Discrimination in the Auto Loan Market

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June 25, 2019

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Acknowledgements: For helpful comments we thank seminar participants at Rice University, Southern Methodist University, Texas Christian University, and University at Buffalo. Any remaining errors are our own.

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compared to the remaining states (0.9 percentage points). We also test whether competition ameliorates discrimination. Whereas statistical discrimination is profitable for lenders and should persist despite competition, taste-based discrimination is costly and should be rooted out by competition (e.g., Buchak and Jørring (2017)). Consistent with taste-based discrimination, we find stronger results in low-competition environments.

Discrimination also affects an intensive margin of credit provision through higher interest rates for minorities. *Ceteris paribus*, minorities pay 70 basis points more on their auto loans (APR) than White borrowers. This magnitude is comparable to the effect of a 37 point drop in credit score. This result is especially notable because we find it in the sample of borrowers who were approved—at lower average approval rates—for the loans. Moreover, the effect of minority status increases to 125 basis points for borrowers in high racial bias states.

Some of these results could reflect an omitted variable bias if minorities are worse credit risks, even net of our extensive controls.[3] If true, it would lead to higher ex post default rates for minorities in our tests. *Ceteris paribus*, we find that minorities have a *lower* default rate in the full sample. In the subprime sample, default rates are a statistically significant 2.3 percentage points lower for minorities, consistent with loans to these marginal minority borrowers being more profitable than loans to marginal White borrowers. These results provide strong evidence that the racial disparities we document in

[3] Such an omitted variable bias would still have difficulties explaining the cross-sectional patterns in discrimination we find, and the results of our falsification test based on credit card applications.

credit approval and interest rates are generated by taste-based discrimination rather than omitted variable bias or statistical discrimination.

In our final set of tests, we evaluate whether increased oversight of auto lenders affects discrimination. We exploit a sharp increase in the CFPB's scrutiny of indirect auto lenders in 2013. Our differences-in-differences tests show that the additional interest (APR) paid by minorities decreased from 84 basis points, to 35 basis points in the post-event period (a 58% decrease). A triple differences test shows that the reduction in discrimination occurred primarily in areas where indirect auto lending is most prevalent, providing evidence that we are indeed capturing the effect of the CFPB's actions. These findings are particularly relevant considering that CFPB oversight is an area of active debate—in fact, in 2018 Congress passed a joint resolution nullifying the 2013 Bulletin the CFPB used to spearhead its anti-discrimination enforcement policies.

Our paper is related to prior work documenting racial disparities in approval rates for mortgages (e.g. Munnell et al. (1996)), credit cards (Cohen-Cole (2011)), and peer-to-peer loans (e.g. Pope and Sydnor (2011)).[4] Studies also show that minorities pay higher interest rates on mortgages (e.g. Bayer, Ferreira, and Ross (2018)). However, prior studies rarely include default rate tests (often due to data constraints), which makes inferences about discrimination precarious. For example, evidence from the mortgage market suggests that Black borrowers default more (e.g. Berkovec et al. (1998)), raising questions about whether racial disparities in approvals and interest rates reflect actual taste-based

[4] Also, see studies on the role of race in high-cost lending (Dobbie et al. (2018)), and small business lending (e.g., Blanchflower, Levine, and Zimmerman (2003) and Fairlie, Robb, and Robinson (2018)).

discrimination. A distinguishing feature of our study is that we provide evidence of discrimination from all three settings—credit approvals, interest rates, and default rates—allowing us to better isolate taste-based discrimination.

The primary contribution of our paper is to provide substantial evidence of lending discrimination in the U.S. auto loan market. Most prior work in this area focuses on discrimination by automobile salespeople in the form of quoting minority shoppers higher prices (e.g. Ayers and Siegelman (1995)). Charles, Hurst, and Stephens (2008) document that Black borrowers pay higher rates on auto loans, but their tests cannot condition on credit scores. Our study provides the first estimates of the effect of race on auto loan approval, robust estimates of the additional interest minorities pay, and the first tests for taste-based discrimination in this market using ex post default rates. Each of our tests provides strong evidence that discrimination is prevalent in the U.S. auto loan market.

2. Background Information on Auto Lending

In this section we provide some general information about the U.S. auto loan market.[5] In 2017, 91% of U.S. Households had automobiles, and roughly 70% of auto purchases were used vehicles.[6] Automobiles are a major household expenditure and the majority of purchases are financed (85% of new vehicles; 54% of used). Over 100 million U.S. consumers have auto debt as of 2017, with aggregate balances over $1.1 trillion.

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[5] Unless otherwise specified, auto lending statistics in this section come from an industry report, which can be found here: https://www.experian.com/assets/automotive/quarterly-webinars/2017-q4-safm.pdf.

