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Race, Redlining, and Subprime Loan Pricing*

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Abstract

We investigate whether race and ethnicity influenced subprime loan pricing during 2005, the peak of the subprime mortgage expansion. We combine loan-level data on the performance of non-prime securitized mortgages with individual- and neighborhood-level data on racial and ethnic characteristics for metropolitan areas in California and Florida. Using a model of rate determination that accounts for predicted loan performance, we evaluate the presence of statistical and taste-based discrimination, as well as disparate impact and disparate treatment discrimination, in mortgage rates. We find evidence of redlining as well as adverse pricing for blacks and Hispanics.

Keywords: Fair Housing Act; Subprime Mortgages; Loan Performance; Discrimination.
JEL Codes: G21, J15, R23, C11

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1 Introduction

An extensive literature examines the role of income and race on consumer lending. Research on mortgages originated prior to 1995, when mortgages were usually underwritten manually, found strong evidence that lenders were denying credit more frequently to black households than to white households with similar observable characteristics.[1] Financial and technological innovation in underwriting processes has made risk-based pricing of credit, rather than mere credit allocation, a more relevant issue in recent years. This is especially true in the subprime market where lenders were much less likely to sell the loan to government-sponsored enterprises (GSEs) and were thus less constrained by firm cutoffs on variables such as loan-to-value (LTV) ratios, loan size, and credit scores. In a world where lenders cope with credit risk by rationing credit, discrimination and redlining manifest themselves primarily in loan denials. In contrast, when borrowers choose among several different sets of loan terms, each with a different price, minorities may be more able to obtain credit but may pay a higher price for it. Indeed, and perhaps in response to more stringent allocation constraints in prime mortgage markets, a disproportionate share of subprime loans were made to black and Hispanic households (Mayer and Pence, 2008).

In this paper, we use data on non-prime mortgages originated in 2005 in California and Florida to examine the influence of race and ethnicity on loan pricing across eight popular subprime mortgage products. We propose a method to identify two broad types of discrimination: *statistical discrimination* and *taste-based discrimination*. Fair lending laws clearly state that it is illegal for lenders to engage in either type of discrimination.

We evaluate the presence of discrimination in loan pricing by analyzing the effect of race and neighborhood characteristics separately on: (1) the assessment by lenders of borrowers' risk profiles in an actuarial stage and (2) the interest rate determination in an underwriting stage. This approach allows us to detect both *disparate treatment* and *disparate impact*

[1] The seminal study is by Munnell, Browne, McEneaney, and Tootell (1996). Ross and Yinger (2002) provide a comprehensive overview and analysis of the literature surrounding that study; see also Ladd (1998). For a model of redlining in a credit-rationing framework, see Lang and Nakamura (1993).

discrimination. The former is manifest when lenders apply different pricing rules based on individual racial or neighborhood characteristics. The latter occurs when policies that do not explicitly take racial or neighborhood characteristics into account result in disparities among racial groups because race is correlated with other variables that may be used in underwriting, even when they are not necessarily good predictors of loan performance.

We also use our approach to detect income- and race-based *redlining*, that is, whether lenders charge higher rates to borrowers living in low-income neighborhoods or in neighborhoods with high concentrations of minorities. Additionally, we analyze whether blacks and Hispanics face more subtle forms of discrimination. For example, as suggested by Ross and Tootell (2004), lenders may require black and Hispanic borrowers to purchase private mortgage insurance (PMI) when they would not require a white borrower with a similar risk profile to do so.[2]

We find adverse pricing effects that cannot be explained entirely by statistical discrimination. Controlling for the effect of race and neighborhood characteristics on loan performance, we find evidence of taste-based discrimination in two of the eight mortgage categories we consider. In particular, for the most popular mortgage product we find that black and Hispanic borrowers face higher interest rates compared with other borrowers, with increases of 28 and 11 basis points, respectively, implied by taste-based discrimination. In one category (5-year Adjustable Rate Mortgages [ARMs]), we find that blacks face lower rates after controlling for differences in default and prepayment propensities. We find evidence of statistical discrimination in this category, however. We also find evidence of income- or race-based redlining that cannot be explained by a statistically higher probability of default or prepayment in those neighborhoods in half of the mortgage products. In total, we find evidence of some form of adverse pricing (statistical discrimination, taste-based discrimination, or redlining) in seven of the eight products we analyze.

Our study is most closely related to that of Haughwout, Mayer, and Tracy (2009) who

[2]A limitation of our study is that we do not know the size of the prepayment penalty (PPP), and it remains possible that there are differences in PPPs across race that we do not account for.

examine 2/28 mortgages originated in August 2005 for the entire United States, but find no evidence of adverse loan pricing from race and ethnicity. Our paper differs from that of Haughwout, Mayer, and Tracy (2009) in four important ways.

First, our methodology allows us to detect both disparate impact and disparate treatment and to distinguish between statistical and taste-based discrimination. In contrast, the methodology of Haughwout, Mayer, and Tracy (2009) is aimed only at detecting disparate treatment discrimination, without exploring the source of potential disparities across racial groups. Second, in our approach we also emphasize detecting income- and race-based redlining. Third, we analyze whether blacks and Hispanics face more subtle forms of discrimination regarding prepayment penalty (PPP) or PMI requirements. Finally, we examine eight different mortgage products whereas Haughwout, Mayer, and Tracy confine their analysis to one category. Our product definitions emphasize the amortization term of the mortgage. Although the mortgage categories in both studies are not directly comparable, we do not find evidence of racial discrimination in ARMs with interest-only payments for the first two years, consistent with the findings of Haughwout, Mayer, and Tracy. However, we do find evidence of income-based redlining in this category.

Additional recent papers that examine the effect of race on consumer credit include those by Woodward (2008), Woodward and Hall (2010), Reid and Laderman (2009), Pope and Sydnor (2011a), and Ravina (2008). Woodward (2008) and Woodward and Hall (2010) examine closing costs and find that they are higher for minorities. Reid and Laderman (2009) study the link between race and ethnicity and the likelihood of obtaining higher-priced loans in California. Rather than focusing on price differences within a product category, Reid and Laderman analyze whether minorities had differential access to mortgage markets and find that this channel, rather than disparate treatment of minorities, led to higher foreclosure rates among minority households. Pope and Sydnor (2011a) and Ravina (2008) analyze the peer-to-peer lending market and find evidence of higher loan pricing for black borrowers compared with white borrowers with similar risk profiles.

In the next section, we describe the data and summarize the matching algorithm. In Section 3, we present the model of rate determination and describe the estimation methodology. We present our results in Section 4 and provide concluding remarks in Section 5.

2 Data

Our data are non-prime, private-label securitized, first-lien mortgages originated in 2005 in California and Florida. We merge detailed data on the performance and terms of the loans from CoreLogic Information Solutions, Inc. (CL) with data on borrower income, borrower race, Census tract income, and Census tract racial composition obtained under the Home Mortgage Disclosure Act (HMDA). To match loans from CL with HMDA data, we use a matching algorithm similar to that of Haughwout, Mayer, and Tracy (2009) that uses lender names, dates of origination, and geographic location.

2.1 Matching CL data with HMDA data

The matching procedure considers first-lien loans with the same purpose (purchase or refinance) and occupancy status (owner-occupied). CL associates each loan with a 5-digit ZIP code, whereas HMDA loans are associated with Census tracts. To match ZIP codes with Census tracts we used Census ZIP Code Tabulation Areas (ZCTAs).[3] We also use geographic information systems (GIS) software program Arcview to establish Census tract search areas associated with any given ZCTA as follows: For each loan in CL, we determined the smallest set of Census tracts that intersect with the associated ZCTA and we allowed for the union of the Census tracts in the intersection to extend over the geographic area defined by any given ZCTA.

Except for the use of ZCTAs, we followed Haughwout, Mayer, and Tracy's (2009) matching algorithm very closely. The procedure entails six stages that use the originator's name,

[3]ZCTAs are statistical entities developed by the Census to tabulate summary statistics from the 2000 Census for geographic areas that approximate the land area covered by each ZIP code.

the loan amount, and the origination dates to obtain the matches. The names are provided by the lenders themselves in the HMDA data, but not in the CL data. As a result, lender names in CL must be cleaned manually before the matching. Loan amounts are provided in dollars in CL, while they are provided in thousands of dollars in HMDA. Furthermore, HMDA allows lenders to round up loan amounts to the nearest thousand dollars if the fraction equals or exceeds $500. The dates are matched to within 5 business days if the CL dates are not imputed or to the same month if they are.[4] A summary of the various stages is as follows:

- Stage 1 considers loans with matched originator names and uses the larger 4-digit ZCTA search areas. Loan amounts are matched allowing a difference of up to and including $1,000.
- Stage 2 ignores originator names and uses 4-digit ZCTA search areas, as in stage 1.
- Stage 3 again considers originator names, but uses the smaller 5-digit ZCTA search areas. Loan amounts are matched allowing a difference of up to but not including $1,000.
- Stage 4 is similar to stage 3 but ignores originator names.
- Stage 5 is similar to stage 1 but loan amounts are matched to within 2.5% of the CL amount.
- Stage 6 is similar to stage 2 but loan amounts are matched to within 2.5% of the CL amount.

At the conclusion of each stage, only one-to-one matches are kept and are removed from the datasets, while loans with multiple matches (either one CL loan to many HMDA loans, or many CL loans to one HMDA loan) are returned to the matching pool for the subsequent

[4] CL origination dates are considered to be imputed if they are exactly two months before the first payment date.

stages. We also applied various data checks to the final sample of loans, including dropping observations with missing or erroneous FICO scores, as well as dropping observations with contract rates smaller than the reported HMDA spread of the loan's annual percentage rate with a Treasury security of comparable maturity. For additional details on the matching algorithm, see the appendix of Haughwout, Mayer, and Tracy (2009).

2.2 Summary statistics

Tables 1 through 4 contain summary statistics on the loans in our sample by race and product type. Table 1 summarizes the counts of mortgages by product and race that were matched. We consider three racial or ethnic categories: Hispanics, non-Hispanic blacks, and the remainder (Other: non-Hispanic and non-blacks).[5] We also consider the largest seven non-prime mortgage categories (which account for about 90 percent of all non-prime loans) and we include a category for the remainder. We define the categories according to the frequency distribution of the CL variable `prod_type` with an amortization period of 30 years.

