ranges: 621-660, 661-720, 721-760, and >760), logged loan amount, LTV ratio at origination (splined into 80%-89%, 90%-99%, and ≥ 100%), amortizing ARM flag, interest only flag, refi flag, pre-payment penalty flag, owner-occupier flag, conventional mortgage flag, and low documentation flag. All regressions are OLS regressions. Standard errors are double-clustered by calendar month and state of origination. t-statistics are reported in brackets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. See Sections 3.1 and 3.2 in text for details on data sources and sample construction.

Dependent variable:	Initial interest rate					
Mean of control sample:	6.44					
	(1)	(2)	(3)	(4)	(5)	(6)
Steered flag	0.288***	0.540***	0.052	0.221***	0.288**	0.496**
	[2.89]	[4.29]	[0.90]	[2.81]	[2.17]	[2.32]
Borrower characteristics	No	Yes	No	Yes	No	Yes
Mortgage characteristics	No	Yes	No	Yes	No	Yes
State*Qtr fixed effects	Yes	Yes	No	No	No	No
State*BHC*Qtr fixed effects	No	No	Yes	Yes	No	No
Matched pair fixed effects	No	No	No	No	Yes	Yes
Observations	26503	19758	26503	19758	26503	19758
Adjusted R^2	0.198	0.428	0.317	0.495	0.405	0.452

Table A.4. Mortgage Types Taken by Steered Borrowers. Strict-matched sample.

The table presents regressions of indicators of mortgage type (interest only, option ARM, prepayment penalty, and low documentation) on steered mortgage flag, as well as a variety of fixed effects and borrower and mortgage characteristics. Borrower and mortgage controls are as in the previous table. All regressions are OLS regressions. Standard errors are double-clustered by calendar month and state of origination. t-statistics are reported in brackets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. See Sections 3.1 and 3.2 in text for details on data sources and sample construction.

Dependent variable:	Interest Only			Option ARM		
Mean of control sample:	0.09			0.08		
	(1)	(2)	(3)	(4)	(5)	(6)
Steered flag	0.190***	0.127***	0.197***	0.195***	0.168***	0.195***
	[8.14]	[6.20]	[6.05]	[4.36]	[3.97]	[2.87]
State*Qtr fixed effects	Yes	No	No	Yes	No	No
State*Bank*Qtr fixed effects	No	Yes	No	No	Yes	No
Matched pair fixed effects	No	No	Yes	No	No	Yes
Borrower and mortgage characteristics	-------- Yes --------			-------- Yes --------		
Observations	20164	20164	20164	20164	20164	20164
Adjusted R^2	0.163	0.129	0.150	0.208	0.246	0.170

Dependent variable:	Prepayment Penalty			Low documentation		
Mean of control sample:	0.15			0.72		
	(1)	(2)	(3)	(4)	(5)	(6)
Steered flag	0.174***	0.152***	0.184**	0.135***	0.047***	0.139***
	[3.82]	[4.26]	[2.55]	[7.41]	[3.09]	[5.39]
State*Qtr fixed effects	Yes	No	No	Yes	No	No
State*BHC*Qtr fixed effects	No	Yes	No	No	Yes	No
Matched pair fixed effects	No	No	Yes	No	No	Yes
Borrower and mortgage characteristics	-------- Yes --------			-------- Yes --------		
Observations	20164	20164	20164	20164	20164	20164
Adjusted R^2	0.235	0.295	0.182	0.068	0.280	0.037

Table A.5. Allocation of Steered Mortgages. Strict-matched sample.

The table presents regressions of indicators for the allocations of mortgage to banks' portfolios, private securitizations, and public (GSE) securitizations on steered mortgage flag, as well as a variety of fixed effects and borrower and mortgage characteristics. Borrower and mortgage controls are defined as in tables above. All regressions are OLS regressions. Standard errors are double-clustered by calendar month and state of origination. t-statistics are reported in brackets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. See Sections 3.1 and 3.2 in text for details on data sources and sample construction.