[6] Household automobile ownership comes from the National Household Travel Survey. The composition of auto purchases comes from the fact that new vehicle purchases totaled 17.1 million in 2017 according to the Bureau of Economic Analysis, and used vehicle purchases totaled 39.2 million according to Edmunds, a leading automotive information provider.

Prime borrowers (credit score greater than 660) accounted for 58% of auto loan originations in 2017, with roughly half of these loans financing used cars.[7] Of the remaining 42% (subprime loans), roughly three quarters were for used cars. The average loan amount is around $30,000 for new and $20,000 for used cars. Average interest rates on auto loans ranged from around 4% for the most creditworthy borrowers, to around 16% for the least creditworthy borrowers.

To understand the structure of the auto lending industry, it is useful to classify lenders into three types: banks (commercial banks, thrifts, credit unions, etc.), indirect auto lenders, and "buy here pay here" lenders. While banks usually interact directly with consumers (direct lending), indirect auto lenders partner with car dealerships to originate loans, and do not interact with the consumer.[8] Indirect auto lenders are either the "captive" financing arm of a major auto manufacturer (e.g. Ford Motor Credit Company) or an independent auto finance company. "Buy here pay here" lenders are typically used car dealerships that originate loans on-site. Based on 2017 originations, the market shares were banks (53.3%), indirect auto lenders (40.3%, mostly from captives), and "buy here pay here" lenders (6.4%).[9]

For auto loans financed indirectly, the consumer and lender never meet. Instead, the dealership helps the consumer obtain financing. For example, a typical scenario would

[7] The credit score mentioned is the Vantage Score, which we use throughout the paper. The three major consumer credit bureaus developed Vantage Score to rival FICO scores, and it is the second most popular credit score. Vantage Score has the same score range as FICO, and is very similar, which led FICO to sue (unsuccessfully) the credit bureaus for producing such a similar product.
[8] Some banks also have indirect lending programs.
[9] "Buy here pay here" dealerships typically do not report their loans to the major consumer credit bureaus, which will prevent these loans from being included in our analyses.

This magnitude is comparable to what we would expect from a 37 point decrease in borrower credit score, and is larger than studies have typically found in other consumer credit markets—e.g., Bartlett et al. (2019) find that minorities pay rates 8 basis points higher in the mortgage market.

Two prior studies also examine racial disparities in auto loan interest rates. Cohen (2012) reports statistics demonstrating that a higher percentage of Black borrowers' loans included dealer markups (and their markups were larger) at several indirect auto lenders targeted in class action lawsuits in the late 1990s and early 2000s.[22] In an analysis closer to ours, Charles, Hurst, and Stephens (2008) use data on auto loans to 2,725 White borrowers and 320 Black borrowers from the 1992-2001 waves of the Survey of Consumer Finances (SCF). The authors estimate quantile regressions, and find that race matters primarily at the 75th percentile of the interest rate distribution, where Black borrowers pay 134 basis point higher rates. The authors control for several self-reported measures of a borrower's credit history, but the SCF data do not contain credit scores. In our data, we estimate the additional interest paid by Black borrowers at the 75th percentile of rates to be 100 basis points using our full set of controls, and 139 basis points if we exclude only *Credit Score* (see Table A.3). These findings suggest that even analyses that control for a set of credit history variables, but not credit scores, likely significantly overstate the effect of race.[23] Omitting credit history variables altogether (even controlling for age, sex,

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[22] These confidential data were accessed as a plaintiff's expert and cannot be used for research purposes.
[23] Direct comparisons of our results to those in Charles, Hurst, and Stephens (2008) should be made with caution in light of the different time periods and imperfect overlap in controls—although we do find similar estimates to theirs when we omit *Credit Score* from the controls. The change in our own estimates when we include/exclude *Credit Score* provides more robust (albeit similar) evidence of its importance. We note that

income, loan characteristics, etc.) leads to estimates that overstate the effect of race by a factor of 2 or more—compare Columns 1 and 2 of Table 7 or see Table A.3.

Next, we take advantage of the rich cross-sectional variation in our data, and test where race has the largest impact on interest rates. The results in Column 3 of Table 7 show that the effect of race is much larger in high racial bias states (top tercile of *Racial Slur GSV*). In these states, minorities pay interest rates 125 basis points (26% of a standard deviation) higher than can be explained by observable characteristics. Race also appears to have a larger effect on interest rates in areas with low banking competition, although this point estimate is statistically insignificant (Table 7, Column 4). The results in Column 5 show no significant difference in the effect of race on interest rates based on the share of non-bank lending where the borrower lives, however, the analysis in Section 7 will shed light on the CFPB's role in this matter. The test in Column 6 suggests that population density does not play a role in the cross-sectional patterns we find.