We estimate our model separately for the different product types because the effect of loan characteristics on performance may differ according to the amortization structure. For example, a high LTV at origination is likely to be a much bigger contribution to default for loans that are interest-only for 10 years than for loans that start amortizing immediately. The categories are 2-year ARMs (with interest-only payments for the first two years with full amortization over the remaining term), 3-year ARMs (with interest-only payments for the first three years with full amortization over the remaining term), 10-year ARMs (with interest-only payments for the first 10 years with full amortization over the remaining term), 10-year fixed-rate mortgages (FRMs) (with interest-only payments for the first 10 years with full amortization over the remaining term), 5-year ARMs (with interest-only payments for

[5] HMDA distinguishes Hispanic borrowers with an ethnicity indicator and provides a separate variable to distinguish among races. Our definition of Hispanics therefore includes borrowers of any race, while our definition of blacks excludes Hispanic borrowers.

the first five years with full amortization over the remaining term), 30-year ARMs, and 30-year FRMs. We include all other loans in the remainder (Other) category.

We matched 281,180 purchase loans and 373,630 refinances, for a total of 654,810 mortgages. Hispanic borrowers obtained 101,576 purchase loans, almost 5 times the amount for black borrowers, and they obtained 96,441 refinancing loans, about 3 times the amount for black borrowers. The most popular products for home purchases across all race categories were 2-year ARMs, 30-year ARMs, and 5-year ARMs. For refinances the most popular products also included 30-year FRMs. For comparison, Haughwout, Mayer, and Tracy (2009) matched only 2/28 ARMs using national data for August 2005 for a total of about 75,000 loans. Although Haughwout, Mayer, and Tracy do not specify how they defined 2/28 mortgages, in addition to `prod_type`, the CL variable `first_rate`, which contains the number of months before the first rate reset, is often used to define hybrid loans that exhibit an initial period of fixed interest rates; for 2/28s, `first_rate`= 24. According to this definition, the hybrid 2/28 may include loans from all the ARM categories we analyzed.

Table 2 summarizes the proportion of loans by product and racial groups that (1) included PPPs, (2) required purchase of PMI, and (3) required full documentation of income (Full Doc). Unconditionally, black and Hispanic borrowers face PPPs more frequently than other borrowers in all product categories. Also, both black and Hispanic borrowers tend to be required to obtain PMI more often than other borrowers for most mortgage products. Finally, black borrowers are also required to provide full documentation of income slightly more often than Hispanics and other borrowers.

As Table 3 indicates, black and Hispanic borrowers tend to have lower FICO scores across most mortgage products (except that for 2-year ARMs Hispanic borrowers show a slightly higher FICO score than other borrowers). Black and Hispanic borrowers also tend to have mortgages with LTV ratios and higher debt-to-income (DTI) ratios. The variable *Good Credit* summarizes these differences; *Good Credit* takes a value of 1 if the borrower has a FICO score above the 50th percentile, the LTV ratio is at or below the 50th percentile,

Table 1: Mortgage counts

	Purchases				Refinances				
Product	Hispanic	Black	Other	Total	Hispanic	Black	Other	Total	Sum
2-yr ARM	9,998	1,461	10,030	21,489	4,178	1,129	7,088	12,395	33,884
3-yr ARM	2,424	457	4,345	7,226	1,478	474	3,483	5,435	12,661
30-yr FRM	4,266	1,050	10,272	15,588	16,452	6,457	43,647	66,556	82,144
30-yr ARM	34,377	9,280	56,083	99,740	46,045	17,307	116,789	180,141	279,881
10-yr FRM	1,385	249	4,848	6,482	1,276	305	5,974	7,555	14,037
10-yr ARM	6,920	1,037	18,347	26,304	2,350	591	9,896	12,837	39,141
5-yr ARM	29,394	4,901	41,090	75,385	13,198	3,925	29,268	46,391	121,776
Other	12,812	1,998	14,156	28,966	11,464	3,710	27,146	42,320	71,286
Total	101,576	20,433	159,171	281,180	96,441	33,898	243,291	373,630	654,810

All loans have terms of 30 years. A 2-yr ARM is an ARM that is interest only for the first two years and fully amortizing over the remaining 28 years. Three-year ARMs, 5-yr ARMs, and 10-yr ARMs are defined in the same way but with interest-only periods of three, five, or ten years. Thirty-year ARMs are fully amortizing over the thirty years as are 30-yr FRMs. Finally, the 10-yr FRM is an FRM with interest-only payments for the first ten years and full amortization over the remaining 20 years.

Table 2: Prepayment Penalties, Private Mortgage Insurance, and Full Documentation

Product	Race	N	PPP	PMI	FullDoc
2-yr ARM	Hispanic	14,176	0.95	0.10	0.40
	Black	2,590	0.94	0.11	0.53
	Other	17,118	0.92	0.11	0.48
	Total	33,884	0.94	0.11	0.45
3-yr ARM	Hispanic	3,902	0.74	0.10	0.46
	Black	931	0.78	0.08	0.61
	Other	7,828	0.61	0.07	0.50
	Total	12,661	0.66	0.08	0.50
30-yr FRM	Hispanic	20,718	0.81	0.19	0.54
	Black	7,507	0.88	0.22	0.66
	Other	53,919	0.72	0.18	0.61
	Total	82,144	0.76	0.19	0.59
30-yr ARM	Hispanic	80,422	0.92	0.19	0.36
	Black	26,587	0.94	0.22	0.50
	Other	172,872	0.87	0.18	0.41
	Total	279,881	0.89	0.18	0.40
10-yr FRM	Hispanic	2,661	0.33	0.05	0.29
	Black	554	0.26	0.04	0.40
	Other	10,822	0.27	0.03	0.39
	Total	14,037	0.28	0.04	0.37
10-yr ARM	Hispanic	9,270	0.48	0.05	0.16
	Black	1,628	0.43	0.07	0.26
	Other	28,243	0.35	0.05	0.26
	Total	39,141	0.38	0.05	0.24
5-yr ARM	Hispanic	42,592	0.90	0.17	0.42
	Black	8,826	0.89	0.16	0.56
	Other	70,358	0.81	0.15	0.52
	Total	121,776	0.85	0.16	0.49
Other	Hispanic	24,276	0.91	0.10	0.30
	Black	5,708	0.92	0.12	0.45
	Other	41,302	0.83	0.11	0.39
	Total	71,286	0.87	0.11	0.37

Prepay, PMI, and FullDoc indicate the shares of mortgages with prepayment penalties, private mortgage insurance, and full documentation, respectively.
All loans have terms of 30 years. A 2-yr ARM is an ARM that is interest only for the first two years and fully amortizing over the remaining 28 years. Three-year ARMs, 5-yr ARMs, and 10-yr ARMs are defined in the same way but with interest-only periods of three, five, or ten years. Thirty-year ARMs are fully amortizing over the thirty years as are 30-yr FRMs. Finally, the 10-yr FRM is an FRM with interest-only payments for the first ten years and full amortization over the remaining 20 years.

and the DTI ratio is at or below the 50th percentile. In summary, a smaller proportion of black and Hispanic borrowers exhibit good credit compared with other borrowers both for purchases and for refinances.

Table 4 summarizes the loan amounts and contract interest rates. It also provides the average spread as provided to HMDA. Loan amounts for blacks and Hispanics are smaller than for other borrowers, and loan amounts for blacks are almost always smaller than for Hispanics. Black and Hispanic borrowers generally face higher contract interest rates than other borrowers. Finally, the difference in the rates paid by black and Hispanic borrowers relative to other borrowers is somewhat less pronounced in the spreads.

We focus on contract rates rather than the annual percentage rates (APRs). HMDA reports only the spread of the APR over a Treasury security of comparable maturity for high-cost loans (i.e., loans for which the spread is 300 basis points or more). Lenders compute the APR for each loan by assuming that the loan is held to maturity and that the loan adjusts to the initial fully indexed rate at origination (which is not necessarily equal to the contract rate). Furthermore, the lender is only required to report the APR rounded to the nearest one-eighth of 1 percent. Given this APR computation method, it is not possible to accurately identify from the APR the amount of points paid by the borrower, although it seems entirely possible that some racial discrimination or redlining may exist in the points paid by borrowers.[6] Since most loans in our sample are prepaid long before maturity, the APR is a much noisier measure of the cost of borrowing than the initial contract rate. For example, the APR for a 30-year ARM with an interest rate that first resets five years after origination largely reflects the hypothetical reset rate (the rate the borrower is assumed to pay for the remaining 25 years on the loan) but a relatively small proportion of borrowers will still have the loan five years after origination. Furthermore, in preliminary analyses, we found much less variation across borrowers in the APR than in the contract rate on almost any dimension. Haughwout, Mayer, and Tracy (2009) also find that lenders seem to price

[6]See Woodward (2008) and Woodward and Hall (2010) on this issue.

Table 3: Borrowers' Credit Characteristics

			Good Credit	FICO		LTV (%)		DTI (%)	
Product	Race	N	Share	Mean	SD	Mean	SD	Mean	SD
2-yr ARM	Hispanic	14,176	0.14	660.18	46.71	81.18	7.31	32.79	18.27
	Black	2,590	0.10	643.68	44.79	81.62	8.87	32.19	18.45
	Other	17,118	0.12	651.55	48.11	81.12	8.34	32.01	18.70
	Total	33,884	0.13	654.56	47.56	81.18	7.97	32.35	18.51
3-yr ARM	Hispanic	3,902	0.26	664.84	56.00	80.05	9.13	18.63	20.55
	Black	931	0.20	649.86	57.44	80.07	9.94	18.30	20.42
	Other	7,828	0.30	668.83	61.02	79.05	9.69	16.82	20.16
	Total	12,661	0.28	666.21	59.46	79.43	9.55	17.49	20.32
30-yr FRM	Hispanic	20,718	0.24	649.75	64.63	69.64	15.96	22.99	21.13
	Black	7,507	0.15	625.73	65.11	71.77	15.82	24.50	20.96
	Other	53,919	0.31	657.27	70.42	70.18	16.23	20.59	20.72
	Total	82,144	0.27	652.49	69.12	70.19	16.14	21.55	20.90
30-yr ARM	Hispanic	80,422	0.18	633.14	68.85	77.35	11.87	27.65	20.08
	Black	26,587	0.10	608.35	65.16	78.48	12.07	28.56	20.07
	Other	172,872	0.26	641.08	76.99	75.61	12.71	24.52	20.27
	Total	279,881	0.22	635.69	74.28	76.38	12.45	25.80	20.26
10-yr FRM	Hispanic	2,661	0.59	709.43	48.10	72.44	13.36	14.36	19.13
	Black	554	0.62	708.08	48.62	71.95	13.59	13.33	18.89
	Other	10,822	0.66	720.15	48.88	69.94	14.66	13.54	18.63
	Total	14,037	0.65	717.64	48.94	70.50	14.41	13.69	18.73
10-yr ARM	Hispanic	9,270	0.46	711.40	43.87	77.57	8.47	25.07	18.81
	Black	1,628	0.42	704.44	46.41	77.40	9.11	26.22	18.55
	Other	28,243	0.50	718.48	44.92	75.78	10.78	25.41	18.00
	Total	39,141	0.49	716.22	44.90	76.27	10.24	25.36	18.22
5-yr ARM	Hispanic	42,592	0.17	667.16	49.71	80.25	7.77	33.67	18.12
	Black	8,826	0.13	651.31	48.76	80.71	8.73	33.63	18.43
	Other	70,358	0.19	666.37	53.11	79.55	9.15	32.07	18.93
	Total	121,776	0.18	665.56	51.79	79.88	8.67	32.74	18.63
Other	Hispanic	24,276	0.19	651.17	60.32	76.32	12.11	30.89	19.38
	Black	5,708	0.15	630.64	61.77	75.96	13.16	30.96	19.30
	Other	41,302	0.29	662.13	70.53	73.96	14.12	27.76	19.31
	Total	71,286	0.25	655.88	67.14	74.92	13.44	29.08	19.39

