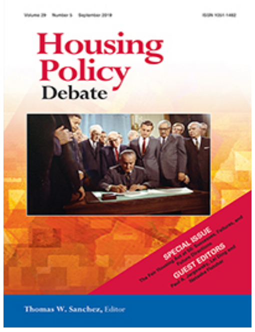

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Real Denial Rates: A New Tool to Look at Who Is Receiving Mortgage Credit

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ABSTRACT
The observed mortgage denial rate (ODR), calculated from Home Mortgage Disclosure Act (HMDA) data, is often used to measure mortgage credit availability, but it does not account for shifts in applicants' credit profiles. In this article, we develop an additional tool, which we call the real denial rate (RDR), as a way to account for credit differences and hence more consistently measure denial rates and mortgage credit accessibility. We match HMDA data with CoreLogic proprietary data to obtain both borrower demographic information (e.g., income and race and ethnicity) and mortgage credit characteristics (e.g., loan-to-value ratios, debt-to-income ratios, and credit scores). We account for shifts in applicants' credit profiles by considering only the denial rate of low-credit-profile applicants. Our RDR results show that conventional mortgages have higher denial rates than government mortgages do, racial and ethnic differences are smaller than the ODR indicates but are not eliminated, and small-dollar mortgages have higher RDRs, particularly in the government loan channel.

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Mortgage credit; denial rate; racial discrimination; Home Mortgage Disclosure Act

The observed mortgage denial rate (ODR), calculated from Home Mortgage Disclosure Act (HMDA) data, is often used to measure mortgage credit availability across time and across different racial and ethnic groups. But this can be a misleading measure of credit availability, as it depends on both the composition of borrowers who are applying for a mortgage and how tight credit standards are. Thus, higher denial rates can be the result of either a tighter credit environment or an increase in applications by borrowers with weaker credit.

The recent housing crisis highlights the importance of striking a balance between credit availability and risk to achieve a sustainable housing market; a good measure of credit access is key. When we use ODR to measure credit access over time, two unintuitive patterns emerge. First, denial rates were higher in 2006 than they were in 2017. The denial rate for all owner-occupied purchase loans was 18% in 2006 versus 11% in 2017. If denial rates were a good measure of credit availability, this would suggest that credit was tighter in 2006, at the peak of the housing bubble, than it has been in recent years, when mortgage credit became overly tight following the crisis.[1] In fact, the loose lending standards encouraged more applicants with weak credit profiles to apply for mortgages in 2006, but the high denial rate would suggest the opposite.

Similarly, government mortgages from the Federal Housing Administration (FHA), the U.S. Department of Veterans Affairs (VA), the Department of Agriculture's (USDA) Rural Housing Service (RHS), and the U.S. Department of Housing and Urban Development's Office of Public and Indian Affairs (PIH) appear to have higher denial rates than conventional mortgages do (12%

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for government mortgages versus 9% for conventional in 2017). This is unintuitive as the government channel has historically been the channel for underserved borrowers who tend to have weaker credit profiles (Ginnie Mae, 2018a).

In this article, we confirm the variation in the credit profile in the applicant pools over time and across origination channels. Moreover, by controlling to a large extent for the variations in credit worthiness, we develop a new tool called the real denial rate (RDR). Ideally, a measure of the denial rate would hold the credit profile of the application pool constant. There are two challenges to creating such a measure: First, HMDA data do not contain borrower credit-related information such as credit score, debt-to-income (DTI) ratio, or loan-to-value (LTV) ratio or loan characteristics such as product type and documentation type. Second, researchers can observe information about the credit characteristics only for applicants who receive loans, not those whose applications are denied.[2]

To circumvent the two challenges, we match HMDA data with proprietary CoreLogic mortgage data to measure the credit characteristics of owner-occupied purchase borrowers. We then divide these borrowers into two groups, higher credit profile (HCP) borrowers and lower credit profile (LCP) borrowers. We define HCP borrowers as borrowers with strong enough credit that they would never be denied a mortgage. All denied mortgages automatically fall into the LCP category. The RDR controls for applicant credit profile by calculating the denial rates only among LCP applicants (denied applicants plus LCP borrowers who received a mortgage).

This measure corrects for some weaknesses in the ODR measure. By adjusting for the quality of the applicant pool, the RDR analysis more accurately reflects credit accessibility over time; it shows that LCP borrowers were more likely to get turned down for a mortgage in 2017 (32%) than in 2006 (29%). More important, only 31% of all applicants are LCP in 2017, half the level for 2006 (62%), suggesting more potential borrowers with weaker credit profiles were absent from the market, either deterred by the strict lending standards or prescreened in the application process. The RDR also more accurately reflects differences across origination channels, with the government channel showing a lower denial rate than the conventional channel. The RDR trends are consistent with leading mortgage credit availability measures such as the Mortgage Bankers Association Mortgage Credit Availability Index,[3] CoreLogic's Housing Credit Index,[4] and the Urban Institute's Housing Credit Availability Index, or HCAI,[5] which have proven RDR to be useful tools to gauge credit access, a critical measure of the health of the housing and mortgage market.

The article also contributes to the extensive literature using the disparity in mortgage denial rates to detect racial discrimination at the mortgage application stage.[6] Higher observed denial rates for minority borrowers are often cited by news reports as evidence of discrimination.[7] In 2017, the ODR for black applicants was 18%, twice the level of white applicants' 9%. It is important to note, however, that we do not know whether the clear racial discrepancy stems from variations in treatment of applicants with the same credit profile (i.e., racial discrimination) or variations in the level of credit weakness among these groups (i.e., minority applicants have weaker credit profiles than white applicants do).

Several previous studies have tried to address the creditworthiness disparity between applicant pools. The Institute on Race and Poverty (IRP, 2009) controls for income in its analysis of 2004–2006 HMDA data in the Minneapolis-Saint Paul, Minnesota Twin Cities metropolitan area. The study found that nonwhite borrowers were denied mortgages at higher rates than white borrowers were, regardless of income. However, this study only relied on income and did not include other key credit-related variables.

In their widely cited research, Munnell, Tootell, Browne, and McEneaney (1996), on behalf of the Federal Reserve Bank of Boston, paired HMDA data with proprietary mortgage data provided by major Boston lenders to run a logit regression on mortgage application outcomes for 700 black/Hispanic borrowers and about 2,300 randomly selected white borrowers in the Boston, Massachusetts, metropolitan area in 1990. The authors selected significant variables by asking Boston lenders to submit data on all factors considered in their mortgage review processes. Before adjusting for these factors, the denial rate was 10% for whites and 28% for people of color. After controlling for probability of default, cost of default, loan characteristics, and personal characteristics of the borrower, the denial rate gap between black and Hispanic borrowers and their white counterparts shrank from 18% to 8%.

Ards, Ha, Mazas, and Myers (2015) studied differences in mortgage denial rates among blacks and whites using data from Freddie Mac's 1999 Consumer Credit Survey (CCS). The CCS asked consumers whether they had been denied a mortgage, in addition to a range of questions gauging consumer credit characteristics. The study finds that on average black applicants have poorer credit and that much of the racial gap in loan denials can be explained by racial disparity in credit scores.

The survey data used by Ards et al. (2015) and Munnell et al. (1996) to control applicants' credit characteristics narrow the scope of their study to their respective samples. Based on the matched HMDA and CoreLogic mortgage data, the RDR offers a new tool that allows us to examine borrower characteristics at the national level, by loan origination channel, and over time. Using the RDR we still find differences in denial rates by race/ethnicity, but these differences are substantially smaller than indicated by the ODRs. In 2017, the ODRs for black families are 2.0 times those for whites, whereas the ODRs for Hispanic familes are 1.4 times those for whites, but the RDRs versus white borrowers are 1.2 for black families and 1.1 for Hispanic families. Although it is impossible to fully control for the credit profile distribution of the mortgage applicants, our attempts clearly indicate the racial gap in observed denial rates can be partly explained by credit profile differences across racial and ethnic groups. This is consistent with findings of both Ards et al. (2015) and Munnell et al. (1996).

In addition, the RDR helps explain the dearth of small-dollar mortgages for low-cost single-family residential home purchases, a dearth that limits affordable homeownership opportunities for creditworthy families living in low-cost underserved housing markets. Recent research by McCargo, Bai, George, and Strochak (2018) has documented that only a quarter of homes sold for $70,000 or less in 2015 were financed through a mortgage, compared with almost 80% of homes worth between $70,000 and $150,000. We demonstrate that RDRs are higher for small-dollar mortgages than for larger loans. The gap in denial rates is a key reason so few sales of lower priced homes are financed with a mortgage.

In the next section, we discuss the RDR methodology and its limitations. In section 2, we show that the RDR produces intuitive mortgage access trends over time and by origination channel. In section 3, we apply this measure to examine the disparity in mortgage denial rates by race and ethnicity. In section 4, we apply our RDR analysis to differences in loan size. We find that the differential denial rates by loan size cannot be explained by differences in the credit profiles of the borrowers. In the final section, we conclude and discuss the policy implications from our findings.

1. Methodology and Data

In this article, we first review the methodology we developed in Li and Goodman (2014a). As in that article, we limit our universe to single-family (one- to four-unit), owner-occupied purchase activity, as we are interested in mortgage credit availability to borrowers purchasing a home for personal use.[8] All approved mortgages go to either high-credit-profile borrowers who will never be denied a mortgage or low-credit-profile borrowers who might be denied. We define HCP applicants as those whose credit profiles are so strong that their probability of default is low; for our analysis, we assume it is zero. To calculate the real denial rate, we compare the number of loans denied (who are, by definition, all assumed to be LCP applicants) with LCP applicants who received mortgages. In other words, RDR controls for applicant credit profiles by excluding HCP borrowers.