[Insert Table 7]

At this point, we consider whether the type of car being purchased (e.g. new versus used), and hence the representative institutions involved in the sale and financing of that type of car, affect the levels of discrimination we find. This analysis is motivated by the fact that automobile dealerships range from large new car dealerships affiliated with manufacturers, to small independent used car dealers. Moreover, in indirect auto lending, employees at car dealerships often help set the interest rate via dealer markup. Admittedly,

numerous other lending discrimination studies argue that the various (often self-reported) credit history indicators they use should proxy well for the credit scores that lenders actually use.

we cannot directly observe the type of car being purchased, or the institutions involved. However, we do observe the loan size, which (especially in the extremes) is likely a good indicator for whether the car is new versus used. We find the most discrimination for the smallest auto loans (likely used cars). This pattern holds for both prime and subprime borrowers. However, even minorities with prime credit scores buying expensive cars that are almost certainly new, pay rates 18 basis points higher than comparable White borrowers (see Table A.4 for these results). In sum, the results in this section show that minorities face discrimination not only at the extensive margin of credit provision (loan approval), but also at an intensive margin (loan pricing).

6. Race and Auto Loan Default Rates

In this section we implement a version of the outcome test proposed in Becker (1957, 1993), to test for discrimination in the auto loan market. Becker (1957, 1993) proposes that, in order to identify taste-based discrimination, researchers should test whether loans to marginal minority borrowers are more profitable than those to marginal White borrowers. The underlying intuition is that this test evaluates whether lenders (or more likely, individual employees of lenders) set the bar higher for minorities due to racial biases/preferences. To implement the outcome test, researchers examine loan performance conditional on loan and borrower characteristics, and lower ex post default rates for minorities are considered strong evidence of discrimination (Ferguson and Peters (1995)). Therefore, we test whether minority auto borrowers are more or less likely to default than comparable White borrowers.

For our default rate tests, we need to make two additional requirements to include auto loans in the sample. First, we end the sample with loans originated in 2015, so that we can track the performance of loans for at least two years. Specifically, we examine the loan's status as of December 31 in the year of origination and the following two calendar years.[24] We mark the loan as a default if the borrower is 90 or more days delinquent at any of these three points, or if the automobile has been repossessed during this time. Second, we require auto loans to be originated after their borrower's match to HMDA, i.e., after their mortgage or refinance loan, so that our sample of auto loans is not affected by any forward-looking bias. Without this filter, a forward-looking bias could arise because a recent auto loan default would hurt a borrower's mortgage application, and thus their chances of making it into our matched sample. Requiring auto loans to be originated after the match to HMDA eliminates this concern.

In the tests presented in Table 8, we regress our indicator for default on *Minority*, and controls for personal, loan, and ZIP code characteristics, as well as state-by-year fixed effects, and indicators for the number of years since the borrower's credit bureau/HMDA match and for the calendar month of origination. The results in Column 1 show that in the full sample, minority status has a negative effect on the probability of default, but the point estimate is statistically insignificant. Subprime borrowers may be a more appropriate sample for the outcome test, as they are more likely to be the marginal borrowers. In the subprime sample (Column 2), minority status has a negative and statistically significant

[24] The credit bureau data only allow us to see detailed information on delinquency status as of when the credit file is extracted (December 31 each year in our sample). However, we include indicators for calendar month of origination, in order to control for any differences in default rates based on where these December 31 points fall in the life of the loan.

effect (2.3 percentage points) on the probability of default. This magnitude is comparable to the effect of a 39 point increase in a borrower's credit score. Column 3 shows that the effect of minority status is insignificant in the sample of prime borrowers. The results from these default rate tests provide evidence that minorities, especially those with subprime credit scores, face taste-based racial discrimination in the auto loan market.

[Insert Table 8]

The tests in this section are an important check on the evidence of discrimination presented in Sections 4 and 5. A serious concern in any study of lending discrimination is that minority status is correlated with an unobserved component of credit risk, creating an omitted variable bias that could skew credit approval and interest rate results in favor of discrimination. However, if this bias exists, it should also skew the default rate results against showing discrimination. Therefore, the default rate approach may be the most conservative. As such, these results may offer the clearest evidence of discrimination.

7. CFPB Oversight and Auto Lending Discrimination

In this section we test whether more intense regulatory oversight reduces discrimination in the auto loan market. In March 2013 the CFPB conspicuously identified in a Bulletin that it intended to hold indirect auto lenders accountable for discrimination. The CFPB solidified its stance in December 2013, when it issued its first major enforcement action against a large indirect auto lender for discriminatory lending practices, ordering Ally Financial to pay $98 million in damages and penalties.

In our first set of tests, we use a differences-in-differences approach to assess whether the increase in regulatory scrutiny caused a reduction in discrimination.

Specifically, we test whether racial disparities in interest rates and credit approval changed after 2013. We use the same samples as our prior tests, and treat 2011-2013 as the pre-intervention period, and 2014-2017 as the post-intervention period.