The variable Good Credit takes a value of 1 if the borrower has a FICO score above the 50th percentile, loan-to-value (LTV) ratio at or below the 50th percentile, and debt-to-income (DTI) ratio at or below the 50th percentile.
All loans have terms of 30 years. A 2-yr ARM is an ARM that is interest only for the first two years and fully amortizing over the remaining 28 years. Three-year ARMs, 5-yr ARMs, and 10-yr ARMs are defined in the same way but with interest-only periods of three, five, or ten years. Thirty-year ARMs are fully amortizing over the thirty years as are 30-yr FRMs. Finally, the 10-yr FRM is an FRM with interest-only payments for the first ten years and full amortization over the remaining 20 years.

Table 4: Loan Amount and Contract Interest Rate

			Loan Amount ($)		Contract Rate (%)		HMDA Spread (%)	
Product	Race	N	Mean	SD	Mean	SD	Mean	SD
2-yr ARM	Hispanic	14,176	316,103	119,105	6.73	0.72	4.45	0.66
	Black	2,590	306,834	128,936	6.78	0.79	4.46	0.74
	Other	17,118	339,721	139,265	6.74	0.77	4.42	0.72
	Total	33,884	327,326	131,016	6.74	0.75	4.44	0.69
3-yr ARM	Hispanic	3,902	303,265	122,460	6.45	0.83	4.43	0.74
	Black	931	288,766	145,428	6.53	0.86	4.50	0.75
	Other	7,828	352,607	178,613	6.32	0.90	4.39	0.80
	Total	12,661	332,706	162,949	6.37	0.88	4.42	0.78
30-yr FRM	Hispanic	20,718	235,716	125,729	6.68	0.84	4.28	0.90
	Black	7,507	196,835	126,474	7.06	1.04	4.31	0.97
	Other	53,919	264,165	184,481	6.68	0.93	4.22	0.93
	Total	82,144	250,837	168,013	6.71	0.93	4.25	0.93
30-yr ARM	Hispanic	80,422	274,441	153,603	6.60	1.91	4.77	0.90
	Black	26,587	236,264	149,899	7.15	1.72	5.02	0.98
	Other	172,872	342,874	249,107	6.27	2.22	4.87	0.98
	Total	279,881	313,083	220,862	6.45	2.11	4.85	0.96
10-yr FRM	Hispanic	2,661	325,813	169,578	6.32	0.54	4.54	0.83
	Black	554	326,014	177,325	6.35	0.55	4.46	0.91
	Other	10,822	390,752	245,285	6.20	0.47	4.32	0.86
	Total	14,037	375,887	231,983	6.23	0.49	4.41	0.86
10-yr ARM	Hispanic	9,270	355,922	169,045	6.14	0.65	4.52	0.80
	Black	1,628	356,047	200,023	6.15	0.72	4.53	0.83
	Other	28,243	438,059	266,626	5.96	0.69	4.43	0.83
	Total	39,141	415,195	247,145	6.01	0.68	4.48	0.82
5-yr ARM	Hispanic	42,592	320,851	131,012	6.63	0.76	4.53	0.77
	Black	8,826	312,547	147,233	6.70	0.82	4.57	0.81
	Other	70,358	355,918	178,554	6.51	0.81	4.42	0.79
	Total	121,776	340,509	162,244	6.57	0.79	4.48	0.78
Other	Hispanic	24,276	313,273	146,037	6.81	1.30	4.74	0.89
	Black	5,708	292,839	160,319	6.99	1.39	4.90	0.97
	Other	41,302	368,615	227,265	6.46	1.69	4.78	0.97
	Total	71,286	343,701	200,317	6.62	1.55	4.78	0.94

HMDA spread denotes the spread between the APR and the yield on a Treasury security of comparable maturity if the loan is a high-cost loan, defined as one for which the spread is 300 basis points or more.
All loans have terms of 30 years. A 2-yr ARM is an ARM that is interest only for the first two years and fully amortizing over the remaining 28 years. Three-year ARMs, 5-yr ARMs, and 10-yr ARMs are defined in the same way but with interest-only periods of three, five, or ten years. Thirty-year ARMs are fully amortizing over the thirty years as are 30-yr FRMs. Finally, the 10-yr FRM is an FRM with interest-only payments for the first ten years and full amortization over the remaining 20 years.

risk primarily in the initial contract rate rather than subsequent reset rates. Additional summary statistics of the variables used in the analysis are presented in Tables 11 to 13 of Appendix B.

3 A Model of Mortgage Rate Determination

In this section, we present a simple reduced-form model of mortgage rate determination derived from a test proposed by Ross and Yinger (2002, ch. 10).[7] In the model, lenders charge a rate based on the expected performance of the loan. Loan performance is judged by the expected probability that it produces adverse outcomes—for example, default or prepayment. Along the lines of Ladd (1998), who discusses various definitions of mortgage discrimination in light of the relevant mortgage laws, we allow for the possibility that lenders may vary the rate charged based on variables used to identify two broad classes of discrimination: *disparate treatment* and *disparate impact*. The former is manifest in rate changes directly associated with race variables. The latter occurs when policies that do not explicitly take race into account result in disparities among racial groups because race is correlated with other non-racial variables that may be used in underwriting, even when they are not necessarily good predictors of loan performance. To this end, we allow loan performance to vary with racial and neighborhood characteristics. Furthermore, by including Census tract characteristics, namely, the tract's median family income relative to the median income of the metropolitan area[8] and the percent of minority population, we can also detect redlining.

The advantage of this approach is that it enables us to detect both disparate impact and disparate treatment discrimination, both of which are illegal. Disparate impact discrimination is illegal because lenders can easily mimic the effect of disparate treatment discrimination using disparate impact discrimination. That is, the lender can change the weight of vari-

[7] Pope and Sydnor (2011b) propose a related methodology but apply it to the Worker Profiling and Reemployment Services system.

[8] The median income of the metropolitan statistical area (MSA) or metropolitan division (MD), as applicable, is reported in HMDA. HUD determines whether lenders should use the MSA or the MD income and provides the relevant income to lenders. We refer to the MSA or MD as the metropolitan area.

ous loan characteristics to discriminate against certain racial groups by taking advantage of correlations between race and non-racial borrower or loan characteristics that influence loan performance.

For example, suppose that a lender would like to charge black people more for their loans than white people. Suppose that the average FICO score of a black person is 100 points lower than the average FICO score of a white person and that a 100-point increase in the FICO score lowers the probability of default by 10 percent. If the actuarially fair reduction in the interest rate is 50 basis points for each 10 percent decrease in the default probability, we should observe that black people have interest rates on average 50 basis points higher than white people. After controlling for the effect of the FICO score on loan performance, we should not find a significant effect of black race on rates. However, if the lender wishes to discriminate against black people, the lender can increase the interest rate by, say, 200 basis points for each 100-point decrease in the FICO score.

The test proceeds as follows:

1. We randomly split the sample of loans for a particular mortgage product in two halves and estimate loan performance models on the first half (using default and prepayment as the adverse outcomes) using loan, individual, and Census tract characteristics *including* the minority status of the borrower, the income of the Census tract, and the racial composition of the Census tract. We label this the *actuarial* stage.

2. We then use the estimation outcomes from stage 1 to compute the *predicted* performance of the loans in the second half of the sample using loan and individual characteristics. In this step, we construct two measures of predicted performance. The first measure *omits* the minority status of the borrower, the Census tract income, and the racial composition of the Census tract. The second measure *includes* these variables; we use this measure of performance to ascertain statistical discrimination.

3. Finally, we estimate a model with the loans from stage 2 using the actual interest rate

as the dependent variable and the predicted probabilities of default and prepayment. We label this the *underwriting* stage.

3.1 Empirical Framework

To formalize, consider the following linear rate-setting equation:

$$R_n = \beta_0 + \beta_p \widehat{\mathbf{P}}_n + \beta_z \mathbf{z}_n + \beta_x \mathbf{x}_n + e_n, \tag{1}$$

where R_n is the rate charged for loan n, $\widehat{\mathbf{P}}_n$ is a $(\pi \times 1)$ vector of measures of predicted loan performance, $\mathbf{z}_n$ is a $(\kappa_z \times 1)$ vector of non-racial variables, and $e_n \sim N(0, \sigma^2)$. The $(\kappa_x \times 1)$ vector of *treatment* variables $\mathbf{x}_n$ includes a set of individual indicators (i.e., borrower race) and a set of neighborhood indicators (e.g., neighborhood racial composition).

To estimate equation (1), we require the vector of predicted loan performance measures, $\widehat{\mathbf{P}}_n$. Loan performance data typically consist of binary measures (e.g., the loan defaults or is prepaid within two years) which would not be available at the time the rate is set. Instead, we construct a vector of expected loan performance, which is composed of the forecasted probability of loan default and the forecasted probability of prepayment. To construct these, we extract from the full sample of loans a subset of loans to use as an *actuarial* sample. From this sample, we estimate models of loan performance and use the resulting estimation to construct predicted performance for loans in a different *underwriting* sample on which we evaluate the presence of discrimination.