To determine whether an originated loan is HCP or LCP, we relied on the credit profiles of the mortgages, just as lenders would when evaluating credit. We first assembled the characteristics for the loans reported in the HMDA database. HMDA contains nearly the entire universe of loans.[9] It includes the applicant's income, loan amount, race or ethnicity, loan purpose, and application outcome. But HMDA does not have information on mortgage credit profile characteristics, such as LTV ratio, DTI ratio, credit score, documentation type (i.e., full, low, or no documentation), or product type. To gather this information, we match HMDA to the CoreLogic proprietary databases. We use both the CoreLogic private-label securities and servicing loan-level databases; there is no overlap, as the private-label securities are excluded from the version of the servicing data we were using. This proprietary database contains mortgage credit characteristics on originated loans but lacks demographic information on income and race or ethnicity. Because both databases are anonymized, we match the data using the databases' common fields, such as geography, loan amount, origination date, loan purpose (e.g., purchase or refinance), loan type, and occupancy. Once we do the matching, we have a rich data set that contains race or ethnicity, income, LTV ratio, DTI ratio, credit score, documentation type, and whether the loan is a risky product. The matching methodology we use and the matching rates are described in the appendix (see also Li et al., 2014, for more details).

The probability that a consumer is an LCP borrower is based on the historical default rates of mortgages with the same credit characteristics. To determine this, we first analyze the expected default rates for various combinations of the LTV ratio, DTI ratio, credit score, documentation type, and whether the loan is a risky product.[10] The expected default rates rely on the actual experience of 2001 and 2002 originations (a proxy for a normal period in which home prices are rising, which is weighted 90%), and the experience of 2005 and 2006 originations (a proxy for a stress period, which is weighted 10%).[11] Li and Goodman (2014b) discuss in depth the expected default risk for 360 different combinations of LTV ratios, DTI ratios, FICO scores, documentation types, and product types.

Based on expected mortgage default rates, we use the following definitions to construct a lookup table for the probability of a consumer being LCP, for various combinations of LTV ratio, DTI ratio, FICO score, documentation type, and product type combinations (Appendix Table A1).

We assign a zero probability of being LCP to consumers who apply for loans without risky features and have a FICO score above 700, an LTV ratio less than 78%, and a DTI ratio less than 30%. This is the lower bound. We do this because we find that these mortgages have a very low expected probability of default (1%). We assign a 100% probability of being LCP to consumers who apply for loans without risky features and have a FICO score below 580, an LTV ratio greater than 95%, and a DTI ratio greater than 50%. This is the upper bound. This represents the combination of lowest FICO score category and highest LTV and DTI ratio categories in our lookup table. We have found that these mortgages have a very high expected probability of default (23%). We do a linear transformation of expected default risk for consumers with credit risk between the upper and lower bounds and assign a probability of being LCP accordingly.

1.1. Calculating the Real Denial Rate

We illustrate the calculation of the RDR in Table 1. Again, the data set used for this analysis is limited to owner-occupied, single-family properties, and all analyses in this article refer solely to this universe.

According to HMDA data, there were 6,779,433 mortgage applications in 2006. Lenders denied 1,219,790 and approved 5,559,643.[12] So the traditional ODR is 18%.

Our matched HMDA and CoreLogic data indicate that of the 5,559,643 approved loans, 2,961,006 (53%) were from LCP consumers and 2,598,637 (47%) were from HCP consumers. Because HCP consumers, by our definition, have a zero probability of default, 4,180,796 (the 6,779,433 applications minus the 2,598,637 from HCP consumers) applications are from LCP borrowers. All denied applications, by definition, come from the LCP pool, so the RDR for LCP applications is 1,219,790 divided by 4,180,796, or 29%.

The difference between the RDR of 29% and the ODR of 18% reflects the fact that, in our calculation of the RDR, we have reduced the denominator to include only the 53% of applicants who are LCP; that is, we have excluded the 47% of applicants who are HCP. In fact, ODRs

Table 1. Calculating the real denial rate.

Variable	Variable name	Calculation/ data source	2006	2017
Total no. of loan applications	A	HMDA	6,779,433	3,809,074
No. of loan applications denied by lenders	B	HMDA	1,219,790	394,448
Loan applications denied by lenders (observed denial rate, %)	ODR	= B/A	18%	11%
No. of loan applications approved by lenders[a]	C	= A-B	5,559,643	3,315,072
Loans to low credit profiles (%)[b]	D	CoreLogic matched with HMDA	53%	24%
No. of approved loan applications by low credit profiles	E	= C × D	2,961,006	811,454
No. of approved loan applications by high credit profiles	F	= C-E	2,598,637	2,614,815
No. of loan applications by high credit profiles[c]	G	= F	2,598,637	2,614,815
No. of denied loan applications by high credit profiles	H	= G-F	0	0
No. of loan applications by low credit profiles	I	= A-G	4,180,796	1,194,259
Loan applications by low credit profiles (%)	J	= I/A	62%	31%
No. of denied loan applications by low credit profiles	K	= B	1,219,790	382,805
Loan applications by low credit profiles denied by lenders (real denial rate, %)	RDR	= K/I	29%	32%

Note. HMDA = Home Mortgage Disclosure Act. ODR = observed denial rates. RDR = real denial rates. The analysis is limited to owner-occupied purchase mortgage applications. Loan applications in 2006 and 2017 are used to illustrate how the RDR is calculated. The raw data for other races or ethnicities, channels, and origination years used for calculating the RDR are available upon request. Data from HMDA, CoreLogic, and the Urban Institute.

[a] Includes both originated loans and loan applications approved by the lenders but not accepted by the applicants. The latter accounts for less than 10% of approved applications.

[b] See the Methodology and Data section for the definition of low credit profiles.

[c] Borrowers with high credit profiles have no chance being denied of a loan application.

understate the difficulty of applicants with marginal credit obtaining a mortgage; the RDR is a more accurate measure.

1.2. Limitations

It is impossible to completely control for mortgage applicant credit characteristics. Although we believe the RDR offers an innovative approach to do so, several important limitations of our approach arise from the key assumptions and the data constraints.

First, the RDR, like the traditional ODR, fails to account for another important way that people fail to access mortgage credit: they are deterred from applying in the first place. In other words, our denial rates do not include potential applicants who were prescreened by lenders before the application or simply deterred from the market. However, the share of LCP applicants does shed some light on the deterrence rate. For example, RDR is 36% in the postcrisis period (2011–2017), slightly lower than in the precrisis period (37%, 1998–2004). But LCP applicant share is much lower in the postcrisis period (32%) than the precrisis period (49%), suggesting that the tighter lending standards following the crisis persist; they have not returned to the precrisis level. Some of this may be caused by structural changes in the market. Many real estate agents require their clients to be prequalified for a mortgage, a postcrisis development. Some potential homeowners may get turned down when they inquire, before submitting a formal application.

Second, for the probability of default calculations, we use CoreLogic loan performance data, constructing two lookup tables, one for traditional products and one for risky products. The latter is defined as mortgages with less than 5 years to the reset, negative-amortization loans, interest-only loans, and loans with prepayment penalties. We do not further sort by loan type; that is, we do not separate government loans from conventional loans, and we do not separate private-label securities from portfolio loans or government-sponsored enterprise (GSE) loans. For loans with product risk, we do not look at the relative performance by type. Although much of the difference in performance stems from the characteristics we use for sorting (credit score, LTV, DTI, and whether it is a risky product), there are differences for any given set of risk characteristics across channels that we are not capturing.

Third, although we choose the weakest combination of LTV, DTI, and FICO categories without a risky feature in our lookup table as the cutoff for the LCP threshold, other cutoff points might work too. We have experimented with different LCP cutoffs, and the conclusions are insensitive to this assumption. Moreover, the RDR makes no distinctions among LCP applicants.

Finally, the CoreLogic and HMDA data sets do not align perfectly; the HMDA data are far more complete. We therefore have unmatched HMDA loans, and a large proportion of the matches are nonunique. We have partially controlled for these difficulties by adding weights to ensure that our final matched data set follows the same race/ethnicity income distribution as the original HMDA data.

2. The Real Denial Rate Over Time and by Channel

The RDR gives more intuitive results versus the ODR over time on two measures. First, whereas the ODR shows denial rates are much higher in 2006 than in 2017, suggesting credit was much tighter then, the RDR shows the opposite. We make the case that this is because fewer LCP borrowers are applying for mortgages. Second, ODRs indicate that denial rates look to be higher in the government channel than in the conventional channel; this is unintuitive, because the government channel has historically been the channel for underserved borrowers (Ginnie Mae, 2018a). The RDR shows that once differences in the credit profiles of the borrowers are accounted for, the pattern is as expected: the government channel has lower denial rates.

2.1. RDR Over Time

Let us look more closely at our results. Table 1 shows the ODR and RDR calculations for all applicants in 2006 and 2017. The ODR in 2006 (18%) is higher than the ODR in 2017 (11%). This result suggests that credit was tighter in 2006 than in 2017, which runs counter to our expectations. We would expect denial rates to be lower during the housing boom, when lenders approved loans they would not have approved in a tighter lending environment, such as that prevailing a decade after the crisis.

Changes in applicants' credit profiles explain the counterintuitive results. In 2006, 62% of loans were to LCP applicants, versus 31% in 2017. Figure 1 shows the ODR over time. It peaked in 2006 and 2007, the period in which we consider credit the loosest, and has come down steadily since then.

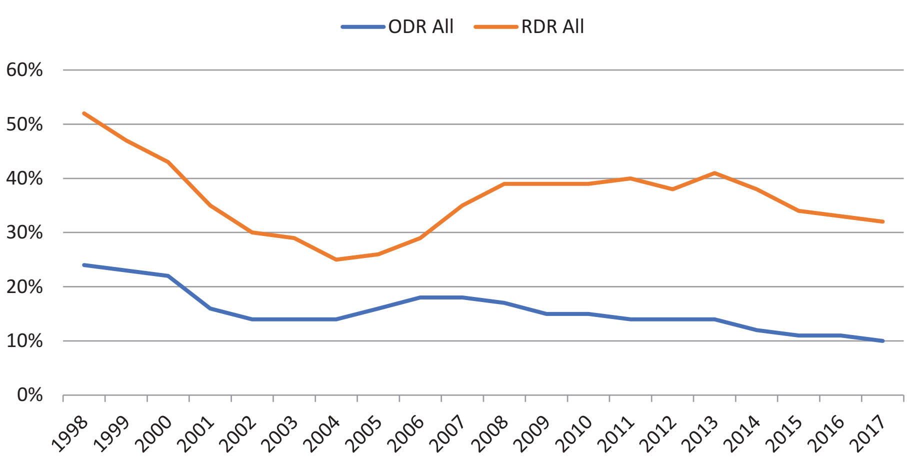

Figure 1. Observed denial rates (ODR) versus real denial rates (RDR), 1998–2017.
Note. Based on owner-occupied purchase mortgage applications. Data from Home Mortgage Disclosure Act, CoreLogic, and the Urban Institute.