The differences-in-differences tests for interest rates and credit approval are shown in Columns 1 and 4 of Table 9, respectively. The results in Column 1 show that the additional interest (APR) paid by minorities decreased from 84 basis points in the pre period to 35 basis points in the post period—a 58% decrease. This large decline is statistically significant at the 1% level. The results in Column 4 show that the reduction in credit approval rates that minorities faced declined from 1.8 percentage points to 1.2 percentage points, although this change was statistically insignificant. It may not be surprising that the pressure from the CFPB had less of an impact on approval rates, given that the Bulletin and the Consent Order against Ally Financial focus primarily on interest rates.[25] Yet, these credit approval results show that pressure to avoid charging minorities disproportionately high dealer markups/rates did not reduce these borrowers' access to credit, as it might have if the rates were necessary to make these loans profitable. Overall, our tests suggest that the CFPB was effective in mitigating discrimination.

[Insert Table 9]

Next, we exploit the fact that the CFPB scrutiny fell on indirect auto lenders, e.g. non-bank lenders like manufacturers' financing arms. We use a triple differences approach to test whether the change in discrimination was larger where non-bank auto lending is

[25] The Consent Order against Ally Financial can be found here: https://files.consumerfinance.gov/f/201312_cfpb_consent-order_ally.pdf

most prevalent. Column 2 of Table 9 presents our results. Interest rate discrimination dropped significantly more in counties with the most non-bank lending, where lenders faced more scrutiny. In fact, the reduction in discrimination in these areas appears to be driving the overall effect in our differences-in-differences test, as the reduction in the remaining areas is statistically insignificant. The actions taken by the CFPB appear to have reduced discrimination, as opposed to a downward trend in discrimination over time.

In Column 5 of Table 9, we conduct a similar triple differences test using credit approval as the outcome variable. The results show no significant difference between the trends in discrimination in high versus low non-bank financing areas. This result is not surprising considering the CFPB's focus was on interest rate discrimination. In Columns 3 and 6 of Table 9, we test whether discrimination is decreasing at a different rate in high versus low racial bias states, and find no such evidence.

Figure 3 shows estimates of the additional interest paid by minorities on auto loans each year from 2011-2017. The point estimates come from a regression of interest rates on the full set of controls, where the *Minority* indicator is interacted with indicators for each year. Panel A shows these estimates for the sample of minorities living in areas with a high share of non-bank auto lending. The results show that there is no major time trend in the additional interest paid by minorities in the period preceding the CFPB's actions. However, there is a large drop in the additional interest paid by minorities from 2013 to 2014—precisely the time of the CFPB's actions. Panel B of Figure 3 shows no such drop in the additional interest paid by minorities in areas that were less affected by the CFPB's actions due to having a low share of non-bank auto lending. These results provide strong evidence that the CFPB's actions led to a reduction in discrimination by non-bank auto lenders.

[Insert Figure 3]

8. Conclusion

Our paper provides evidence of lending discrimination in the U.S. auto loan market. We find that Black and Hispanic applicants face lower credit approval rates than White applicants after controlling for credit score, income, and a broad set of personal, demographic, and geographic characteristics. The point estimates and a back-of-the-envelope calculation suggest that approximately 80,000 minority applicants fail to obtain auto loans each year due to discrimination.

The effect of minority status on credit approval is larger for applicants living in areas where racial biases are more prevalent, and where banking competition (which should limit discrimination) is less intense. Moreover, minority auto loan applicants, in the same borrower-years, do not face lower approval rates on the applications they submit to credit card lenders, who take the human element out of the lending process. These findings provide evidence that the racial disparities we document in auto loan approval rates stem from discrimination, rather than an omitted variables problem.

When they receive auto loans, minority borrowers (especially those in high racial bias states) pay higher interest rates than White borrowers, controlling for a broad set of borrower, loan, demographic, and geographic characteristics. Furthermore, controlling for these characteristics, we find that minority borrowers default *less*. The results from this outcome test (Becker (1957, 1993)) provide evidence that minorities face taste-based discrimination in the auto loan market.

We show that the CFPB's increased scrutiny of auto lenders starting in 2013 led to almost a 60% decrease in the additional interest that minorities pay on auto loans, with no concomitant decrease in credit approval rates. However, CFPB oversight is an area of active debate, and in 2018, Congress passed a joint resolution nullifying the 2013 Bulletin that the CFPB used to spearhead its initiative. Further exploration of the determinants of discrimination in this market, and of the viability of future policy interventions are promising areas for future research.