We partition the full set of loans into an M loan actuarial sample and an N loan underwriting sample. Let $\mathbf{P}_m$ represent the vector of π different performance measures for loan m from the actuarial sample. Let $\mathbf{q}_m$ represent the $(\kappa_q \times 1)$ vector of non-racial characteristics that affect loan performance (e.g., FICO score, LTV ratio), and let $\mathbf{w}_m$ represent the $(\kappa_w \times 1)$ vector of racial and neighborhood characteristics (black and Hispanic indicators, tract income, etc.) that may affect loan performance. For any loan m in the actuarial sample, the probability that the event outlined by performance measure i occurs (e.g., that loan m defaults), $P_{im} = 1$, can be specified as a probit:

$$\Pr\left[P_{im} = 1\right] = \Phi\left(\alpha_{i0} + \alpha_{iq}\mathbf{q}_m + \alpha_{iw}\mathbf{w}_m\right), \tag{2}$$

where the link function, $\Phi(.)$, is the standard normal cumulative distribution function (cdf) and $\alpha_i = [\alpha_{i0}, \alpha_{iq}, \alpha_{iw}]$ are slope coefficients specific to the ith performance measure. From (2), the predicted probabilities for loans from the underwriting subsample are computed as

$$\widehat{P}_{in} = \Phi\left(\widehat{\alpha}_{i0} + \widehat{\alpha}_{iq}\mathbf{q}_n\right), \tag{3}$$

where, again, $\Phi(.)$ is the standard normal cdf, and $\widehat{\alpha}_0$ and $\widehat{\alpha}_q$ represent the estimated parameters of equation 2. Note that the vector of race and neighborhood variables, $\mathbf{w}_m$, is excluded from the calculation of the actuarially consistent predicted loan performance measures. The use of these variables as predictors of loan performance is illegal; therefore, we must extract their effect from the loan performance model to properly assess the effect of other measures.

3.2 Identifying Types of Discrimination

Discrimination may result from taste-based discrimination (animosity or prejudice against minorities) or from statistical discrimination (the lender uses race or ethnicity to estimate the borrower's credit worthiness). To differentiate the two forms, the predicted loan performance used in underwriting (3) is rewritten to include the treatment variables, $\mathbf{w}_m$. In this case, discrimination causes a change in the loan's predicted performance through a difference in the probability of, say, default. To capture this possibility, we can compute an alternative measure of predicted performance that accounts for the effect of racial and neighborhood characteristics:

$$\widetilde{P}_{in} = \Phi\left(\widehat{\alpha}_{i0} + \widehat{\alpha}_{iq}\mathbf{q}_n + \widehat{\alpha}_{iw}\mathbf{w}_m\right). \tag{4}$$

Standard (classical) tests for discrimination might examine the statistical significance of the coefficients on the $\mathbf{x}_n$s in alternative versions of equation (1), one which uses predicted performance as in equation (3) and one which uses predicted performance as in equation (4). We instead opt for a Bayesian environment in which we can assess the probability that discrimination is present in the sample. The model identifies statistical discrimination via a nonlinear, borrower-specific, effect on loan performance based on racial and tract characteristics. Taste-based discrimination, on the other hand, is identified as a uniform direct effect of race on interest rates. That is, we identify the form of discrimination by comparing price-setting models in which lenders use race to predict loan performance (statistical discrimination) and models in which race affects interest rates directly (taste-based discrimination).

To accomplish this, we modify the rate equation to account for the change in expected loan performance. We augment the rate equation with two vectors of model indicator dummies, γ and δ:

$$R_n = \beta_0 + \beta_p \left((\mathbf{1}_\pi - \delta) \odot \widehat{\mathbf{P}}_n + \delta \odot \widetilde{\mathbf{P}}_n \right) + \beta_z \mathbf{z}_n + \gamma \odot \beta_x \mathbf{x}_n + e_n, \tag{5}$$

where $\odot$ denotes the Hadamard product and $\mathbf{1}_\pi$ is a vector of 1s with dimension $(\pi \times 1)$. The model indicators γ and δ are vectors of 0s and 1s with dimensions $(\kappa_x \times 1)$ and $(\pi \times 1)$, respectively. Individual elements of γ will determine the presence of disparate treatment or redlining in the rate: If $\gamma_k = 1$ then $\mathbf{x}_k$ is turned on. Because we restrict β_p to be the same in both the $\widehat{\mathbf{P}}_n$ and $\widetilde{\mathbf{P}}_n$ terms, the δs can be thought of as a model selection variable that determines the presence of statistical discrimination; that is, if $\delta_i = 1$ then $\widetilde{\mathbf{P}}_i$ is turned on.

3.3 Estimation

The rate equations (1) and (5)use predicted performance and, therefore, suffer from a generated regressor problem (see Pagan, 1984). In a classical environment, the probit model could be estimated using, say, maximum likelihood and then a bootstrap to estimate the standard errors (see Kilian, 1998). Instead, we estimate the model in a Bayesian environment. We use a set of relatively uninformative standard priors. The slope coefficients in both the rate equation and in the probit have mean zero normal priors; the variance of the innovations in the rate equation has an inverse gamma prior. The priors for each of the model indicators are flat.

The posteriors used for inference are generated from the Gibbs sampler using two Metropolis-in-Gibbs steps. The Gibbs sampler is a Markov Chain Monte Carlo technique that iteratively draws each parameter from its conditional distribution. The collection of draws converges to the full set of parameters' joint posterior. Inference is performed on a subset of draws, some of which are discarded to allow for convergence.

Our algorithm is a three-step procedure. In the first step, we draw the slope parameters of the probit. Second, after allowing for convergence, for each draw of α, we compute two predicted performance measures, $\widehat{\mathbf{P}}_n$ and $\widetilde{\mathbf{P}}_n$, conditional on the draw of α. In the third step, for each $\widehat{\mathbf{P}}_n$ and $\widetilde{\mathbf{P}}_n$ combination, we then iteratively draw 1,500 samples of β, δ, and γ, burning the first 1,000 to account for convergence. The first step is repeated 500 times after convergence is achieved. We store every tenth draw of β, δ, and γ, which yields 500 draws of α and 25,000 draws of β, δ, and γ, which are then pooled. Note that the sampling algorithm described here accounts for the sampling uncertainty in α that would create the generated regressor problem in $\widehat{\mathbf{P}}_n$ and $\widetilde{\mathbf{P}}_n$. The final result is a set of posterior distributions for α and β and a set of model inclusion probabilities for each of the $\widetilde{\mathbf{P}}_n$s and $\mathbf{x}_n$s. Details of the sampling methods, including the specifications for the priors and the posterior draws, are included in Appendix A.

4 Results

4.1 Loan performance

As discussed in the previous section, we randomly divide the sample for each mortgage product in half. We use the first half to form the actuarial sample and estimate the probit model for two measures of loan performance: default within 2 years and prepayment within 2 years of closing.[9]

Tables 5 and 6 present the results from the loan performance models using the actuarial sample. Table 5 shows the results for the default measure, and Table 6 shows the results for the prepayment measure.[10] The coefficients in the tables represent the medians of the posterior distributions of the parameters. We shade out cases in which 0 is contained in the 90 percent coverage interval, indicating that a variable is not an important determinant of the corresponding performance measure. The results from the loan performance models indicate that standard measures of credit worthiness, such as FICO scores, LTV ratios, and DTI ratios are important determinants of both default and prepayment for most product categories. The coefficients on the refinance dummy variable indicate that refinances are associated with lower default and higher prepayment. Borrowers with 30-year FRMs, 30-year ARMs, and 10-year FRMs are more likely to default in Florida than in California, while most mortgage products are less likely to be prepaid in Florida than in California. Black and Hispanic borrowers are more likely to default in five of the eight mortgage product

[9]We consider a loan in default if the CL variable MBA_STAT takes a value of 9 (90-days or more delinquent), F (in foreclosure), or R (REO). We consider a loan prepaid if the loan leaves the database or has an MBA_STAT of 0 in a particular month and the MBA_STAT variable does not take a value of 6 (60-days delinquent), 9, F, or R in the month before the loan leaves the database. To keep our model parsimonious, we do not construct loan performance measures for other horizons; see Demyanyk (2009) for evidence on the large proportion of subprime loans that terminate within two or three years of origination.

[10]Models of mortgage performance often include a prepayment option variable (i.e., the spread between the rate on the loan at origination and the current market rate). We do not include a prepayment option variable here for two reasons. First, all loans were originated in a short period (2005) such that the spread would not differ much from loan to loan based on market conditions. Rather, differences in that spread most likely would be due to credit characteristics which we control for directly in our estimation of loan performance. Second, the performance measures are calculated quite discretely (a single performance measure for default and prepayment) rather than in a hazard framework or for each loan-month observation.

Table 5: Probit performance estimation: Default within 2 years

	Variable	2-yr ARM	3-yr ARM	30-yr FRM	30-yr ARM	10-yr FRM	10-yr ARM	5-yr ARM	Other
	Constant	-1.0533	-1.3193	-1.7114	-1.2387	-1.8275	-1.6349	-1.1750	-1.0590
q	LTV	0.0515	0.1287	0.2154	0.1711	0.2276	0.1977	0.1107	0.2830
	PPP	0.2510	0.3758	0.2014	0.1986	0.0825	0.2863	0.3312	0.2903
	DTI	-0.0320	-0.0591	-0.0077	0.0399	0.0472	0.0179	-0.0073	0.0800
	FICO	-0.2217	-0.3327	-0.4244	-0.4237	-0.4173	-0.2870	-0.2846	-0.4468
	PMI	0.0438	0.0368	-0.0984	-0.0434	-0.2196	-0.1507	-0.0201	0.0182
	Amount	0.1282	0.0923	0.0733	0.0703	0.0622	0.0826	0.1216	0.0874
	FullDoc	-0.2159	-0.2860	-0.1791	-0.1489	-0.4170	-0.3386	-0.2074	-0.2599
	Refi	-0.4727	-0.3713	-0.1971	-0.3074	-0.3090	-0.3061	-0.3884	-0.5141
	FL	0.0125	0.0440	0.1447	0.0978	0.1284	-0.0276	-0.0443	-0.1316
w	Black	0.1842	0.0371	0.3610	0.1742	0.0861	0.1039	0.2585	0.2770
	Hispanic	0.1485	0.0400	-0.0827	0.0565	0.0828	0.2004	0.1458	0.0605
	PPP × Black	-0.0848	-0.0646	-0.3080	-0.0838	-0.1576	0.1492	-0.1726	-0.1370
	PPP × Hispanic	-0.1801	-0.1330	-0.0278	-0.0521	-0.0557	-0.0447	-0.0903	-0.0240
	PMI × Black	0.1686	0.1089	0.0145	-0.0199	0.3771	-0.1492	0.0716	-0.0782
	PMI × Hispanic	-0.0111	-0.0976	0.0369	0.0061	-0.3013	-0.1050	0.0206	0.0092
	Tract income	-0.0324	0.0215	-0.0390	-0.0315	-0.0463	-0.0477	-0.0273	-0.0348
	Tract minority	-0.0538	0.0017	-0.0283	-0.0324	-0.0460	-0.0492	-0.0389	-0.0468
	No. obs.	16692	6244	41185	139999	6978	19557	60898	35685

The coefficients represent the medians of the posterior distributions. The grayed-out coefficients indicate that 0 is contained in the 90 percent coverage interval.
LTV is loan-to-value ratio, *DTI* is debt-to-income-ratio, *PPP* is a dummy for prepayment penalties. *PMI* is a dummy for private mortgage insurance, *FullDoc* is a dummy for full income documentation, *Refi* is a dummy for refinances, *FL* is a dummy for Florida. *PPP×race* is the interaction of the prepayment penalty and race indicators. Similarly, *PMI×race* is the interaction of the private mortgage insurance and race indicators. *Tract income* is equal to the Census tract median family income relative to the U.S. Department of Housing and Urban Development (HUD) estimate of the metropolitan area's family income provided in the HMDA data. *Tract minority* is the Census tract percent of minority population from the 2000 Census.
All loans have terms of 30 years. A 2-yr ARM is an ARM that is interest only for the first two years and fully amortizing over the remaining 28 years. Three-year ARMs, 5-yr ARMs, and 10-yr ARMs are defined in the same way but with interest-only periods of three, five, or ten years. Thirty-year ARMs are fully amortizing over the thirty years as are 30-yr FRMs. Finally, the 10-yr FRM is an FRM with interest-only payments for the first ten years and full amortization over the remaining 20 years.