Because the RDR measures denial rates for only LCP applicants, it reveals a more intuitive pattern. The RDR is 32% in 2017 versus 29% in 2006. More precisely, the RDR rose sharply after the housing crisis, peaked at 41% in 2013, and has declined over the past few years, reflecting the loosened credit box.

Table 2 shows the share of LCP applicants, which has decreased steadily since the financial crisis. The share of LCP applicants was 49% from 1998 to 2004, 58% from 2005 to 2007, 39% from 2008 to 2010, and 32% from 2011 to 2017.

There are three widely cited mortgage credit availability indices: the Mortgage Bankers Association (MBA) Mortgage Credit Availability Index, CoreLogic's Housing Credit Index, and the Urban Institute's HCAI. The three indices use very different methodologies (MBA looks at lender guidelines, CoreLogic uses a principal component analysis, and the Urban Institute measures the ex ante probability of default of mortgages underwritten in any given period), but they all show exactly the same pattern: loose credit from 2005 to 2007, a dramatic tightening until 2013, and a marginal loosening since. Figure 2 displays results from Urban's HCAI, showing the market is taking less than half the credit risk it was taking before the crisis. The RDR explains why.

After controlling for the variability in the applicant mix through the boom and bust, the RDR analysis shows that denial rates were similar to what they were in the prebubble period (that is, 36% for 2011–2017 compared with 37% for 1998–2004). Table 2 shows that the share of LCP applicants is lower, as fewer marginal applicants are applying for loans. From 2011 to 2017, 32% of applicants were LCP, but from 1998 to 2004, 49% of applicants were LCP.

2.2. *The RDR More Accurately Reflects Credit Differentials by Channel*

At the point of loan application, a borrower chooses either a government mortgage or a conventional mortgage. The government channel includes loans insured by the FHA, the VA, the USDA, or the Department of Public and Indian Housing within the U.S. Department of Housing and Urban

Table 2. Observed denial rate versus real denial rate and share of low-credit-profile applicants and borrowers in all channels.

	Denial rates (%)		Low-credit-profile shares (%)	
Year(s)	ODR—all	RDR—all	Applicants	Borrowers
1998	24	52	47	30
1999	23	47	49	34
2000	22	43	50	37
2001	16	35	45	35
2002	14	30	46	37
2003	14	29	48	40
2004	14	25	55	48
2005	16	26	60	52
2006	18	29	62	53
2007	18	35	53	42
2008	17	39	43	31
2009	15	39	38	27
2010	15	39	37	26
2011	14	40	36	25
2012	14	38	36	26
2013	14	41	33	23
2014	12	38	33	23
2015	11	34	32	24
2016	11	33	32	24
2017	11	32	31	24
1998–2004	18	37	49	37
2005–2007	17	30	58	49
2008–2010	16	39	39	28
2011–2017	12	36	32	24

Note. ODR = observed denial rates, RDR = real denial rates. Based on owner-occupied purchase mortgage applications. Data from Home Mortgage Disclosure Act, CoreLogic, and the Urban Institute.

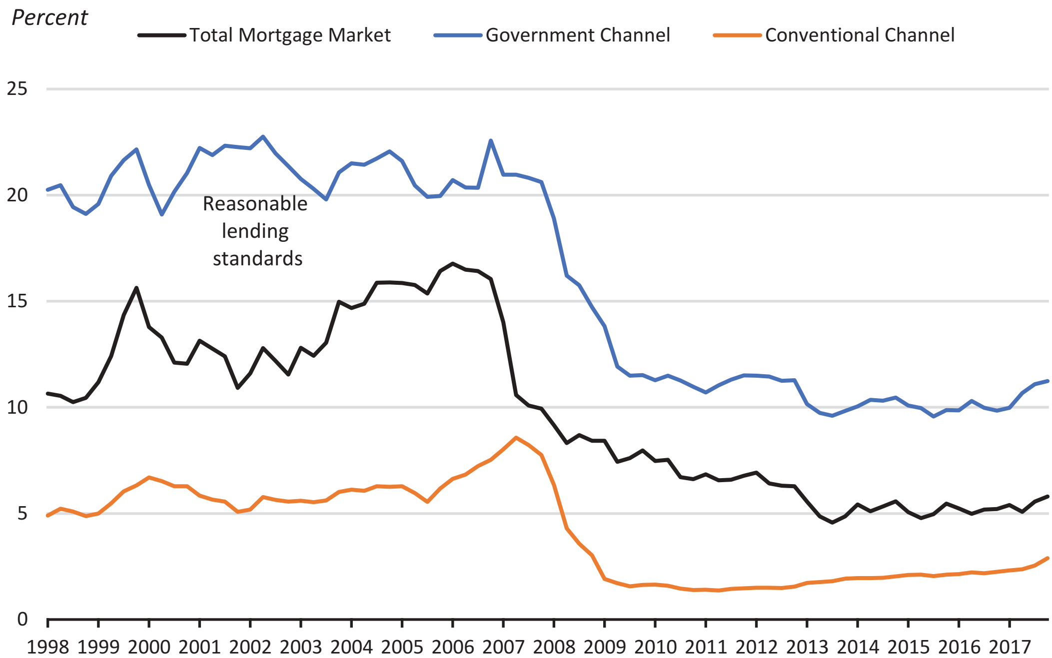

Figure 2. Default risk taken by the mortgage market (measured according to the Urban Institute's Housing Credit Availability Index). *Note*. Data from eMBS, CoreLogic, Home Mortgage Disclosure Act, Inside Mortgage Finance, and the Urban Institute.

Development. The conventional channel includes executions by the GSEs, bank portfolio, and private-label securities. In the postbubble years, as the private-label securities market has all but disappeared, the GSEs (Fannie Mae and Freddie Mac) are the main issuers in the conventional market.

Because of its low down-payment requirements, the government channel has traditionally been used to a disproportionate extent by low- and moderate-income borrowers and minority consumers, and we would assume it is easier to qualify for a government loan than for a conventional loan. Therefore, we would assume denial rates in the government channel are lower than in the conventional channel.

The ODR measure in Figure 3 confirms this was the case before the financial crisis. After the crisis, an ODR analysis suggests that the conventional channel had lower denial rates than the government channel did.

Credit profile changes in the loan applicant pool explain these counterintuitive results. Table 3 shows that the average share of LCP applicants in the conventional channel was 45% in the prebubble years of 1998 to 2004, 56% in the bubble years of 2005 to 2007, 25% in the crisis years of 2008 to 2010, and 20% in the postcrisis years of 2011 to 2017. Low-credit-profile shares in the government channel were 65%, 77%, 55%, and 52%, respectively, in those periods.

Following the crisis, the conventional channel changed its pricing to be more risk based (Wachter, 2015), whereas the government channel does not use risk-based pricing. The GSEs imposed loan-level pricing adjustments, a system of up-front risk-based charges. The private mortgage insurers recalibrated their risk models to reflect greater differentiation by risk bucket. (The GSEs, by charter, cannot be in a first-loss position on any loan with an LTV ratio over 80%; further credit enhancement is required. Private mortgage insurance makes up the overwhelming majority of this additional credit enhancement.) Moreover, the GSEs and their regulator, the Federal Housing Finance Agency (FHFA), imposed risk-based capital charges on the mortgage insurers with their adoption of the Private Mortgage Insurer Eligibility Requirements. These rules went into effect in 2015. These requirements, which must be adhered to for a mortgage insurer to do business with the GSEs, further increased the cost of more risky GSE loans. It is now more economical for LCP

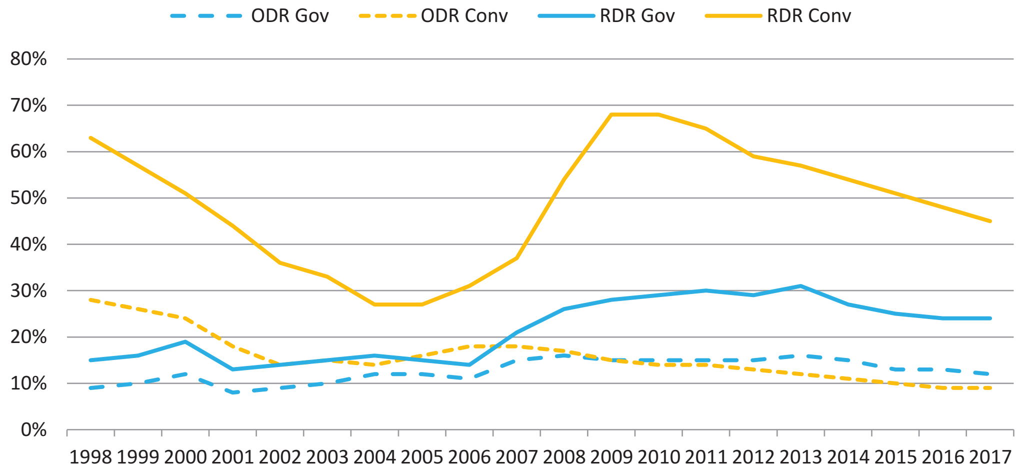

Figure 3. Observed denial rates (ODR) versus real denial rates (RDR) in the government and conventional channels.
Note. Based on owner-occupied purchase mortgage applications. Data from the Home Mortgage Disclosure Act, CoreLogic, and the Urban Institute.