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Table 1: Summary of the Credit Bureau/HMDA Match

This table summarizes the match between mortgages in the credit bureau data and mortgages in the Home Mortgage Disclosure Act (HMDA) data. This match ultimately leads to our panel dataset of credit bureau records with information on financial outcomes and borrower race/ethnicity (from HMDA). The starting sample of credit bureau mortgages contains both home purchase mortgages and refinance loans originated from 2010-2016. The borrower is required to apply for the loan on their own (i.e. joint applications are excluded), and to live (after the loan is originated) within a metropolitan statistical area, and the mortgage must be the borrower's only first-lien mortgage (i.e. mortgages for second homes are excluded). The matching between credit bureau mortgages and HMDA mortgages is done based on the following characteristics: whether the loan is for home purchase or refinancing, the loan origination year, the census tract of the property, the loan amount, whether the mortgage is conventional or through the Federal Housing Administration (FHA) or Veterans Administration (VA), and whether the loan is purchased by Fannie Mae or Freddie Mac on the secondary market. Only the mortgages in the HMDA data that are unique based on these matching variables are used as potential matches. Panel A shows the success rate of the matching approach. Panel B summarizes loan and borrower characteristics for the home purchase mortgages in the credit bureau data, the subsample that were successfully matched to HMDA, and the unmatched loans. The final two columns show the normalized difference and the result of a t-test comparing the mean of the matched sample to the mean of the unmatched sample. Panel C provides similar summary statistics for refinance loans.

Panel A: Match Rate			
	Credit Bureau Sample	Matched to HMDA	Match Rate
Home Purchase Mortgages	107,085	66,345	61.96%
Refinance Loans	65,046	52,115	80.12%
All Loans	172,131	118,460	68.82%

Panel B: Home Purchase Mortgages					
	Credit Bureau Sample	Matched to HMDA	Unmatched	Matched vs. Unmatched	
	(N = 107,085)	(N = 66,345)	(N = 40,740)	Norm. Diff	t-stat
Match Criteria					
Conventional Loan	0.631	0.623	0.643	-0.03	-4.70
FHA Loan	0.289	0.293	0.283	0.01	2.47
VA Loan	0.080	0.084	0.074	0.03	5.38
Fannie Mae	0.243	0.251	0.231	0.03	5.89
Freddie Mac	0.149	0.158	0.134	0.05	9.98
Loan Amount	192,142	193,758	189,508	0.02	3.99
Non-Match Characteristics					
Credit Score $_{t-1}$	717	719	715	0.04	7.78
Age	42.0	41.1	43.3	-0.12	-21.97
Have Mortgage $_{t-1}$	0.310	0.254	0.401	-0.23	-33.37
Total Debt $_{t-1}$	78,802	66,519	98,895	-0.19	-24.01
Past Due Debt $_{t-1}$	311	283	356	-0.02	-3.43
Auto Debt $_{t-1}$	8,176	8,145	8,227	-0.00	-1.00

Panel C: Refinance Loans					
	Credit Bureau Sample	Matched to HMDA	Unmatched	Matched vs. Unmatched	
	(N = 65,046)	(N = 52,115)	(N = 12,931)	Norm. Diff	t-stat
Match Criteria					
Conventional Loan	0.815	0.814	0.821	-0.01	-1.85
FHA Loan	0.125	0.125	0.124	0.00	0.27
VA Loan	0.060	0.061	0.055	0.02	2.74
Fannie Mae	0.307	0.308	0.301	0.01	1.49
Freddie Mac	0.202	0.210	0.171	0.07	9.86
Loan Amount	196,062	193,971	204,491	-0.06	-7.21
Non-Match Characteristics					
Credit Score $_{t-1}$	738	738	739	-0.01	-1.04
Age	49.4	49.6	48.7	0.05	7.61
Have Mortgage $_{t-1}$	1.00	1.00	1.00	.	.
Total Debt $_{t-1}$	214,145	212,926	219,054	-0.03	-3.97
Past Due Debt $_{t-1}$	233	229	250	-0.00	-0.62
Auto Debt $_{t-1}$	8,128	8,058	8,409	-0.02	-2.67

Table 2: Does Borrower Race Affect the Credit Bureau/HMDA Match?

This table presents regressions that examine the determinants of whether a mortgage in the Home Mortgage Disclosure Act (HMDA) data is matched to a credit bureau record through the process described in Section 3.3. The sample includes all home purchase mortgages and refinance loans in the HMDA data that are first liens on owner-occupied properties located in metropolitan statistical areas, originated from 2010-2016. The loans are also required to have only one applicant (i.e. joint applications are excluded). Through the matching process described in Section 3.3, these mortgages from HMDA are matched to mortgages reported in a nationally representative 1% sample of credit bureau records. For the regressions in this table, the outcome variable is an indicator for whether the HMDA mortgage was matched to a credit bureau record, and the explanatory variables are loan and borrower characteristics from the HMDA data. Columns 1, 2, and 3 present the results for the full sample, the sample of home purchase mortgages, and the sample of refinance loans, respectively. The coefficients are reported in terms of percentage points (i.e. a coefficient of one indicates that a unit increase in the explanatory variable predicts a one percentage point increase in the probability of being matched). The standard errors are clustered by census tract–year.