Dependent variable:	Portfolio			Private (PLS) securitization			Public (GSE) securitization		
Mean in the control sample:	0.16			0.54			0.30		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Steered flag	-0.161***	-0.099***	-0.177***	0.123***	0.101***	0.117**	0.040	-0.001	0.063
	[-13.77]	[-6.29]	[-7.60]	[4.02]	[3.44]	[2.44]	[1.36]	[-0.04]	[1.39]
State*Qtr fixed effects	Yes	No	No	Yes	No	No	Yes	No	No
State*BHC*Qtr fixed effects	No	Yes	No	No	Yes	No	No	Yes	No
Matched pair fixed effects	No	No	Yes	No	No	Yes	No	No	Yes
Borrower and mortgage characte	-------- Yes --------			-------- Yes --------			-------- Yes --------		
Observations	19199	19199	19199	19199	19199	19199	19199	19199	19199
Adjusted R^2	0.140	0.456	0.031	0.322	0.373	0.320	0.350	0.400	0.386

Table A.6. Characteristics of Steered Borrowers. Strict-matched sample.

The table presents regressions of whether mortgages were steered on borrower personal characteristics and area characteristics, as well as well as a variety of fixed effects as described in text. The regression sample is constructed using propensity-score matching on a number of borrower and mortgage characteristics in McDash Analytics data mortgage servicing data. All regressions are OLS regressions. Standard errors are double-clustered by calendar month and state of origination. t-statistics are reported in brackets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. See Sections 3.1 and 3.2 in text for details on data sources and sample construction.

Dependent variable:	Borower Steered (0/1)		
	(1)	(2)	(3)
African-American	-0.054**	-0.010	-0.117*
	[-2.22]	[-0.63]	[-1.76]
Hispanic	-0.011	0.002	-0.016
	[-0.60]	[0.26]	[-0.33]
Female	0.051***	0.023***	0.114***
	[14.49]	[5.15]	[11.37]
No cosigner	0.122***	0.001	0.251***
	[8.86]	[0.10]	[6.49]
Low/Moderate Income	0.043***	0.011	0.094***
	[4.27]	[1.27]	[2.98]
Share with some college education or above	0.209***	0.095***	0.407***
	[7.42]	[3.72]	[4.40]
State*Qtr fixed effects	Yes	No	No
State*Rejecting BHC*Qtr fixed effects	No	Yes	No
Matched pair fixed effects	No	No	Yes
Observations	24047	24047	24047
Adjusted R^2	0.021	0.625	-0.904

Appendix B. Variable Definition

Variable	Description	Source
Steered flag	1 if rejected mortgage application is approved soon after by an affiliated lender; 0 if unaffiliated	HMDA, authors' calculations
Log borrower income	Borrower income at origination, as reported	HMDA
FICO	FICO score at origination	McDash
Log loan amount	First-lien mortgage amount at origination	McDash
LTV	First-lien loan-to-value ratio at origination	McDash
FRM flag	1 if a mortgage is identified as having a fixed interest rate	McDash
Amortizing ARM flag	1 if a mortgage has an adjustable interest rate but amortizes over a pre-determined period of time	McDash
Option ARM flag	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
Interest only flag	1 if a mortgage calls for interest only payments for a pre-specified number of years, fixed amortization schedule thereafter	McDash
Refi flag	1 if a mortgage is identified as refinancing an existing loan	McDash
Pre-payment penalty flag	1 if a mortgage contract has a penalty for refinancing before a pre-specified time	McDash
Owner-occupied flag	1 if a property is reported to be owner-occupied	McDash
Conventional flag	1 for mortgages originated outside of FHA/VA	McDash
Jumbo flag	1 for mortgages that exceed GSE loan size limit	McDash
Low documentation flag	1 for mortgages that are listed as not being underwritten on the basis of fully documented income and assets	McDash
HPI growth, lagged 12 months	Annual change in ZIP or MSA home price index in the 12 months preceding mortgage origination	CoreLogic