Table 3. Share of low-credit-profile applicants and borrowers by channel.

	Low-credit-profile applicants (%)			Low-credit-profile borrowers (%)		
Year	LCPA gov	LCPA conv	LCPA all	LCPO gov	LCPO conv	LCPO all
1998	57	44	47	53	23	30
1999	60	46	49	56	27	34
2000	62	47	50	57	30	37
2001	63	40	45	59	27	35
2002	67	41	46	64	31	37
2003	70	44	48	66	35	40
2004	76	53	55	73	45	48
2005	78	58	60	74	50	52
2006	79	60	62	76	51	53
2007	73	50	53	68	39	42
2008	62	32	43	54	17	31
2009	52	22	38	44	8	27
2010	51	21	37	43	8	26
2011	51	21	36	42	8	25
2012	54	21	36	45	10	26
2013	53	21	33	43	10	23
2014	54	20	33	46	10	23
2015	52	20	32	45	11	24
2016	51	20	32	44	11	24
2017	51	20	31	45	12	24
1998–2004	65	45	49	61	31	37
2005–2007	77	56	58	73	47	49
2008–2010	55	25	39	47	11	28
2011–2017	52	20	32	45	11	24

Note. LCPA = low-credit-profile applicants, LCPO = low-credit-profile borrowers. Based on owner-occupied purchase mortgage applications. Data from Home Mortgage Disclosure Act, CoreLogic, and the Urban Institute.

borrowers to apply for mortgages through the government channel than through the conventional channel, leading to few LCP applicants in the conventional channel.[13]

The RDR consistently conforms to our intuition. Referring to Figure 3, the conventional channel consistently has a higher RDR than the government channel, but the two curves have the least differential during the bubble years. This makes sense because during the bubble years, conventional underwriting standards declined as nontraditional products (e.g., interest-only mortgages, 40-year mortgages, mortgages with negative amortization, mortgages with an initial teaser payment and a reset period shorter than 5 years) accounted for a significant portion of originations. In contrast, nontraditional products remained a small part of government origination.

More recently, although the conventional channel continues to have higher RDRs than the government channel does, both have experienced declines since 2013. These declines stem from both the GSEs and FHA attempting to give lenders reassurance that they will only be responsible for manufacturing defects, not subsequent performance, as well as the rise of nonbank originators. The first factor has been more important to the GSEs, the second more important to the FHA.

In the aftermath of the crisis, lenders were putting overlays on both the GSE and FHA credit box. That is, lenders were imposing more stringent standards on GSE and FHA loans than what the agencies required, as the lenders were afraid they would be forced to repurchase the GSE loans—a frequent occurrence in 2009–2012—or would be sued by the government for triple damages for defective FHA loans under the False Claims Act. The GSEs took a series of steps, beginning in 2012, to assure lenders that the lender would be responsible for defects in the manufacturing of the loan but would not be responsible for subsequent borrower performance. Moreover, enhancements in technology have allowed the GSEs to waive some of the representations and warranties—such as representations about borrower income and property value—at the point of origination. For a complete description of the steps the GSEs and the FHFA took, see Goodman (2017b).

The FHA, the largest participant in the government channel, has lagged behind the GSEs and the FHFA in its attempts to reduce lender uncertainty. Although the FHA has taken some actions (Goodman, 2017b), lenders still do not have the reassurances they need that they are not liable under the False Claims Act, a powerful tool that the U.S. Department of Justice has used to pursue expensive claims against mortgage originators (Goodman, 2015).

Much of the opening of the government credit box has been because of the increasing role of nonbank originators. Since 2013, the nonbank share of government originations has increased from 35% to 81%, and the nonbank share of GSE originations has increased from 35% to 56% (Goodman et al., 2018). These originators are less concerned about the reach of the False Claims Act because they have less at stake—less of an established reputation, usually in only one business so that there is no reputational impact on other activities, and less capital. The nonbanks have opened up the credit box. The median bank FICO score for government loans in March 2018 was 696, and the median nonbank score was 674. The median bank DTI ratio for government loans in March 2018 was 40.8%, and the median nonbank DTI ratio was 42.6% (Ginnie Mae, 2018a; Goodman et al., 2018).

3. Differentials in Denial Rates by Race and Ethnicity

We have established that the RDR is a useful tool for looking at credit availability over time. Let us now look at it in the context of denial rates by race/ethnicity. The ODR indicates that denial rates are consistently highest for blacks and Hispanics and are lower for non-Hispanic whites (hereafter whites) and Asians (see Figure 4(a)). In 2017, the ODR indicates that black applicants had twice the denial rates of white applicants, Hispanic applicants had 1.4 times the white denial rate, and Asian applicants had 1.2 times the white denial rate. Some news articles have used these ODRs at the local level to allege redlining in mortgage lending (Glantz & Martinez, 2018). Our RDR analysis shows that this claim is a gross oversimplification.

The differences in denial rates across groups primarily reflect differences in credit characteristics. In 2017, the average LCP share was 47% among black applicants, 40% among Hispanic applicants, 29% among white applicants, and 24% among Asian applicants (Appendix Tables A2 and A3).

More intuitively, Table 4 shows the median characteristics by racial and ethnic group for approved loans in 2017, based on the HMDA–CoreLogic matched data. The median black and Hispanic borrowers have lower FICO scores, higher LTV and DTI ratios, and lower incomes than their white counterparts. The median FICO score is 697 for black borrowers, 708 for Hispanic

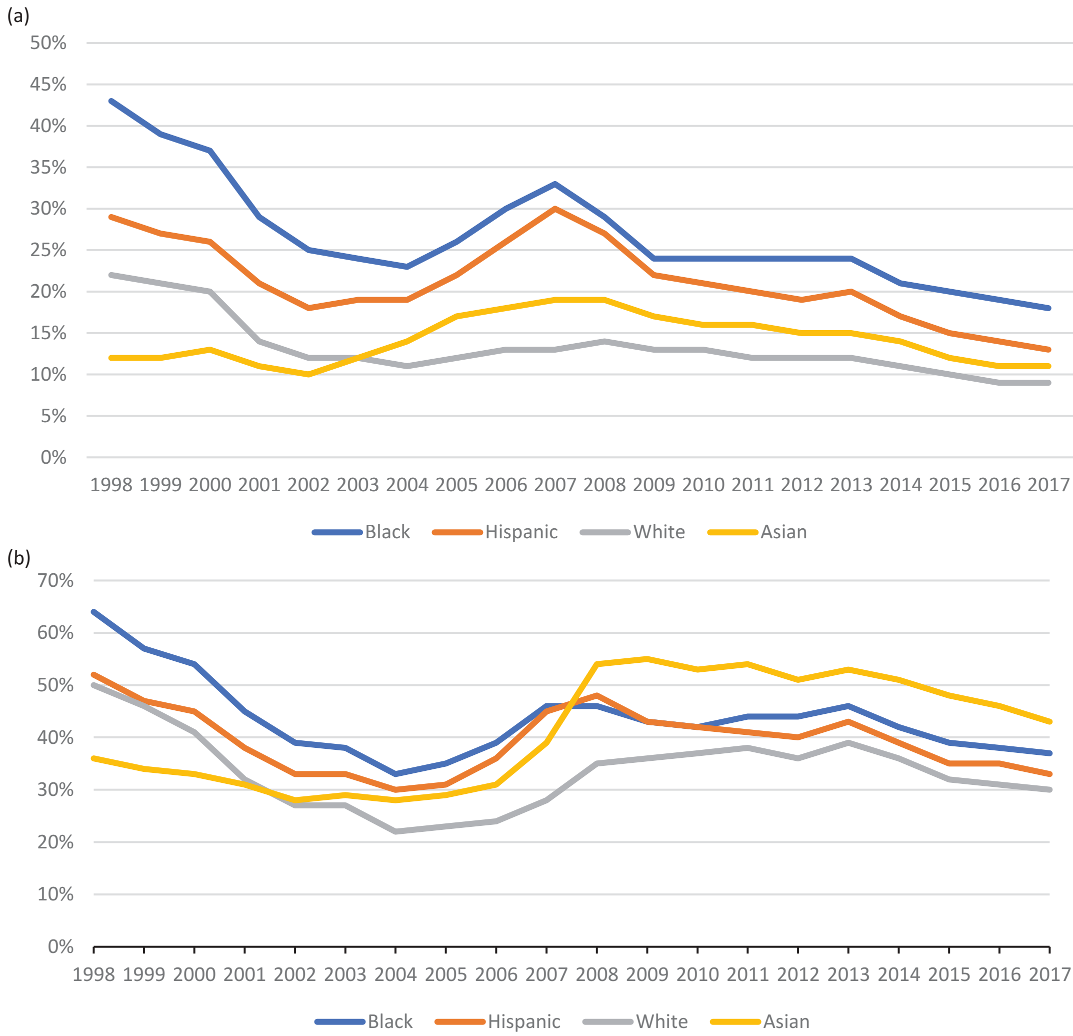

Figure 4. (a) Observed denial rates by race and ethnicity. (b) Real denial rates by race and ethnicity.
Note. Based on owner-occupied purchase mortgage applications. Data from the Home Mortgage Disclosure Act, CoreLogic, and the Urban Institute.

Table 4. Borrower characteristics by race and ethnicity for 2017 purchase mortgage originations.

Median value	Black	Hispanic	White	Asian	All
FICO	696.7	708.2	738	751.3	733.9
LTV	96.7	95	88.7	81.8	89.8
DTI	39	39	36.4	37	37
Income ($)	67,000	65,000	80,000	102,000	78,000
Income/AMI	0.9	1	1.2	1.3	1.1

Note. LTV = loan-to-value ratio; DTI = debt-to-income ratio; AMI = area median income. Based on owner-occupied purchase mortgage originations. Data from Home Mortgage Disclosure Act, CoreLogic, and the Urban Institute.

borrowers, and 738 for white borrowers. The median LTV ratio for black owner occupants is 97%, the median for Hispanics is 95%, and the median for whites is 89%. These figures apply only to borrowers who had mortgages approved and originated; we cannot observe credit profiles for denied applicants. Denied applicants are likely to have weaker credit profiles, as applicants tend to have more LCP consumers than borrowers do for all races and ethnicities (Appendix Table A3).