	Full Sample	Home Purchase Mortgages	Refinance Loans
	Matched	Matched	Matched
	(1)	(2)	(3)
Match Criteria			
FHA Loan	0.008	-0.116^{***}	0.005
	(0.006)	(0.008)	(0.010)
VA Loan	0.057^{***}	-0.025^{**}	0.021
	(0.009)	(0.012)	(0.016)
Purchased by Fannie Mae	0.107^{***}	0.212^{***}	0.093^{***}
	(0.005)	(0.010)	(0.006)
Purchased by Freddie Mac	0.130^{***}	0.281^{***}	0.114^{***}
	(0.006)	(0.013)	(0.007)
Log(Loan Amount)	0.026^{***}	-0.016^{*}	-0.003
	(0.005)	(0.009)	(0.006)
Non-Match Characteristics			
Black	-0.157	-0.167	-0.345
	(0.154)	(0.225)	(0.215)
Hispanic	-0.013	-0.320^{*}	0.137
	(0.129)	(0.184)	(0.188)
Black X Log(Income)	0.012	0.012	0.031
	(0.014)	(0.020)	(0.019)
Hispanic X Log(Income)	0.001	0.027	-0.011
	(0.012)	(0.017)	(0.017)
Log(Income)	-0.137^{***}	-0.189^{***}	-0.060^{***}
	(0.004)	(0.008)	(0.005)
Census Tract-by-Year FE	Yes	Yes	Yes
R-Squared	0.022	0.044	0.042
Observations	18,085,605	8,921,824	9,141,794

Table 3: Summary Statistics from the Credit Bureau/HMDA Matched Panel

This table presents summary statistics describing the Credit Bureau/HMDA Matched Panel (see Section 3.3 for information about the construction of this dataset). Panel A provides a snapshot of the matched dataset in 2010, and compares it to a 2010 snapshot of the full credit bureau dataset for reference. Column 1 presents the sample means and standard deviations (in brackets) for the full credit bureau dataset, Column 2 shows these statistics for the Credit Bureau/HMDA Matched Panel, and Columns 3-5 show the statistics for the White, Black, and Hispanic borrowers in the matched dataset, respectively. The *Income* and *Debt to Income* variables are only available for borrowers in the matched dataset because they use HMDA reported income. Panel B shows similar summary statistics for the person-years in which individuals apply for auto loans from 2005-2017.

Panel A: 2010 Snapshot					
	Full Credit Bureau Sample (N = 2,597,877)	Matched Sample (N = 78,932)	White (N = 65,207)	Black (N = 6,338)	Hispanic (N = 7,387)
Credit Score $_{t-1}$	669	707	715	660	678
	[113]	[87.2]	[84.0]	[94.9]	[89.9]
Age	49.8	42.3	42.6	42.8	39.9
	[18.9]	[13.9]	[14.1]	[13.5]	[12.9]
Have Mortgage $_{t-1}$	0.295	0.552	0.577	0.431	0.428
	[0.456]	[0.497]	[0.494]	[0.495]	[0.495]
Total Debt $_{t-1}$	67,475	123,552	129,415	92,478	98,034
	[164,108]	[166,047]	[170,688]	[125,459]	[148,536]
Past Due Debt $_{t-1}$	1,890	805	654	1,609	1,457
	[12,611]	[4,750]	[4,319]	[6,797]	[5,991]
Auto Debt $_{t-1}$	3,665	6,587	6,468	7,161	7,152
	[8,917]	[11,019]	[10,958]	[11,065]	[11,478]
Income	.	73,295	75,805	62,686	60,239
	.	[83,244]	[88,953]	[37,173]	[51,847]
Debt to Income $_{t-1}$	.	1.86	1.89	1.54	1.82
	.	[2.64]	[2.42]	[2.30]	[4.30]

Panel B: Auto Loan Applicants (2005-2017)					
	Full Credit Bureau Sample (N = 4,406,635)	Matched Sample (N = 218,476)	White (N = 175,911)	Black (N = 18,408)	Hispanic (N = 24,157)
Credit Approval (Auto)	0.722	0.832	0.847	0.783	0.757
	[0.448]	[0.374]	[0.360]	[0.412]	[0.429]
Credit Score $_{t-1}$	663	697	705	655	673
	[105]	[82.4]	[79.8]	[88.6]	[82.1]
Age	43.2	41.7	42.0	42.2	39.7
	[14.9]	[13.1]	[13.2]	[12.9]	[12.3]
Have Mortgage $_{t-1}$	0.401	0.643	0.661	0.560	0.569
	[0.490]	[0.479]	[0.473]	[0.496]	[0.495]
Total Debt $_{t-1}$	102,200	152,308	158,553	120,910	130,351
	[193,180]	[185,190]	[192,014]	[132,993]	[162,920]
Past Due Debt $_{t-1}$	1,667	639	521	1,269	1,027
	[8,360]	[4,725]	[4,663]	[4,779]	[5,066]
Auto Debt $_{t-1}$	9,170	10,986	10,880	10,814	11,906
	[15,190]	[15,752]	[15,748]	[15,159]	[16,191]
Income	.	78,395	81,578	65,480	65,061
	.	[97,191]	[104,641]	[38,979]	[64,490]
Debt to Income $_{t-1}$	.	2.18	2.18	1.98	2.31
	.	[2.74]	[2.47]	[2.21]	[4.48]