Table 6: Probit performance estimation: Prepayment within 2 years

	Variable	2-yr ARM	3-yr ARM	30-yr FRM	30-yr ARM	10-yr FRM	10-yr ARM	5-yr ARM	Other
	Constant	0.6543	-0.0223	-0.4352	0.2747	-0.8346	-0.3168	-0.1931	-0.3156
q	LTV	-0.0278	-0.0443	0.0639	-0.0545	-0.0064	0.0203	-0.0260	-0.0191
	PPP	-1.1678	-0.5041	-0.1718	-0.4454	-0.3011	-0.3129	-0.4599	-0.2758
	DTI	0.0365	-0.0418	0.0412	0.0037	-0.0342	-0.0176	0.0307	-0.0079
	FICO	-0.0119	-0.1116	-0.2179	-0.0583	-0.1506	-0.0780	-0.0712	-0.0828
	PMI	-0.0287	0.1538	0.0768	0.1197	0.2740	-0.0331	0.1584	0.0270
	Amount	-0.1340	-0.0965	-0.1684	-0.0455	-0.0465	0.0122	-0.1057	-0.0164
	FullDoc	-0.0537	-0.1028	-0.0772	-0.0039	-0.1020	-0.1592	-0.0621	-0.1421
	Refi	0.5400	0.3216	0.0964	0.2334	0.0829	0.0778	0.4210	0.3286
	FL	-0.0885	-0.0594	-0.2012	-0.2682	0.0319	-0.1579	-0.1310	-0.1766
w	Black	-0.1989	0.1839	0.1809	0.0216	0.0828	-0.0163	-0.0234	0.0920
	Hispanic	-0.2268	0.0080	0.0277	-0.0255	0.0725	-0.0593	0.0174	0.0488
	PPP × Black	0.3061	-0.0160	-0.1901	-0.0419	0.1743	0.0534	0.0335	-0.0857
	PPP × Hispanic	0.1878	0.0060	-0.0228	-0.0172	-0.1158	-0.0363	-0.0824	-0.1327
	PMI × Black	-0.2782	-0.3561	-0.0477	-0.0045	-0.2113	-0.0723	-0.0989	0.1253
	PMI × Hispanic	-0.0459	-0.0583	0.0532	-0.0331	-0.2681	0.0926	-0.0991	-0.0276
	Tract income	0.0550	0.0684	-0.0056	0.0178	0.0233	0.0265	0.0558	0.0149
	Tract minority	0.1223	0.1234	0.0785	0.0742	0.1046	0.0874	0.1331	0.0839
	No. obs.	16692	6244	41185	139999	6978	19557	60898	35685

The coefficients represent the medians of the posterior distributions. The grayed-out coefficients indicate that 0 is contained in the 90 percent coverage interval.
LTV is loan-to-value ratio, *DTI* is debt-to-income-ratio, *PPP* is a dummy for prepayment penalties. *PMI* is a dummy for private mortgage insurance, *FullDoc* is a dummy for full income documentation, *Refi* is a dummy for refinances, *FL* is a dummy for Florida. *PPP×race* is the interaction of the prepayment penalty and race indicators. Similarly, *PMI×race* is the interaction of the private mortgage insurance and race indicators. *Tract income* is equal to the Census tract median family income relative to the U.S. Department of Housing and Urban Development (HUD) estimate of the metropolitan area's family income provided in the HMDA data. *Tract minority* is the Census tract percent of minority population from the 2000 Census.
All loans have terms of 30 years. A 2-yr ARM is an ARM that is interest only for the first two years and fully amortizing over the remaining 28 years. Three-year ARMs, 5-yr ARMs, and 10-yr ARMs are defined in the same way but with interest-only periods of three, five, or ten years. Thirty-year ARMs are fully amortizing over the thirty years as are 30-yr FRMs. Finally, the 10-yr FRM is an FRM with interest-only payments for the first ten years and full amortization over the remaining 20 years.

categories. PPPs for black and Hispanics appear to be associated with lower default rates for some products; they have a positive impact on the probability of prepayment for 2-year ARMs and a negative impact on prepayment in some other mortgage products. Higher tract income (measured as Census tract median family income relative to the metropolitan area) and a higher tract share of minority population are associated with both lower default probability and higher prepayment probability across most product categories.[11]

4.2 Loan pricing

Table 7 presents the estimation of the rate-setting equation, equation (5). The estimated coefficients are separated in four panels corresponding to the constant; the measures of predicted performance, $\hat{\mathbf{P}}$; the non-racial variables, $\mathbf{z}$; and the race and neighborhood variables, $\mathbf{x}$. As in Tables 5 and 6, the coefficients represent the medians of the posterior distribution and the shaded out coefficients in the $\hat{\mathbf{P}}$ and $\mathbf{z}$ panels indicate that 0 is contained in the 90 percent coverage interval. The bold italicized coefficients in the $\hat{\mathbf{P}}$ panel additionally indicate that the model inclusion probability (the probability that the value of δ in equation (5) is equal to 1) exceeds 90 percent, which indicates the presence of statistical discrimination.

The coefficients associated with the treatment variables in the $\mathbf{x}$ panel also represent the medians of the posterior distributions, conditional on the corresponding inclusion variable γ, for cases in which the model inclusion probability (that the value of γ in equation (5) is equal to 1) exceeds 90 percent, which indicates the presence of taste-based discrimination.

We do not report estimated coefficients of the race and neighborhood variables, $\mathbf{x}$, if the estimation procedure does not indicate that the corresponding $\mathbf{x}$ variable should be turned on at least 90 percent of the time. We do, however, report the model inclusion probabilities for both statistical and taste-based discrimination, $\Pr(\delta = 1)$ and $\Pr(\gamma = 1)$, in Table 8. In this table, the bold entries correspond to the coefficients reported in Table 7.

[11] In the benchmark specification, we do not include borrower income directly in our performance estimation due to concerns that (back-end) DTI, mortgage amount, and income would be collinear. We have estimated the model with borrower income and the results are quite similar to the benchmark case, however; these

Table 7: Rates estimation

	Variable	2-yr ARM	3-yr ARM	30-yr FRM	30-yr ARM	10-yr FRM	10-yr ARM	5-yr ARM	Other
	Constant	5.2274	4.9852	5.2940	1.7470	5.8512	4.5469	4.7789	4.0514
$\widehat{\mathbf{P}}$	Default	5.4322	5.8011	***6.6981***	12.5621	4.7786	4.3686	***5.1304***	5.2732
	Prepay	2.0190	1.1489	2.6971	5.1107	0.1235	2.0368	1.7874	***2.7781***
$\mathbf{z}$	PPP	-0.2488	0.0410	0.1433	0.3323	-0.0274	0.1392	0.0231	-0.0889
	PMI	0.1400	0.0588	0.0185	0.4009	0.1467	0.2656	0.0873	0.1629
	Amount	-0.0876	-0.0740	-0.0288	-0.3243	0.0057	-0.0447	-0.0892	-0.2093
	FL	0.5049	0.4203	0.4088	0.8048	0.1843	0.2686	0.5070	0.8572
$\mathbf{x}$	Black				0.2839			-0.1331	
	Hispanic				0.1061		0.0515		
	PPP × Black						0.1579		
	PPP × Hispanic								
	PMI × Black				-0.2837				
	PMI × Hispanic				-0.1603				
	Tract income	-0.1165			-0.0843				
	Tract minority				0.0725	0.1022		0.2025	
	No. obs.	17192	6417	40959	139882	7059	19584	60878	35601

The coefficients represent the medians of the posterior distributions. The grayed-out coefficients indicate that 0 is contained in the 90 percent coverage interval.
The coefficients of the $\mathbf{x}$ variables represent the medians of the posterior distributions conditional on the modal value of the corresponding γ for cases in which the inclusion probability $\Pr(\gamma = 1)$ exceeds 90 percent.
The bold italicized coefficients of the $\widehat{\mathbf{P}}$ panel represent the medians of the posterior distributions for the cases in which the inclusion probability $\Pr(\delta = 1)$ exceeds 90 percent, indicating statistical discrimination.
PPP is a dummy for prepayment penalties. *PMI* is a dummy for private mortgage insurance, *FL* is a dummy for Florida. *PPP×race* is the interaction of the prepayment penalty and *race* indicators. Similarly, *PMI×race* is the interaction of the private mortgage insurance and *race* indicators. *Tract income* is equal to the Census tract median family income relative to the U.S. Department of Housing and Urban Development (HUD) estimate of the metropolitan area's family income provided in the HMDA data. *Tract minority* is the Census tract percent of minority population from the 2000 Census.
All regressions include 11 dummies for the month of origination. Their coefficients are not reported.
All loans have terms of 30 years. A 2-yr ARM is an ARM that is interest only for the first two years and fully amortizing over the remaining 28 years. Three-year ARMs, 5-yr ARMs, and 10-yr ARMs are defined in the same way but with interest-only periods of three, five, or ten years. Thirty-year ARMs are fully amortizing over the thirty years as are 30-yr FRMs. Finally, the 10-yr FRM is an FRM with interest-only payments for the first ten years and full amortization over the remaining 20 years.