Given the differences in credit characteristics, the RDR shows smaller racial and ethnic gaps (see Figure 4(b)). In 2017, black applicants had 1.2 times the denial rate of white applicants, Hispanic applicants had 1.1 times the white denial rate, and Asian applicants had 1.4 times the white denial rate. Our RDR analysis shows that once we control for differences in credit characteristics, racial and ethnic differences in denial rates get smaller. We controlled for LTV ratio, credit score, DTI ratio, and product and documentation type, but we did not control for income and did not have data on assets or reserves, which are factors in underwriting. Thus, we would not have completely controlled for credit differentials.

The RDR is highest for Asians because Asians frequent the conventional channel more than other groups, and the conventional channel has higher denial rates.

Figure 5 shows the RDR by channel and race and ethnicity. In both channels, Asian applicants have RDRs just above but close to those for Hispanic applicants in 2017 (52% for Asians and 51% for Hispanics in the conventional channel; 26% for Asians and 25% for Hispanics in the government channel). The discrepancy in Figure 4(b) arises because 84% of Asian applicants use the conventional channel, compared with 48% of Hispanic applicants. We believe this is because Asian borrowers tend to live in high-cost coastal areas that rely more heavily on conventional loans (which have higher denial rates than government loans do).

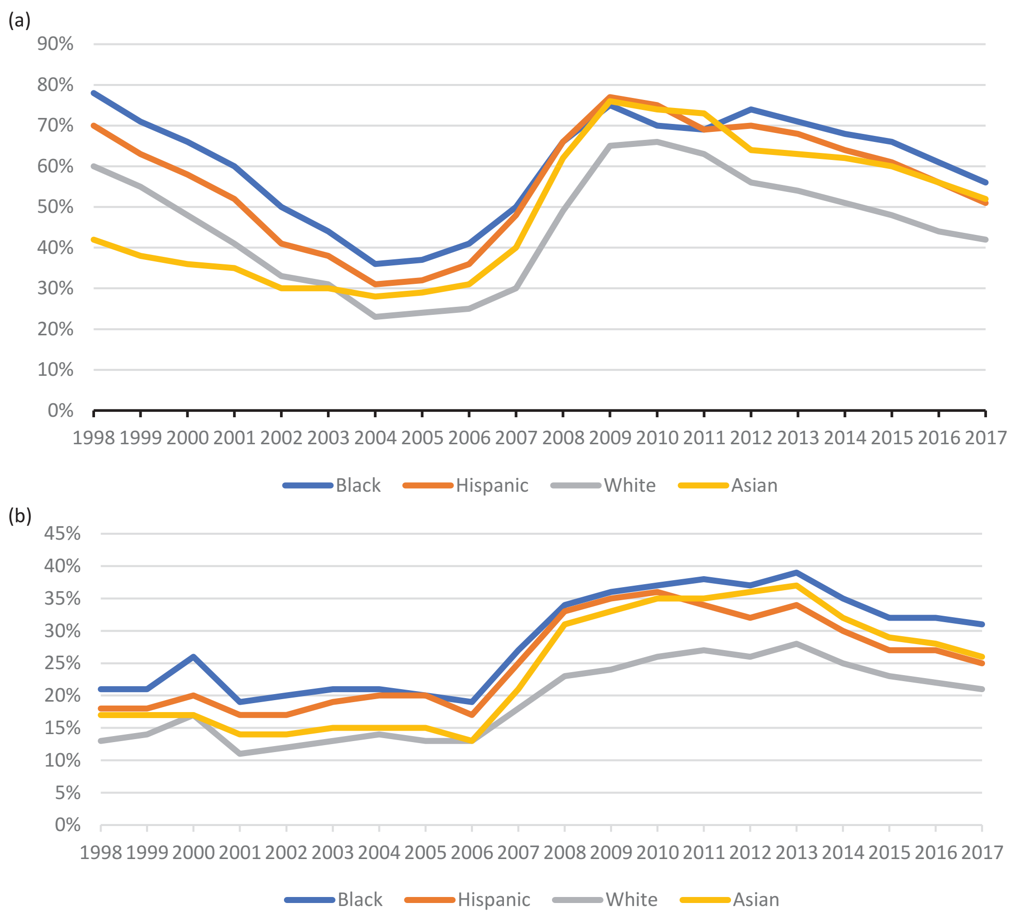

Figure 5. (a) Real denial rates by race and ethnicity in the conventional channel. (b) Real denial rates by race and ethnicity in the government channel.
Note. Based on owner-occupied purchase mortgage applications. Data from the Home Mortgage Disclosure Act, CoreLogic, and the Urban Institute.

The appendix contains detailed tables for ODRs, RDRs, and shares of LCP applicants and borrowers, sorted by channel and race or ethnicity. (Tables A4 and A5 contain the results for the conventional channel; Tables A6 and A7 contain the results for the government channel). It is very clear from these tables that the RDRs show smaller racial/ethnic gaps than do the ODRs, controlling for channel; the convergence is more pronounced in the conventional channel. For example, comparing Hispanics with whites in the conventional channel, the RDR ratio is 1.2, much closer than the 1.6 ODR ratio.

4. Higher Denial Rates for Small-Dollar Mortgages

Recent research has documented the dearth of small-dollar mortgages for low-cost single-family residential home purchases, limiting affordable homeownership opportunities for creditworthy families living in low-cost underserved housing markets. McCargo et al. (2018) reveal that only a quarter of homes sold for $70,000 or less were financed through a mortgage, whereas almost 80% of homes worth between $70,000 and $150,000 were bought with a mortgage in 2015. We believe that denial rate differentials are a major factor in this discrepancy.

Figure 6 shows that the ODR for small-dollar mortgages (up to $70,000) is 18%, double that for larger loans (more than $150,000) in 2017.[14] There is little variation in applicants' credit profile compositions by loan size: the share of LCP applicants was 34% for loans up to $70,000, 35% for loans between $70,000 and $150,000, and 30% for loans of more than $150,000. After controlling for applicant credit profiles, the RDR gap remains large across the three loan size buckets. In 2017, the RDR for small loans (up to $70,000) was 52%, compared with 29% for large loans (more than $150,000).

What is behind the high RDRs for small-dollar mortgages? Figure 7 shows that small-dollar mortgages have higher RDRs than larger mortgages do within each channel. The RDR for conventional mortgages is 56% for mortgages up to $70,000, 1.3 times higher than the 43% for mortgages of more than $150,000. The gap between the two loan size groups is more pronounced in the government channel: 44% for the small-loan group versus 21% for the large-loan group. Small loans in the government channel have an RDR 2.09 times that for larger loans. The RDR for small-dollar government mortgages is slightly higher than the RDR for conventional mortgages over $150,000, despite that fact that overall the conventional channel has considerably higher RDRs than the government channel.

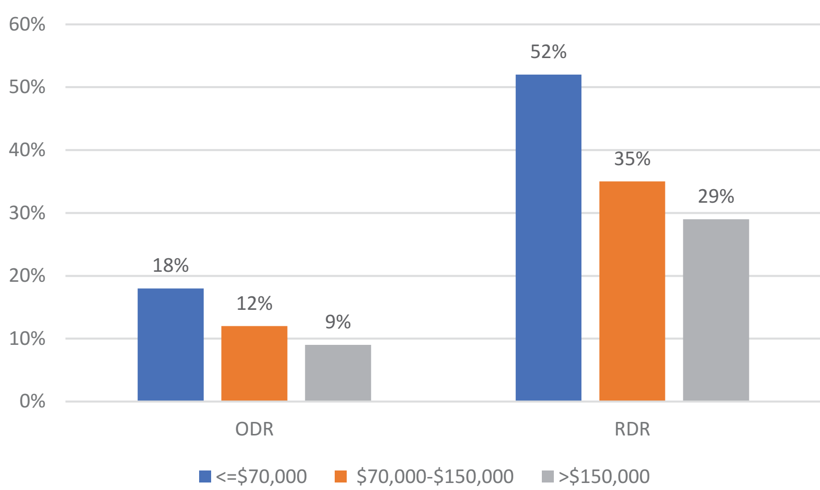

Figure 6. Denial rates by loan size among 2017 purchase mortgage applications.
Note. ODR = observed denial rates. RDR = real denial rates. Based on owner-occupied purchase mortgage applications. Data from Home Mortgage Disclosure Act, CoreLogic, and the Urban Institute.

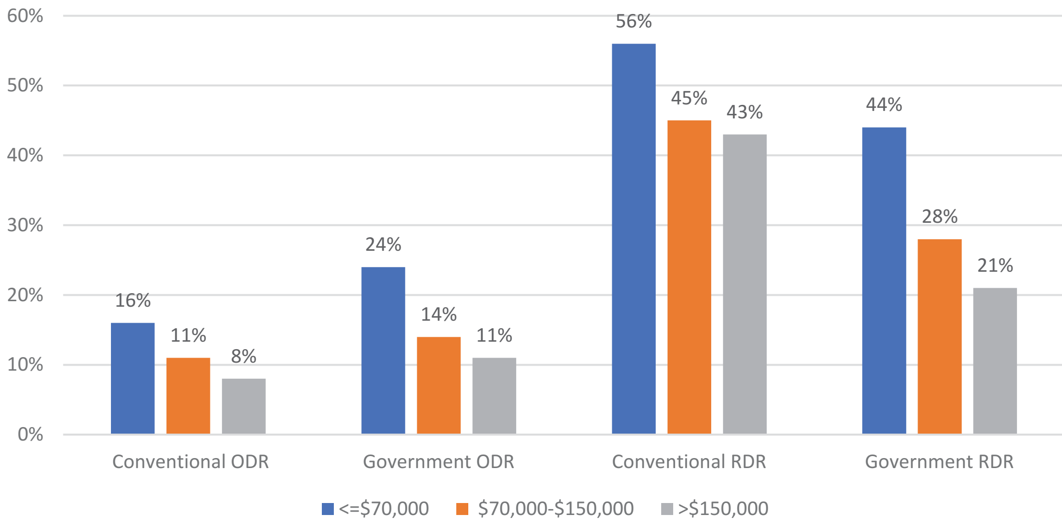

Figure 7. Denial rates by loan size and channel among 2017 purchase mortgage applications.
Note. ODR = observed denial rates. RDR = real denial rates. Based on owner-occupied purchase mortgage applications. Data from the Home Mortgage Disclosure Act, CoreLogic, and the Urban Institute.