Table 4: The Effect of Applicant Race on Auto Credit Approval

This table presents regressions of measures of access to auto loans and credit cards on applicant race, individual characteristics, and ZIP code characteristics. The outcome variables are indicators for the borrower successfully opening a new auto loan (Columns 1-5) or a new credit card (Column 6). The sample in Columns 1-3 includes all person-years where the individual applies for an auto loan during the year. Columns 4 and 5 restrict the sample to applicants with subprime, and prime credit scores, respectively. The sample in Column 6 includes person-years where the individual applies for both auto credit and a credit card during the year. The individual level data consist of credit bureau records that have been matched to Home Mortgage Disclosure Act records (see Section 3.3 for details). The coefficients are reported in terms of percentage points (i.e. a coefficient of one indicates that a unit increase in the explanatory variable predicts a one percentage point increase in the probability of credit approval). The standard errors are clustered by state-year.

	Full Sample			Subprime Borrowers	Prime Borrowers	Falsification Test:
	Credit Approval (Auto)	Credit Approval (Auto)	Credit Approval (Auto)	Credit Approval (Auto)	Credit Approval (Auto)	Credit Approval (Credit Card)
	(1)	(2)	(3)	(4)	(5)	(6)
Demographics						
Minority	-4.465^{***}	-1.480^{***}	-1.661^{***}	-2.375^{***}	-0.840^{***}	0.147
	(0.289)	(0.259)	(0.332)	(0.399)	(0.271)	(0.368)
Minority X Hispanic			0.328			
			(0.410)			
Female	1.598^{***}	1.115^{***}	1.126^{***}	1.492^{***}	1.133^{***}	3.069^{***}
	(0.173)	(0.169)	(0.169)	(0.352)	(0.180)	(0.300)
Age	0.042^{***}	-0.067^{***}	-0.066^{***}	0.017	-0.072^{***}	0.055^{***}
	(0.008)	(0.008)	(0.008)	(0.015)	(0.009)	(0.012)
Log(Income)	3.886^{***}	1.704^{***}	1.711^{***}	4.586^{***}	0.736^{***}	-0.482
	(0.184)	(0.180)	(0.181)	(0.407)	(0.199)	(0.329)
Credit Characteristics						
Credit Score $_{t-1}$		0.057^{***}	0.057^{***}	0.161^{***}	0.013^{***}	0.055^{***}
		(0.002)	(0.002)	(0.004)	(0.003)	(0.003)
Log(Total Debt $_{t-1}$)		0.866^{***}	0.866^{***}	0.403^{***}	0.868^{***}	0.131^{*}
		(0.053)	(0.053)	(0.070)	(0.077)	(0.069)
Debt to Income $_{t-1}$		-0.032	-0.032	0.040	-0.220^{***}	-0.299^{***}
		(0.062)	(0.062)	(0.119)	(0.079)	(0.098)
Log(Past Due Debt $_{t-1}$)		-1.179^{***}	-1.178^{***}	-0.745^{***}	-0.413^{***}	-1.304^{***}
		(0.051)	(0.051)	(0.061)	(0.066)	(0.062)
ZIP Code Characteristics						
Log(Personal Income Per Capita)	1.087^{*}	-0.095	-0.076	0.573	-0.350	-0.301
	(0.629)	(0.611)	(0.611)	(1.088)	(0.701)	(1.060)
Log(Population Density)	-0.014	0.009	0.010	0.067	0.037	0.976^{***}
	(0.065)	(0.065)	(0.065)	(0.142)	(0.072)	(0.120)
Bachelors Degree	5.108^{***}	1.406	1.373	3.907	1.765	3.407
	(1.254)	(1.236)	(1.238)	(2.374)	(1.372)	(2.279)
Commute Using Car	12.020^{***}	10.569^{***}	10.533^{***}	12.663^{***}	8.640^{***}	6.047^{***}
	(1.194)	(1.149)	(1.146)	(2.317)	(1.276)	(2.213)
State-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Time Relative to Match Indicators	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.047	0.085	0.085	0.105	0.047	0.074
Observations	218,300	214,534	214,534	68,494	146,036	124,739

Table 5: Where Does Applicant Race Have the Largest Impact on Auto Credit Approval?