The results from Table 7 indicate that both measures of forecasted performance (default within 2 years and prepayment within 2 years) have a positive impact on rate determination. The increase in the rate from a 1-percentage-point increase in the probability of default ranges from 4 to 13 basis points depending on the product. The increase in the rate from a 1-percentage-point increase in the probability of prepayment ranges from 1 to 5 basis points depending on the product. We find that the effect of predicted performance reflects statistical discrimination in three of the mortgage products analyzed. In particular, lenders seem to be using information on race and neighborhood characteristics in their forecasts of default for 30-year FRMs and 5-year ARMs, and of prepayment for the "Other" category.

PPPs are associated with higher rates in three of the mortgage product categories but have a negative association with rates in two categories. Similarly, the PMI requirement has a positive association with rates in four of the eight mortgage products. Higher loan amounts reduce interest rates in most categories, and loans in Florida exhibit higher interest rates than in California in all mortgage categories.

In addition to the effects on loan pricing from statistical discrimination, Table 7 indicates that the black and Hispanic indicators also have a positive effect on interest rates for 30-year ARMs, indicating that black borrowers face higher rates for this product by about 28 basis points, while Hispanic borrowers face higher rates by about 11 basis points, relative to other borrowers. The Hispanic indicator also has a positive impact on rates for 10-year ARMs, suggesting a disparity of about 5 basis points relative to other borrowers. Black borrowers face lower interest rates in the 5-year ARM category but lenders appear to be statistically discriminating in this category. Table 8 illustrates that for 30-year FRMs, a direct impact from the black indicator is a borderline case in which the model inclusion probability does not meet the threshold we set to indicate discrimination; the inclusion probability is 88%.

The interaction of the indicator for blacks and PPPs has a positive effect on rates for 10-year ARMs, and the purchase of PMI among black and Hispanic borrowers lowers interest

results are available upon request.

rates in 30-year ARMs.

A higher tract income is associated with lower interest rates in 2-year ARMs and 30-year ARMs, indicating income-based redlining that is not due to borrowers in those tracts defaulting or prepaying at a higher rate. Income in the regression is measured relative to the median income in the metropolitan area such that the interpretation of the results in Table 8 is that a household that lives in a Census tract with double the median income of the income in the metropolitan area enjoys a 2-year ARM mortgage rate that is 12 basis points lower than a borrower who lives in a Census tract with median income equal to that of the metropolitan area.

A higher share of minorities in a Census tract leads to higher interest rates for 30-year ARMs, 10-year FRMs, and 5-year ARMs. The increase in the rate from moving from a Census tract with no minorities to a Census tract with only minorities ranges from 7 to 20 basis points. The race-based redlining occurs despite our finding that a higher minority share in a neighborhood actually reduces the probability of default (see Table 5). The high correlation between the share of minorities and tract income likely makes it difficult for both variables to be statistically relevant at the same time in most categories. We see some evidence of race-based redlining in 10-year ARMs; the model inclusion probability is 89 percent which is slightly below our threshold of 90 percent as shown in Table 8.

Our results for the 2-year ARM category are consistent with the findings of Haughwout, Mayer, and Tracy (2009) for 2/28 mortgages. However, we find evidence of income-based redlining in this category; Haughwout, Mayer, and Tracy (2009) do not include Census tract income in their specification although they do include controls for the homeownership and unemployment rates. Haughwout, Mayer, and Tracy find evidence that a high share of blacks or Hispanics in a neighborhood actually reduces the interest rate; we do not find this in our specification. Since our datasets differ, we cannot determine whether the difference in our findings is due to differences in the sample, the procedure used to detect discrimination, or differences in the product definition. In contrast to Haughwout, Mayer, and Tracy, we distinguish between taste-based and statistical discrimination and find evidence of both forms of discrimination.

The magnitude of the adverse pricing effects we find for minorities is somewhat smaller than the magnitudes Pope and Sydnor (2011a) and Ravina (2008) find in the peer-to-peer personal loan market. Pope and Sydnor (2011a) find that blacks face interest rates that are 60 to 80 basis points higher than whites while Ravina (2008) finds that black borrowers pay 139 to 146 basis points more for their loans than whites. The smaller magnitude of the effects in our study is likely due to more stringent regulation of the mortgage market than the peer-to-peer personal loan market.

4.3 Disparate impact

The evaluation of discrimination outlined in Section 3 focused on distinguishing between statistical and taste-based discrimination, depending on whether disparities in loan rates across racial and neighborhood characteristics manifested indirectly via the forecasted loan performance or directly in the loan pricing equation.

Identifying disparate impact discrimination requires determining whether disparities across racial groups or neighborhood characteristics are the result of uniform underwriting standards across groups that, nevertheless, allow for embedded bias that negatively affects certain groups. In the context of our evaluation procedure, one way to approach this possibility is to calculate measures of predicted performance that are based on actuarial estimations that ignore the predictive content of individual race and neighborhood characteristics and allow non-racial credit risk indicators to carry all the predictive content. In particular, consider estimating the following model of loan performance:

$$\Pr\left[P_{im} = 1\right] = \Phi\left(\alpha_{i0} + \alpha_{iq}\mathbf{q}_m\right). \tag{6}$$

Constructing the implied measure of forecasted performance with parameter estimates $\breve{\alpha}_0$

and $\breve{\alpha}_q$ yields

$$\breve{P}_{in} = \Phi\left(\breve{\alpha}_{i0} + \breve{\alpha}_{iq}\mathbf{q}_n\right). \tag{7}$$

Disparate impact discrimination can then be assessed if any disparities in the x variables, initially identified in the rate equation with the predicted performance defined in equations (2) and (3), are reduced or eliminated once we use the measure of performance in equation (7) that allows for bias in the probit coefficients.

We studied this possibility and found no evidence of disparate impact. In other words, allowing for bias in the estimated coefficients of loan performance did not seem to affect the magnitude or nature of the disparities in the rate equation. In the interest of brevity, we do not report additional tables. Results are available upon request.

4.4 Discussion

Our results indicate that disparities in loan pricing for minorities compared with other borrowers cannot be explained entirely by the effect of race or neighborhood characteristics on the probabilities of either default or prepayment. In particular, a model that allows lenders to use information on race and neighborhood characteristics to forecast default or prepayment probabilities (a practice that is prohibited) indicates that, in addition to facing statistical discrimination, minorities and individuals in lower-income neighborhoods seem to face adverse pricing practices in some of the most popular mortgage products.

In particular, for 30-year ARMs (by far the most frequently used mortgage product, representing over 40 percent of all the mortgages we analyzed), we find disparities in interest rates originating from race and neighborhood characteristics. The latter indicate the presence of disparate treatment, as well as income-based and race-based redlining, that serves no apparent business purpose. We find evidence of some type of adverse pricing (redlining, taste-based discrimination, or statistical discrimination) in seven of the eight categories we analyze; these products comprise 98% of the mortgages in our sample.

It is important to note that, according to Tables 5 and 6, both tract income and tract minority share are important determinants of both default and prepayment for most product categories, while race is an important determinant of default for most products but an important determinant of prepayment for only some products. These results suggest that statistical discrimination on prepayment largely reflects the predictive power of neighborhood characteristics for this measure of loan performance.

Finally, it bears repeating that our procedure identifies racial discrimination and redlining that *cannot be explained by higher default or prepayment probabilities.* It is important to make this distinction because fair lending law is quite clear that both statistical and taste-based discrimination against minorities is illegal. While redlining is not explicitly forbidden, many federal housing policies (e.g., the affordable housing goals of the GSEs and the Community Reinvestment Act) are aimed at reducing the prevalence of this practice. If we did not attempt to distinguish between statistical and taste-based discrimination, that is, if we only estimated equation (1) with a measure of predicted performance that ignores the effect of race and neighborhood characteristics as in equation (3) (or equivalently, estimate equation (5) setting $\delta \equiv 0$), all forms of discrimination and redlining would manifest in the term $\gamma \odot \beta_x \mathbf{x}_n$. This is the specification that Ross and Yinger (2002) propose to detect any discrimination or redlining. Table 9 shows the results from estimating equation (5) with $\delta \equiv 0$. In this case, we see more indications of both discrimination and redlining. We see redlining in every product and racial discrimination, primarily directed at Hispanic borrowers, in four products. The magnitudes of the effects are similar to the results in Table 7. Our procedure allows the data to determine δ, and instead of identifying only discrimination, our procedure also identifies the channel through which discrimination is taking place. For example, column 3 in Table 9 (corresponding to 30-year FRMs) indicates the presence of income-based redlining. Accounting for statistical discrimination (as in Table 7) illustrates that for this category, the effect of tract income should be attributed to statistical discrimination because of its importance in determining the probability default (as indicated by a bold coefficient) and not to a uniform effect on rates.

5 Conclusions

In this paper we examined the effect of race and ethnicity on the pricing of subprime mortgages in California and Florida during 2005. We estimated a reduced-form model of mortgage rate determination in which the lender takes into account the predicted loan performance when making the rate-setting decision. We assessed the effect of race and ethnicity, as well as the effect of neighborhood characteristics, both in the loan performance evaluation and in the lender's rate decision.

The estimation procedure disentangles various forms of discrimination contemplated in U.S. mortgage laws. Furthermore, we assess the presence of statistical discrimination in lenders' predictions of loan performance.

In contrast to previous studies of the subprime market, we find evidence of taste-based discrimination against black or Hispanic borrowers in two of the mortgage products we considered. These products represent about half of the mortgages in our sample. These effects lead to rate increases ranging from 5 to 28 basis points. To the extent that black and Hispanic borrowers live in low-income neighborhoods and in neighborhoods with high proportions of minority borrowers, they may face an additional increase in their rates due to redlining; we find adverse pricing effects in lower-income neighborhoods or in neighborhoods with a high proportion of racial minorities in four categories that do not appear to be due to a higher probability of default or prepayment by borrowers in these neighborhoods. The increase in the rate from an increase in the minority population share from 0% to 100% ranges from 7 to 20 basis points. We also find that for black borrowers the purchase of PMI seems to be associated with obtaining lower interest rates. We find evidence of statistical discrimination or redlining related to loan performance in three products.