Moreover, small loans are overrepresented in the conventional channel, which has higher RDRs. Figure 8 shows that conventional loans account for 82% of small-dollar applications but only 65% of mortgage applications for more than $150,000. The FHA serves 12% of the small-dollar mortgage market, 28% of the $70,000–$150,000 market, and 21% of the over-$150,000 market. Part of the reason for this is that lending institutions tend to make conventional loans, and many small-balance loans are held in the portfolios of the small banks and credit unions that serve rural communities. Part of the reason for this is math; for any given property value, conventional loans, which have a higher down payment, are by definition going to be smaller; hence, more will fall into the small balance category.

Moreover, the fixed costs of originating a loan and servicing a loan make small loans less attractive to originate (McCargo et al., 2018). But banks, which have moved away from the FHA

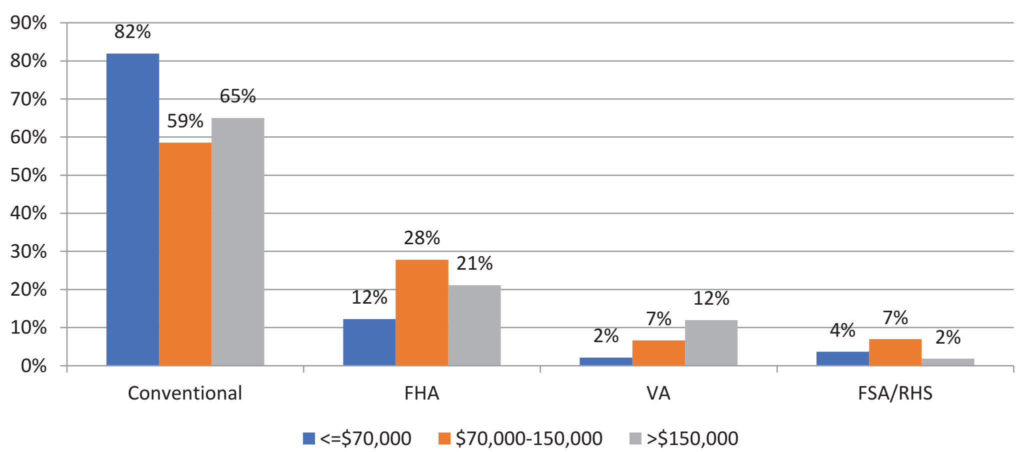

Figure 8. Market share by channel and loan size among 2017 purchase mortgage applications.
Note. FHA = Federal Housing Administration, VA = the US Department of Veterans Affairs, FSA/RHS = Farm Service Agency or Rural Housing Service. Based on owner-occupied purchase mortgage applications. Data from the Home Mortgage Disclosure Act, CoreLogic, and the Urban Institute.

market[15] and are more likely to originate conventional loans, have certain requirements under the Community Reinvestment Act (CRA). They must meet the credit needs of the communities in which they operate, including the needs of low- and moderate-income neighborhoods, as long as this can be done in a manner consistent with safe and sound operations. Many of these small loans would count for CRA purposes, giving banks an incentive that compensates them for the higher fixed costs of origination and servicing. But nonbanks have no CRA obligations.

The higher RDRs for small loans come from the fact that (a) most of these loans are conventional, which have higher RDRs than loans in the government channel, and within the conventional channel, small loans have a higher denial rate than large loans; and (b) within the government channel, the denial rate for loans up to $70,000 is more than twice that for loans of more than $150,000.

5. Conclusion

In this article, we introduce an additional tool for looking at mortgage denial rates that we have called the real denial rate, or RDR. The RDR shows a more intuitive pattern over time than the ODR, as it holds the applicant credit quality constant. We find it better explains both the denial rate differentials by channel and denials patterns over time.

We show that the RDR peaked in 2013 and has been dropping ever since. But the share of low-credit-profile borrowers has been steadily declining. Thus, the increase in credit availability from 2013 to 2017 reflects a decrease in the denial rate of those applying, not a broadening of the applicant pool. That is, although the RDR among low-credit applicants has declined to precrisis levels, low-credit applicants account for a smaller share of applicants in recent years (31%) than they did from 1998 to 2004 (49%).

The RDR analysis confirms the overly tight credit in the mortgage market during the postcrisis years, deterring more potential applicants, and preventing them from becoming homeowners, at exactly the point in the economic cycle when it is advantageous to do so. These individuals hence lose a valuable opportunity to build wealth. The RDR started to decline in recent years, partly driven by recent efforts by the GSEs, FHFA, and FHA to reduce lender uncertainty. Urgent efforts are needed to include more responsible potential borrowers who are currently deterred from the market.

Our results also show that the racial and ethnic disparities in traditional ODRs are partially because of differences in credit profiles. These differences include differences in credit scores and in DTI and LTV ratios. Using ODRs to judge whether redlining has occurred, as many recent news articles have done, is misleading as ODRs do not account for differences in the credit profiles of applicants. When one constructs RDRs that account for differentials in credit quality, as we have, the differences by race and ethnicity do not disappear but are much narrower. Although we have not accounted for all the factors that go into loan underwriting because of data constraints, which could explain some of the remaining differentials, it is likely there is still a significant unexplained differential.

The postcrisis tight mortgage credit revealed by the RDR analysis leads to important public policy considerations. Goodman, Zhu, and Bai (2016) estimated that about 6.3 million additional loans would have been made between 2009 and 2015 if lending standards had been set at the more reasonable level of 2001. The large number of missing loans means fewer households have the opportunity to build wealth through home ownership. Minority borrowers have been affected more strongly than their white counterparts, and the consequences of tight credit will grow over time as the overwhelming majority of new homeowners going forward are expected to be Hispanic or nonwhite, groups that have lower credit scores, less wealth, and lower incomes than their non-Hispanic white counterparts (Goodman, 2017b). Thus, it is important to consider policies that could alter the mortgage acceptance criteria used in the market today to enable more creditworthy borrowers to obtain a mortgage, with the benefits going heavily to minority borrowers. Examples include the adoption of newer and more inclusive credit score models[16] and more flexible consideration of income sources in the mortgage underwriting process.[17]

Finally, we demonstrate that RDRs are higher for small-dollar mortgages (up to $70,000) than for larger loans. The differences in denial rates are a key reason why so few low-balance home sales are financed with a mortgage. We show that the large difference in mortgage denial rates by size cannot be explained by the very small differences in credit quality. Certainly, the higher fixed costs of originating and servicing a loan makes it less attractive to lenders to originate in this space. We need further research on creative solutions to service this sector.

Notes

1. See the Urban Institute's Housing Credit Availability Index at https://www.urban.org/policy-centers/housing-finance-policy-center/projects/housing-credit-availability-index
2. Although a few proprietary mortgage databases, such as CoreLogic's, collect information on originated loans, the HMDA is the only source of mortgage application data that contains a mortgage applicant's income, loan amount, race or ethnicity, and application outcome. But HMDA data do not include information on common risk factors, such as credit score, LTV ratio, DTI ratio, or loan products. Therefore, an applicant's credit profile is unknown from HMDA data.
3. See the Mortgage Bankers Association Mortgage Credit Availability Index at https://www.mba.org/news-research-and-resources/research-and-economics/single-family-research/mortgage-credit-availability-index
4. See CoreLogic's Housing Credit Index at https://www.corelogic.com/products/corelogic-hpi.aspx
5. See the Urban Institute's Housing Credit Availability Index at https://www.urban.org/policy-centers/housing-finance-policy-center/projects/housing-credit-availability-index
6. The denial rate does not measure the potential discrimination at other stages of the mortgage lending process. Lenders could discriminate in their selection of their service areas, or in the prescreening process in the setting of mortgage quality and cost (Munnell, 1996). Massey, Rugh, Steil, and Albright (2016) code and evaluate the statements and testimonies from federal lawsuits of four mortgage lenders who violated fair lending laws during the great recession. They use these data to show structural discrimination toward black and Hispanic borrowers in the form of higher interest rates, high-pressure marketing, deceptive information, and so on. Massey et al. argue that even if denial rates are not higher for these borrowers, they are receiving riskier and lower quality loans.
7. See the article at *The Hill*, http://thehill.com/blogs/congress-blog/politics/375831-why-is-there-bipartisan-support-in-the-senate-to-cover-up; a report from the Center for Investigative Reporting at https://www.revealnews.org/article/for-people-of-color-banks-are-shutting-the-door-to-homeownership/; and a Zillow research report at https://www.zillow.com/research/black-white-mortgage-denials-19616/.
8. The choice to limit the analysis was also done for consistency over time. The underwriting for nonowner-occupied mortgages is different, as the property's cash flow plays a role. A refinance application is heavily dependent on interest rates. Moreover, various streamlined programs have allowed for loans to refinance that would not meet the criteria for a new loan, on the grounds that the refinance helps the borrowers and reduces the probability of loan default, to the benefit of the holder.
9. HMDA is considered the universe of mortgage originations because federal law requires that almost all mortgage applications, except from lenders who make few loans, to be reported in HMDA (see Bhutta, Laufer, and Ringo, 2017, for a more complete description). The reporting requirements have changed slightly. In 2016, all depository institutions with more than $44 million in assets that made at least one loan insured or guaranteed by a federal agency were required to report. Nondepository institutions that made more than 100 purchase loans or had assets over $10 million were required to report. In 2017, the reporting requirements were changed so that all institutions that made more than 25 closed-end loans in the preceding two years were required to report their closed-end loans.
10. Loan products without risky features include fixed-rate mortgages and all hybrid adjustable-rate mortgages with an initial fixed-interest-rate period of 5 years or longer, without any of the following features: prepayment penalty, balloon terms, interest-only terms, and negative amortizations.
11. We do this because we found that over the past 100 years there have been 19 business cycles, only two of which caused distress in the housing market (the Great Depression and the Great Recession).
12. Our categorization of denied is as follows: denied = denied; application or preapproval request approved but not accepted = approved; loan originated = approved. We excluded loans purchased by a financial institution. Because only originated HMDA loans can be matched with CoreLogic loans, we assume approved but not originated applications have the same share of LCP applicants as originated loans.
13. Goodman et al. (2018) shows that for a 95 LTV borrower, the government channel will be the better execution for borrowers with credit scores of less than 720. The GSE channel dominates for higher credit scores.
14. Earlier years show denial rate patterns similar to those for 2017. Data are available upon request.
15. The nonbank share of FHA purchase mortgage originations rose from 34% in 2013 to 83% in the first quarter of 2018 (see Ginnie Mae 2018b, p. 31).