Two limitations of our study are that we cannot infer whether discrimination exists in

Table 8: Model Inclusion Probabilites in the Rates estimation

	Variable	2-yr ARM	3-yr ARM	30-yr FRM	30-yr ARM	10-yr FRM	10-yr ARM	5-yr ARM	Other
$\Pr(\delta = 1)$	Default	0.00	0.30	**0.90**	0.00	0.21	0.00	**1.00**	0.76
	Prepay	0.00	0.23	0.00	0.00	0.41	0.00	0.00	**1.00**
$\Pr(\gamma = 1)$	Black	0.04	0.15	0.88	**1.00**	0.07	0.06	**0.90**	0.40
	Hispanic	0.03	0.14	0.20	**1.00**	0.10	**0.92**	0.37	0.48
	PPP × Black	0.03	0.16	0.87	0.71	0.15	**0.99**	0.52	0.50
	PPP × Hispanic	0.04	0.25	0.39	0.23	0.06	0.15	0.76	0.62
	PMI × Black	0.09	0.24	0.37	**1.00**	0.22	0.12	0.79	0.38
	PMI × Hispanic	0.06	0.45	0.41	**1.00**	0.11	0.13	0.55	0.81
	Tract income	**1.00**	0.30	0.27	**1.00**	0.73	0.44	0.31	0.49
	Tract minority	0.03	0.71	0.63	**0.95**	**0.94**	0.89	**1.00**	0.49

The probabilities in the top panel correspond to the evaluation of statistical discrimination. The probabilities in the bottom panel correspond to the evaluation of taste-based discrimination. Bold coefficients denote the cases in which the probabilities equal or exceed 90 percent.
PPP×race is the interaction of the prepayment penalty and race indicators. Similarly, *PMI×race* is the interaction of the private mortgage insurance and race indicators. *Tract income* is equal to the Census tract median family income relative to the U.S. Department of Housing and Urban Development (HUD) estimate of the metropolitan area's family income provided in the HMDA data. *Tract minority* is the Census tract percent of minority population from the 2000 Census.
All loans have terms of 30 years. A 2-yr ARM is an ARM that is interest only for the first two years and fully amortizing over the remaining 28 years. Three-year ARMs, 5-yr ARMs, and 10-yr ARMs are defined in the same way but with interest-only periods of three, five, or ten years. Thirty-year ARMs are fully amortizing over the thirty years as are 30-yr FRMs. Finally, the 10-yr FRM is an FRM with interest-only payments for the first ten years and full amortization over the remaining 20 years.

Table 9: Rates estimation. (Not distinguishing statistical discrimination)

	Variable	2-yr ARM	3-yr ARM	30-yr FRM	30-yr ARM	10-yr FRM	10-yr ARM	5-yr ARM	Other
	Constant	5.2477	4.9561	5.3662	1.7744	5.8480	4.5499	4.9584	4.0505
$\widehat{\mathbf{P}}$	Default	5.5346	5.8023	6.7065	12.5271	4.6948	4.3962	5.2083	5.2514
	Prepay	1.9835	1.0228	2.7002	5.0950	0.1354	2.0162	1.7621	2.8459
$\mathbf{z}$	PPP	-0.2485	0.0584	0.1388	0.3213	-0.0261	0.1349	0.0166	-0.1131
	PMI	0.1272	0.0443	0.0190	0.4066	0.1251	0.2673	0.0837	0.1626
	Amount	-0.0862	-0.0790	-0.0308	-0.3276	0.0046	-0.0430	-0.0912	-0.2074
	FL	0.5137	0.4214	0.4070	0.8028	0.1789	0.2737	0.5031	0.8524
$\mathbf{x}$	Black				0.2772				
	Hispanic				0.1052		0.0515	0.1334	0.1137
	PPP × Black						0.1566		
	PPP × Hispanic							-0.1195	
	PMI × Black				-0.2822				
	PMI × Hispanic				-0.1596				-0.2081
	Tract income	-0.1166		-0.0669	-0.0850			-0.1023	-0.1115
	Tract minority		0.1366		0.0712	0.0940	0.0763		
	No. obs.	17192	6417	40959	139882	7059	19584	60878	35601

The coefficients represent the medians of the posterior distributions. The grayed-out coefficients indicate that 0 is contained in the 90 percent coverage interval.
The coefficients of the $\mathbf{x}$ variables represent the medians of the posterior distributions conditional on the modal value of the corresponding γ for cases in which the inclusion probability $\Pr(\gamma = 1)$ exceeds 90 percent.
PPP is a dummy for prepayment penalties. *PMI* is a dummy for private mortgage insurance, *FL* is a dummy for Florida. *PPP×race* is the interaction of the prepayment penalty and race indicators. Similarly, *PMI×race* is the interaction of the private mortgage insurance and race indicators. *Tract income* is equal to the Census tract median family income relative to the U.S. Department of Housing and Urban Development (HUD) estimate of the metropolitan area's family income provided in the HMDA data. *Tract minority* is the Census tract percent of minority population from the 2000 Census.
All regressions include 11 dummies for the month of origination. Their coefficients are not reported.
All loans have terms of 30 years. A 2-yr ARM is an ARM that is interest only for the first two years and fully amortizing over the remaining 28 years. Three-year ARMs, 5-yr ARMs, and 10-yr ARMs are defined in the same way but with interest-only periods of three, five, or ten years. Thirty-year ARMs are fully amortizing over the thirty years as are 30-yr FRMs. Finally, the 10-yr FRM is an FRM with interest-only payments for the first ten years and full amortization over the remaining 20 years.

the prime market and are unable to directly address whether minorities were steered into the subprime mortgage market. To the extent that the subprime market relies more heavily on manual underwriting than the prime market, it is possible that automated underwriting has eliminated discrimination and redlining in the prime market. However, we cannot confirm or dispel this notion without a direct examination of the prime market.

It is possible that some of what we are identifying as discrimination and redlining is due to a lack of competition in the mortgage market in certain neighborhoods, mortgage market segmentation[12], or reduced search efforts or a lower ability of certain borrowers to compare across sets of loan terms instead of an explicit intent by lenders to discriminate against minorities or to redline.[13] Regardless of this possibility, our results show that despite decades of policies to eliminate racial discrimination and redlining, minorities are paying more for their loans and borrowers in historically credit-disadvantaged neighborhoods still do not have equal access to credit markets.

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[12] See Nichols, Pennington-Cross, and Yezer (2005) for a discussion of segmentation of the subprime and prime mortgage markets.

[13] Indeed, Woodward and Hall (2010) find evidence that minorities pay more in closing costs, a finding they attribute to consumer confusion.

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Appendix

A: Estimation Details

This appendix describes the Bayesian methods used to estimate the model in Section 3. The model is estimated with an iterative technique – the Gibbs sampler – which requires a prior.

For the slope parameters in the rate equation (5), we assume a normal prior. The innovation variance of the rate equation has an inverse gamma prior. Each of the model indicators has a flat prior. The hyper-parameters for the prior distributions are shown in Table 10.

Table 10: Priors for Estimation

Parameter	Prior Distribution	Hyperparameters
α_i	$N(\mathbf{a}_0, \mathbf{A}_0)$	$\mathbf{a}_0 = \mathbf{0}_{1+\kappa_q+\kappa_w}$; $\mathbf{A}_0 = \mathbf{I}_{1+\kappa_q+\kappa_w}$
β_{-p}	$N(\mathbf{b}_0, \mathbf{B}_0)$	$\mathbf{b}_0 = \mathbf{0}_{1+\kappa_x+\kappa_z}$; $\mathbf{B}_0 = \mathbf{I}_{1+\kappa_x+\kappa_z}$
β_p	$N(\mathbf{d}_0, \mathbf{D}_0)$	$\mathbf{d}_0 = \mathbf{0}_\pi$; $\mathbf{D}_0 = \mathbf{I}_\pi$
σ^{-2}	$\Gamma\left(\frac{\nu_0}{2}, \frac{\Upsilon_0}{2}\right)$	$\nu_0 = 6$; $\Upsilon_0 = 0.01$

Estimation of the parameters of (2) can be accomplished by data augmentation (Tanner and Wong, 1987). Define a latent variable, y_{im}, which has mean $\alpha_{i0} + \alpha_{iq}\mathbf{q}_m + \alpha_{iw}\mathbf{w}_m$, unit variance, and is restricted such that $y_{im} > 0$ iff $P_{im} = 1$. Then, conditional on α_i, $y_i = \{y_{im}\}_{m=1}^{M}$ can be drawn independently from truncated normal distributions. Let $\mathbf{q} = (q_1, ..., q_M)'$ and $\mathbf{w} = (w_1, ..., w_M)'$. Then, conditional on the drawn y_{im}, we draw α_i from a normal posterior as follows:

$$\alpha_i | y_i \sim N(\mathbf{a}_i, \mathbf{A}_i),$$

where $\mathbf{a}_i = \left(\mathbf{A}_0^{-1} + \mathbf{X}_i'\mathbf{X}_i\right)^{-1}$, $\mathbf{a}_i = \mathbf{A}_i\left(\mathbf{A}_0^{-1}\mathbf{a}_0 + \mathbf{X}_i'\mathbf{y}_i\right)$, $\mathbf{y}_i = (y_{i1}, ..., y_{iM})'$, and $\mathbf{X}_i = (\mathbf{1}_M, \mathbf{q}, \mathbf{w})$. After a suitable number of draws are discarded to obtain convergence, we use the draws of the α_i to generate predictions for performance of the N loans to be used for underwriting. For each draw, we compute $\widehat{\mathbf{P}}_n$ and $\widetilde{\mathbf{P}}_n$ from (3) and (4), respectively.

For each (post-convergence) draw of $\widehat{\mathbf{P}}_n$, we sample 1,000 draws from the posterior distributions of the model parameters β_{-p}, β_p, γ, δ, and σ^2. Conditional on δ and σ^2, the model inclusion parameters, γ, and the vector of slopes (excluding β_p), β_{-p}, can be drawn jointly from a reversible-jump Metropolis-Hastings-in-Gibbs step (see Troughton and Godsill, 1997, and Holmes and Held, 2006).[14] The joint move uses a proposal density of the form

$$q\left(\gamma^*, \beta^*_{-p}; \gamma, \beta_{-p}\right) = p\left(\beta^* | \gamma^*, \beta_{-p}\right) q\left(\gamma^* | \gamma\right),$$

which means we draw the candidate γ^* first and then, conditional on γ^*, we draw β^*_{-p}. The candidate γ^* is generated by drawing a random index from a discrete uniform distribution. The element corresponding to the drawn index is switched – 1 to 0, 0 to 1. Then, conditional on γ^*, the prior for β_{-p} is

$$\beta^*_{-p} \sim N\left(\mathbf{b}^*_0, \mathbf{B}^*_0 | \gamma^*\right),$$

where $\mathbf{b}^*_0$ and $\mathbf{B}^*_0$ are the hyperparameters corresponding to the candidate covariate set. The candidate β^* is drawn from

$$\beta_{-p} \sim N\left(\mathbf{b}^*, \mathbf{B}^* | \gamma^*\right),$$

with parameters

$$\mathbf{b}^* = \mathbf{B}^* \left(\mathbf{B}^{*-1}_0 \mathbf{b}^*_0 + \sigma^{-2} \zeta' \mathbf{R}\right)$$

and

$$\mathbf{B}^* = \left(\mathbf{B}^{*-1}_0 + \sigma^{-2} \zeta' \zeta\right)^{-1},$$

where $\mathbf{R} = \left(R_1 - \beta_p \left(\delta \widehat{\mathbf{P}}_1 - (1-\delta)\, \widetilde{\mathbf{P}}_1\right), ..., R_N - \beta_p \left(\delta \widehat{\mathbf{P}}_N - (1-\delta)\, \widetilde{\mathbf{P}}_N\right)\right)'$, $\zeta_n = (1, \mathbf{z}'_n, \mathbf{x}'_n)'$, and $\zeta = (\zeta_1, ..., \zeta_N)$. We accept the joint draw $\left[\gamma^*, \beta^*_{-p}\right]$ with probability

$$\Pi = \min\left\{1, \frac{|\mathbf{B}_0|^{1/2}}{|\mathbf{B}^*_0|^{1/2}} \frac{|\mathbf{B}^*|^{1/2}}{|\mathbf{B}|^{1/2}} \frac{\exp\left(\frac{1}{2}\mathbf{b}^* \mathbf{B}^{*-1} \mathbf{b}^*\right)}{\exp\left(\frac{1}{2}\mathbf{b}\mathbf{B}^{-1}\mathbf{b}\right)}\right\},$$

[14]Turning elements of the indicator γ on and off changes the model dimension. The resulting variation in the model dimension across Gibbs iterations makes joint sampling more efficient.

where the unstarred $\mathbf{b}$, $\mathbf{B}$, and $\mathbf{B}_0$ correspond to the hyperparameters computed conditional on the last (accepted) iteration of γ.

Next, we draw the joint pair (δ, β_p) by again selecting a candidate δ^* and drawing β_p^* from a normal proposal, conditional on δ. The proposals for δ and β_p – as well as the acceptance probability – have forms similar to those expressed above. For brevity, we omit the formalities.

The final step in the Gibbs loop is the draw of σ^2 conditional on β_{-p}, β_p, γ, δ, and the data. Given the prior, the innovation variance can be drawn from the inverse gamma posterior

$$\sigma^{-2}|\gamma, \delta, \beta, \mathbf{R} \sim \mathbf{\Gamma}\left(\frac{\nu_0 + N}{2}, \frac{\Upsilon_0 + \mathbf{e}\prime\mathbf{e}}{2}\right),$$

where $\mathbf{e} = \mathbf{R} - \beta\zeta$ and $\zeta = \left(\mathbf{1}_N, \delta\widehat{\mathbf{P}}_N - (1-\delta)\,\widetilde{\mathbf{P}}_N, \mathbf{z}'_N, \mathbf{x}'_N\right)'$.

B: Summary Statistics

Table 11: Summary statistics by product: Closing rate and performance measures

	2-yr ARM	3-yr ARM	30-yr FRM	30-yr ARM	10-yr FRM	10-yr ARM	5-yr ARM	Other	Total
Closing rate	6.738	6.374	6.712	6.448	6.226	6.011	6.566	6.622	6.505
(%)	(0.753)	(0.880)	(0.927)	(2.109)	(0.492)	(0.685)	(0.795)	(1.554)	(1.579)
Default	0.149	0.101	0.0536	0.123	0.0401	0.0634	0.146	0.154	0.117
(share)	(0.356)	(0.301)	(0.225)	(0.328)	(0.196)	(0.244)	(0.353)	(0.361)	(0.322)
Prepayment	0.392	0.394	0.283	0.473	0.200	0.310	0.324	0.324	0.384
(share)	(0.488)	(0.489)	(0.450)	(0.499)	(0.400)	(0.463)	(0.468)	(0.468)	(0.486)

Entries represent the mean of each variable across the entire sample with standard deviation in parentheses.
Default and prepayment of the loan are dummy variables equal to 1 if the corresponding event occurs within 2 years of loan origination.
All loans have terms of 30 years. A 2-yr ARM is an ARM that is interest only for the first two years and fully amortizing over the remaining 28 years. Three-year ARMs, 5-yr ARMs, and 10-yr ARMs are defined in the same way but with interest-only periods of three, five, or ten years. Thirty-year ARMs are fully amortizing over the thirty years as are 30-yr FRMs. Finally, the 10-yr FRM is an FRM with interest-only payments for the first ten years and full amortization over the remaining 20 years.

Table 12: Summary statistics by product: Individual and loan specific risk factors

	2-yr ARM	3-yr ARM	30-yr FRM	30-yr ARM	10-yr FRM	10-yr ARM	5-yr ARM	Other	Total
LTV	81.18	79.43	70.19	76.38	70.50	76.27	79.88	74.92	76.27
(%)	(7.972)	(9.551)	(16.14)	(12.45)	(14.41)	(10.24)	(8.672)	(13.44)	(12.56)
PPP	0.937	0.663	0.757	0.890	0.278	0.381	0.849	0.865	0.818
(share)	(0.243)	(0.473)	(0.429)	(0.313)	(0.448)	(0.486)	(0.358)	(0.342)	(0.386)
DTI	32.35	17.49	21.55	25.80	13.69	25.36	32.74	29.08	26.81
(%)	(18.51)	(20.32)	(20.90)	(20.26)	(18.73)	(18.22)	(18.63)	(19.39)	(20.17)
FICO	654.6	666.2	652.5	635.7	717.6	716.2	665.6	655.9	653.7
	(47.56)	(59.46)	(69.12)	(74.28)	(48.94)	(44.90)	(51.79)	(67.14)	(69.24)
PMI	0.107	0.0754	0.187	0.184	0.0362	0.0526	0.157	0.108	0.154
(%)	(0.309)	(0.264)	(0.390)	(0.388)	(0.187)	(0.223)	(0.364)	(0.311)	(0.361)
Amount	327,326	332,706	250,836	313,083	375,886	415,194	340,509	343,700	322,274
($)	(131,016)	(162,949)	(168,013)	(220,862)	(231,983)	(247,145)	(162,243)	(200,316)	(203,051)
Full Doc	0.449	0.499	0.593	0.401	0.370	0.236	0.486	0.365	0.431
(share)	(0.497)	(0.500)	(0.491)	(0.490)	(0.483)	(0.425)	(0.500)	(0.481)	(0.495)
Refi	0.366	0.429	0.810	0.644	0.538	0.328	0.381	0.594	0.571
(share)	(0.482)	(0.495)	(0.392)	(0.479)	(0.499)	(0.469)	(0.486)	(0.491)	(0.495)
FL	0.163	0.240	0.440	0.396	0.262	0.252	0.205	0.214	0.320
(share)	(0.370)	(0.427)	(0.496)	(0.489)	(0.440)	(0.434)	(0.404)	(0.410)	(0.466)

Entries represent the mean of each variable across the entire sample with standard deviation in parentheses.
LTV is loan-to-value ratio, *DTI* is debt-to-income-ratio, *PPP* is a dummy for prepayment penalties, *PMI* is a dummy for private mortgage insurance, *FullDoc* is a dummy for full income documentation, *Refi* is a dummy for refinances, *FL* is a dummy for Florida.
All loans have terms of 30 years. A 2-yr ARM is an ARM that is interest only for the first two years and fully amortizing over the remaining 28 years. Three-year ARMs, 5-yr ARMs, and 10-yr ARMs are defined in the same way but with interest-only periods of three, five, or ten years. Thirty-year ARMs are fully amortizing over the thirty years as are 30-yr FRMs. Finally, the 10-yr FRM is an FRM with interest-only payments for the first ten years and full amortization over the remaining 20 years.

Table 13: Summary statistics by product: Race and neighborhood characteristics

	2-yr ARM	3-yr ARM	30-yr FRM	30-yr ARM	10-yr FRM	10-yr ARM	5-yr ARM	Other	Total
Black	0.0764	0.0735	0.0914	0.0950	0.0395	0.0416	0.0725	0.0801	0.0830
	(0.266)	(0.261)	(0.288)	(0.293)	(0.195)	(0.200)	(0.259)	(0.271)	(0.276)
Hispanic	0.418	0.308	0.252	0.287	0.190	0.237	0.350	0.341	0.302
	(0.493)	(0.462)	(0.434)	(0.453)	(0.392)	(0.425)	(0.477)	(0.474)	(0.459)
PPP × Black	0.0719	0.0572	0.0806	0.0890	0.0103	0.0180	0.0648	0.0734	0.0743
	(0.258)	(0.232)	(0.272)	(0.285)	(0.101)	(0.133)	(0.246)	(0.261)	(0.262)
PPP × Hispanic	0.399	0.229	0.204	0.265	0.0624	0.112	0.315	0.311	0.264
	(0.490)	(0.420)	(0.403)	(0.441)	(0.242)	(0.316)	(0.464)	(0.463)	(0.441)
PMI × Black	0.00812	0.00592	0.0202	0.0206	0.00164	0.00284	0.0114	0.00975	0.0153
	(0.0897)	(0.0767)	(0.141)	(0.142)	(0.0404)	(0.0532)	(0.106)	(0.0983)	(0.123)
PMI × Hispanic	0.0437	0.0292	0.0476	0.0541	0.00997	0.0113	0.0596	0.0346	0.0477
	(0.204)	(0.168)	(0.213)	(0.226)	(0.0994)	(0.106)	(0.237)	(0.183)	(0.213)
Tract income	0.887	0.948	0.923	0.938	1.037	1.036	0.923	0.920	0.937
	(0.311)	(0.338)	(0.332)	(0.354)	(0.387)	(0.408)	(0.328)	(0.344)	(0.349)
Tract minority	0.541	0.475	0.445	0.458	0.371	0.407	0.492	0.494	0.466
	(0.266)	(0.269)	(0.291)	(0.283)	(0.250)	(0.256)	(0.268)	(0.276)	(0.279)

Entries represent the mean of each variable across the entire sample with standard deviation in parentheses.
PPP×race is the interaction of the prepayment penalty and race indicators. Similarly, *PMI×race* is the interaction of the private mortgage insurance and race indicators. *Tract income* is equal to the Census tract median family income relative to the U.S. Department of Housing and Urban Development (HUD) estimate of the metropolitan area's family income provided in the HMDA data. *Tract minority* is the Census tract percent of minority population from the 2000 Census.
All loans have terms of 30 years. A 2-yr ARM is an ARM that is interest only for the first two years and fully amortizing over the remaining 28 years. Three-year ARMs, 5-yr ARMs, and 10-yr ARMs are defined in the same way but with interest-only periods of three, five, or ten years. Thirty-year ARMs are fully amortizing over the thirty years as are 30-yr FRMs. Finally, the 10-yr FRM is an FRM with interest-only payments for the first ten years and full amortization over the remaining 20 years.