16. The GSEs and FHA are using dated FICO models. Later FICO or Vantage models score more borrowers with greater accuracy (Goodman, 2017a). More importantly, many borrowers do not use credit and hence do not have a credit score; they are currently squeezed out of the market. Credit information is available on these individuals, but the monthly payments they make, such as rental payments and telecom and utility bills, are not included in credit scores. Technological advances now allow this information to be harnessed from bank statements and counted toward credit. In addition, when there are multiple borrowers, the lower credit score is used, forcing some families to try to qualify for a mortgage with only one income, as the second has too low a credit score.
17. Mortgage applications often undercount income. That is, income is generally considered only if it is consistent and the borrower has been in the same job or industry for 2 or more years. Borrowers who are particularly affected by this undercount include those who work partly on commission, those who are self-employed, those who have not held their job long enough, and those that always have a second, seasonal income. In multigenerational families, there are borrowers not on the mortgage who contribute to the costs of the home, but that income is not counted. Again, bank statements can be used to harness this information.

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Disclosure Statement

No potential conflict of interest was reported by the authors.

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Appendix

Table A1. Probability of being a low-credit-profile borrower, calculated from the expected default risk of the loans.

		Nonrisky loan products (%)							Risky loan products (%)						
DTI	CLTV	Avg	> 740	(700,740]	(660,700]	(620,660]	(580,620]	≤ 580	Avg	> 740	(700,740]	(660,700]	(620,660]	(580,620]	≤ 580
Average	Average	18%	6	16	24	38	57	80	81	49	76	87	93	95	96
	(0,68]	3	0	2	5	13	22	39	21	4	18	28	38	42	58
	(68,78]	9	2	9	16	25	33	58	51	21	45	60	72	70	84
	(78,82)	12	4	12	19	28	34	54	74	40	65	79	94	91	99
	[82,90]	18	7	17	24	32	43	69	89	62	89	95	88	95	100
	(90,95]	19	7	15	21	32	44	69	82	58	76	80	87	100	100
	> 95	56	29	42	52	70	93	100	97	86	94	99	100	100	100
Low or no doc	Average	30	13	30	41	55	73	93	83	57	82	89	94	90	93
	(0,68]	4	0	5	11	21	34	59	22	5	20	29	38	40	58
	(68,78]	16	5	19	29	41	49	82	54	26	50	64	75	68	83
	(78,82)	21	10	22	33	49	53	80	78	48	71	84	98	84	99
	[82,90]	35	19	36	46	53	62	86	92	71	96	100	91	99	100
	(90,95]	36	21	36	42	50	61	99	84	67	83	84	90	100	100
	> 95	69	51	65	65	71	88	100	100	100	100	100	100	100	100
Full doc and ≥ 50	Average	17	5	13	23	40	52	62	88	43	71	87	95	99	97
	(0,68]	3	0	0	5	14	23	27	35	9	24	37	50	63	61
	(68,78]	9	1	8	14	26	34	41	60	15	45	63	84	84	84
	(78,82)	11	3	10	18	29	34	37	72	31	52	63	79	100	100
	[82,90]	19	7	13	24	38	47	56	91	50	78	83	85	97	100
	(90,95]	22	10	16	26	39	52	61	91	60	71	81	99	100	100
	> 95	53	23	33	51	78	100	100	98	74	90	100	100	100	100
Full doc and [40,50)	Average	17	4	11	21	35	54	71	86	40	65	85	93	98	98
	(0,68]	2	0	0	4	11	18	27	27	3	15	28	38	50	56
	(68,78]	7	0	5	12	21	28	40	51	13	31	47	64	77	87
	(78,82)	10	2	8	15	23	34	45	73	27	47	65	85	100	100
	[82,90]	15	4	9	18	28	40	64	85	37	58	74	78	90	100
	(90,95]	17	6	11	19	31	43	60	83	43	59	70	81	100	100
	> 95	51	20	30	47	73	100	100	96	65	83	100	100	100	100
Full doc and [30,40)	Average	12	1	6	15	29	50	69	74	26	51	72	89	97	97
	(0,68]	1	0	0	1	9	17	27	19	1	11	21	40	43	50
	(68,78]	4	0	2	7	16	27	42	38	9	23	35	55	76	85
	(78,82)	5	0	4	10	17	27	40	57	18	37	52	76	100	100
	[82,90]	8	1	5	12	21	33	53	76	27	50	68	76	84	100
	(90,95]	12	2	6	14	25	37	55	74	33	53	65	77	100	100
	> 95	41	12	21	38	66	98	100	89	47	69	91	100	100	100

(*Continued*)

Table A1. (Continued).

		Nonrisky loan products (%)							Risky loan products (%)						
DTI	CLTV	Avg	> 740	(700,740]	(660,700]	(620,660]	(580,620]	≤ 580	Avg	> 740	(700,740]	(660,700]	(620,660]	(580,620]	≤ 580
Full doc and (0,30)	Average	6	0	3	9	22	41	63	58	13	35	60	83	94	96
	(0,68]	1	0	0	0	6	15	30	11	0	6	11	31	45	58
	(68,78]	2	0	0	4	11	22	39	26	3	13	30	45	64	86
	(78,82)	2	0	1	5	12	21	34	42	9	26	45	70	98	98
	[82,90]	5	0	3	8	18	29	51	71	22	46	59	71	86	100
	(90,95]	9	0	4	11	23	35	55	68	23	43	63	76	100	100
	> 95	36	8	18	32	59	92	100	84	33	59	86	100	100	100

Note. DTI = debt-to-income ratio, CLTV = combined loan-to-value ratio, doc = documentation. Based on owner-occupied purchase mortgage applications. Data from HMDA, CoreLogic, and Urban Institute.

Table A2. Observed denial rate and real denial rate in all channels.

	Observed denial rate (%)				Real denial rate (%)			
	Black	Hispanic	White	Asian	Black	Hispanic	White	Asian
1998	43	29	22	12	64	52	50	36
1999	39	27	21	12	57	47	46	34
2000	37	26	20	13	54	45	41	33
2001	29	21	14	11	45	38	32	31
2002	25	18	12	10	39	33	27	28
2003	24	19	12	12	38	33	27	29
2004	23	19	11	14	33	30	22	28
2005	26	22	12	17	35	31	23	29
2006	30	26	13	18	39	36	24	31
2007	33	30	13	19	46	45	28	39
2008	29	27	14	19	46	48	35	54
2009	24	22	13	17	43	43	36	55
2010	24	21	13	16	42	42	37	53
2011	24	20	12	16	44	41	38	54
2012	24	19	12	15	44	40	36	51
2013	24	20	12	15	46	43	39	53
2014	21	17	11	14	42	39	36	51
2015	20	15	10	12	39	35	32	48
2016	19	14	9	11	38	35	31	46
2017	18	13	9	11	37	33	30	43

Note. Based on owner-occupied purchase mortgage applications. Data from HMDA, CoreLogic, and Urban Institute.

Table A3. Share of low-credit-profile applicants and borrowers in all channels.

	Applicants (%)				Borrowers (%)			
	Black	Hispanic	White	Asian	Black	Hispanic	White	Asian
1998	68	57	44	33	43	39	28	24
1999	68	58	47	36	48	42	32	27
2000	68	58	48	39	50	44	35	30
2001	64	55	42	36	49	43	33	28
2002	63	56	43	37	51	46	35	30
2003	65	59	45	42	53	49	38	34
2004	70	64	51	51	61	56	45	43
2005	72	69	55	57	63	60	49	49
2006	76	73	56	58	65	63	49	49
2007	71	66	47	48	56	52	39	36
2008	63	56	39	35	48	40	29	20
2009	57	51	35	30	43	38	26	17
2010	56	50	34	29	43	37	24	16
2011	55	48	33	29	41	36	23	16
2012	56	49	33	30	41	36	24	17
2013	52	46	31	28	37	32	21	15
2014	51	44	30	27	37	33	21	15
2015	50	44	30	26	38	33	22	15
2016	49	41	30	25	37	32	22	15
2017	47	40	29	24	36	31	22	15

Note. Based on owner-occupied purchase mortgage applications. Data from HMDA, CoreLogic, and Urban Institute.

Table A4. Observed denial rate and real denial rate in the conventional channel.

	Observed denial rate (%)				Real denial rate (%)			
	Black	Hispanic	White	Asian	Black	Hispanic	White	Asian
1998	54	38	25	12	78	70	60	42
1999	49	35	24	13	71	63	55	38
2000	46	33	22	13	66	58	48	36
2001	37	25	15	11	60	52	41	35
2002	30	21	13	10	50	41	33	30
2003	27	21	13	12	44	38	31	30
2004	24	19	11	14	36	31	23	28
2005	26	22	13	17	37	32	24	29
2006	31	26	14	18	41	36	25	31
2007	35	31	13	19	50	48	30	40
2008	35	31	14	19	66	66	49	62
2009	33	27	13	16	75	77	65	76
2010	30	24	12	15	70	75	66	74
2011	29	23	12	15	69	69	63	73
2012	28	21	11	14	74	70	56	64
2013	26	20	11	14	71	68	54	63
2014	22	17	10	13	68	64	51	62
2015	21	16	9	12	66	61	48	60
2016	20	14	8	11	61	56	44	56
2017	18	13	8	10	56	51	42	52

Note. Based on owner-occupied purchase mortgage applications. Data from HMDA, CoreLogic, and Urban Institute.

Table A5. Share of low-credit-profile applicants and borrowers in the conventional channel.

	Applicants (%)				Borrowers (%)			
	Black	Hispanic	White	Asian	Black	Hispanic	White	Asian
1998	69	55	41	30	32	26	22	20
1999	68	55	44	33	39	31	26	23
2000	69	56	45	37	42	35	29	27
2001	61	49	38	33	39	32	26	24
2002	59	50	38	34	42	37	29	27
2003	61	55	41	40	47	43	33	32
2004	68	62	49	51	57	54	42	42
2005	71	68	54	57	61	59	47	49
2006	75	73	54	58	64	63	47	49
2007	69	65	45	47	52	49	36	35
2008	53	47	28	30	28	23	17	14
2009	44	35	20	22	16	11	8	6
2010	43	32	19	20	19	11	7	6
2011	43	33	19	21	19	13	8	7
2012	38	30	20	22	14	11	10	9
2013	36	29	20	21	14	12	10	9
2014	33	27	19	21	13	12	10	9
2015	31	26	18	19	14	12	11	9
2016	32	26	19	19	16	13	11	10
2017	32	26	19	19	17	15	12	10

Note. Based on owner-occupied purchase mortgage applications. Data from HMDA, CoreLogic, and Urban Institute.

Table A6. Observed denial rate and real denial rate in the government channel.

	Observed denial rate (%)				Real denial rate (%)			
	Black	Hispanic	White	Asian	Black	Hispanic	White	Asian
1998	13	11	7	9	21	18	13	17
1999	14	11	8	10	21	18	14	17
2000	17	12	11	10	26	20	17	17
2001	12	11	7	9	19	17	11	14
2002	14	12	8	9	20	17	12	14
2003	15	14	9	10	21	19	13	15
2004	17	16	10	12	21	20	14	15
2005	17	16	10	11	20	20	13	15
2006	16	14	10	10	19	17	13	13
2007	22	19	13	15	27	25	18	21
2008	24	22	13	19	34	33	23	31
2009	22	20	12	17	36	35	24	33
2010	22	20	13	18	37	36	26	35
2011	22	19	13	18	38	34	27	35
2012	23	19	13	19	37	32	26	36
2013	23	19	14	20	39	34	28	37
2014	21	17	13	17	35	30	25	32
2015	19	15	11	15	32	27	23	29
2016	18	14	11	14	32	27	22	28
2017	17	13	11	13	31	25	21	26

Note. Based on owner-occupied purchase mortgage applications. Data from HMDA, CoreLogic, and Urban Institute.

Table A7. Share of low-credit-profile applicants and borrowers in the government channel.

	Applicants (%)				Borrowers (%)			
	Black	Hispanic	White	Asian	Black	Hispanic	White	Asian
1998	62	58	56	57	56	53	53	52
1999	65	61	59	60	59	56	56	55
2000	66	62	61	60	59	57	57	56
2001	66	64	62	62	62	59	59	59
2002	70	69	66	67	66	65	63	64
2003	73	72	68	70	68	67	65	66
2004	80	78	75	76	76	74	72	73
2005	82	80	76	76	78	77	73	73
2006	83	81	78	77	80	78	75	75
2007	79	77	71	71	74	71	67	66
2008	70	66	59	61	61	57	53	52
2009	60	58	50	52	49	47	43	42
2010	60	57	49	51	48	46	41	41
2011	59	55	48	51	47	44	41	41
2012	62	58	51	54	50	48	44	43
2013	60	57	51	54	47	46	42	43
2014	60	57	52	55	50	49	44	45
2015	59	56	50	53	49	48	44	44
2016	57	53	50	50	48	46	43	42
2017	56	53	49	51	47	46	43	43

Note. Based on owner-occupied purchase mortgage applications. Data from HMDA, CoreLogic, and Urban Institute.

Matching HMDA and CoreLogic Loans

To obtain borrower credit profile information, we matched Home Mortgage Disclosure Act (HMDA) origination data to CoreLogic's proprietary loan-level databases (using both their private-label securities and servicing databases), which provide complementary information. HMDA is considered the universe of mortgage loans, as federal law requires that almost all mortgage originations be reported in HMDA (only a few small lenders are exempt). CoreLogic covers most of the residential mortgage market over the study period. To expand the size of the matched database beyond unique matches, we assigned weights to each matched HMDA–CoreLogic loan pair to reflect how close the match is, and we supplemented information in each database with information from the other using this weight.

We matched every HMDA loan to every CoreLogic loan to create a Cartesian product of the two databases. We first looked at each HMDA loan, filtering out CoreLogic loans where the common fields between the two databases were inconsistent with each other. First, if the loans were originated in different years, we did not include the pair in the matched loan database. Second, if an HMDA loan and a CoreLogic loan had a loan amount difference of at least $2,000, we dropped the pair. Third, loan pairs passed through a geographic filter—that is, a pair of loans with properties from different geographic locations was dropped out of the matched loan database. We required the census tract information from HMDA to be consistent with the zip code information from CoreLogic. We were left with loan pairs from the same issue year for the same amount with a geographic match. Because HMDA reports data by census tract and CoreLogic by zip code, the geographic filter is not straightforward. To solve this issue, we used the U.S. Department of Housing and Urban Development's zip code and census tract cross-walk file to match CoreLogic loans in a zip code to HMDA loans in a census tract and to assign geographic weights to the matched loans.

Suppose the ith HMDA loan from census tract X_i matched to the jth CoreLogic loan from zip code Y_j; $i = 1,\ldots I$, $j = 1,\ldots J$. X_i and Y_j overlap at Z_{ij}. Let X_i, Y_j, and Z_{ij} also denote the number of residential properties in each of the areas. The probability that the HMDA loan i is in Z_{ij} is given by

$$P_i = {}^{Z_{ij}}\!/_{X_i} \tag{A1}$$

assuming that i has an equal chance of being located anywhere in X_i. Similarly, the probability that CoreLogic loan j is in Z_{ij} is given by

$$P_j = {}^{Z_{ij}}\!/_{Y_j} \tag{A2}$$

The joint probability that both the HMDA loan i and the CoreLogic loan j are in Z_{ij} is given by

$$P_{ij} = {}^{Z_{ij}^2}\!\Big/_{X_i Y_j} \tag{A3}$$

which is the geographic weight for the matched loan pair of HMDA loan i and CoreLogic loan j.

For the other common variables between HMDA and CoreLogic, we adopted a fuzzy matching algorithm to filter out inconsistence pairs. The other common variables are loan type (e.g., Federal Housing Administration, Veterans Affairs or conventional), loan purpose (e.g., purchase or refinance), occupancy, lien, and type of purchaser (e.g., Fannie Mae, Ginnie Mae, private-label securities, or portfolio). But for the same common variable, HMDA and CoreLogic might be coded differently. Moreover, both data sources have missing values. Missing values are wild cards and could expand the range of matches. So we adopted a fuzzy matching algorithm for this step. Any match on a common variable between an HMDA loan and a CoreLogic loan is in one of three matching categories: a perfect match, a perfect nonmatch, and a fuzzy match. A perfect match is assigned a weight of 1, a perfect nonmatch is assigned a weight of 0, and a fuzzy match, with equal likelihood of being a perfect match and nonmatch, is assigned a weight of 0.5.

The fuzzy matching approach can generate multiple CoreLogic matches for a given HMDA loan. We need to determine which is the most likely and assign weights accordingly. If the weight assigned to the match between the ith HMDA loan and jth CoreLogic loan on the kth common variable is W_{ijk}, $k = 1,\ldots K$, the probability that HMDA loan i and CoreLogic loan j are a true match is given by

$$Q_{ij} = P_{ij} \times \prod_{k=1}^{K} W_{ijk} \tag{A.4}$$

For HMDA loan i, any supplemental information obtained from the CoreLogic loan j is weighted by Q_{ij}. For example, if an HMDA loan has two matched CoreLogic loans, with weights q1 and q2, and credit scores cs1 and cs2, respectively, the inferred credit score for the HMDA loan would be calculated by (q1*cs1+ q2*cs2)/(q1+ q2).

Matching Rate

Table A8 shows the matching rate between HMDA and CoreLogic loans for 2012 through 2017. In 2017, there are 3,426,269 owner-occupied purchase mortgage originations in the original HMDA data. After passing through the matching steps described above, there are 2,345,951 HMDA loans, each matched with at least one CoreLogic loan. Sixty-eight percent of HMDA loans find at least one match with CoreLogic loans in 2017, and 29% of these are unique matches.

Table A8. Match rates between Home Mortgage Disclosure Act (HMDA) and CoreLogic loans, 2012–2017.

Origination year	HMDA loans	Matched HMDA loans	Match rate (%)
2012	2,210,872	1,762,760	80
2013	2,548,282	1,965,170	77
2014	2,646,439	1,959,384	74
2015	3,005,118	2,188,192	73
2016	3,315,072	2,405,776	73
2017	3,426,269	2,345,951	68

Note. The data are limited to owner-occupied purchase mortgage originations with nonmissing race and ethnicity information. Data from HMDA, CoreLogic and Urban Institute.

We used a two-step weighting approach to make the matched loans representative of the mortgage market on credit score composition and representative of the original HMDA loans on any combination of important variables (e.g., origination year, race or ethnicity, income, loan amount, and channel). Each matched loan is first weighted to reflect the same credit score distribution of the mortgage market for that year (weighted separately for the conventional and government channel) and then weighted to reflect the same joint distribution as the original HMDA loan characteristics above.