The tests in this table regress a measure of auto credit approval on race, individual characteristics, and ZIP code characteristics. The outcome variable is an indicator for the person successfully opening a new auto loan, and the sample includes all person-years in which individuals apply for auto loans. The explanatory variables of interest are indicators for the applicant belonging to a racial minority, and the interaction of *Minority* with indicators for living in a state in the top tercile of racial bias (based on Google Search Volume for racial slurs), living in a county in the top tercile of the Herfindahl index for bank deposits (*Low Banking Competition*), living in a ZIP code in the bottom tercile of population density (*Rural*), or living in a county in the top quartile in terms of the share of non-bank auto lending (*High Non-Bank Financing*). These county quartile assignments come from Benmelech et. al. (2017) who compute them as of 2008Q1 using proprietary data. The individual level data are from the matched dataset of credit bureau records and Home Mortgage Disclosure Act records (see Section 3.3 for details). The dataset includes credit bureau records for the years 2005-2017. The included individual controls and ZIP code controls are the same as those reported in Table 4. The coefficients are reported in terms of percentage points (i.e. a coefficient of one indicates that a unit increase in the explanatory variable predicts a one percentage point increase in the probability of credit approval). The standard errors are clustered by state-year.

	Credit Approval (Auto) (1)	Credit Approval (Auto) (2)	Credit Approval (Auto) (3)	Credit Approval (Auto) (4)
Minority	-0.906^{***}	-1.268^{***}	-1.259^{***}	-1.509^{***}
	(0.254)	(0.255)	(0.298)	(0.246)
Minority X High Racial Bias State	-1.910^{***}			
	(0.443)			
Minority X Low Banking Competition		-0.728^{*}		
		(0.424)		
Low Banking Competition		0.214		
		(0.207)		
Minority X High Non-Bank Financing			-0.351	
			(0.401)	
High Non-Bank Financing			-0.782^{***}	
			(0.241)	
Minority X Rural				0.117
				(0.461)
Rural				-0.124
				(0.303)
Individual Controls	Yes	Yes	Yes	Yes
ZIP Code Controls	Yes	Yes	Yes	Yes
State-by-Year FE	Yes	Yes	Yes	Yes
Time Relative to Match Indicators	Yes	Yes	Yes	Yes
R-Squared	0.085	0.085	0.085	0.085
Observations	214,534	214,534	214,534	214,534

Table 6: Summary Statistics on the Auto Loans in the Credit Bureau/HMDA Matched Panel

This table presents summary statistics on the auto loans in the Credit Bureau/HMDA Matched Panel. The sample is constructed at the auto loan level and includes one observation for each new auto loan originated from 2011-2017 (the time period over which interest rates are available). To be included, the loan must be the borrower's only outstanding auto loan at origination, so that the loan's performance can be tracked in the credit bureau data. For *Auto Loan Default*, the statistics are based on the 2011-2015 subsample, because we need 2 years after origination to compute this variable. Column 1 presents the sample means and standard deviations (in brackets) for the full sample. Columns 2-5 present these statistics for the subsamples of White, minority, subprime, and prime borrowers respectively.

	Full Sample (N = 25,697)	White Borrowers (N = 20,823)	Minority Borrowers (N = 4,874)	Subprime Borrowers (N = 6,115)	Prime Borrowers (N = 19,574)
Demographics					
Female	0.425	0.422	0.437	0.407	0.430
	[0.494]	[0.494]	[0.496]	[0.491]	[0.495]
Age	43.5	43.7	42.7	40.2	44.5
	[13.7]	[13.8]	[13.0]	[12.5]	[13.9]
Income	67,354	69,276	59,144	59,396	69,847
	[40,075]	[41,296]	[33,143]	[32,920]	[41,758]
Auto Loan Variables					
Auto Loan Default	0.017	0.013	0.035	0.055	0.004
	[0.130]	[0.114]	[0.184]	[0.228]	[0.066]
Auto Loan APR	0.060	0.057	0.077	0.100	0.048
	[0.048]	[0.045]	[0.058]	[0.063]	[0.034]
Auto Loan Amount	21,233	21,017	22,157	20,058	21,603
	[10,201]	[10,178]	[10,244]	[9,897]	[10,266]
Auto Loan to Income Ratio	0.389	0.373	0.455	0.400	0.385
	[0.248]	[0.238]	[0.279]	[0.248]	[0.249]
Auto Loan Term (Months)	65.1	64.6	67.5	66.9	64.6
	[13.2]	[13.2]	[12.7]	[13.6]	[13.0]
Credit Characteristics					
Credit Score $_{t-1}$	717	724	685	604	752
	[78.4]	[75.3]	[83.3]	[44.7]	[47.0]
Total Debt $_{t-1}$	129,567	133,584	112,407	96,101	140,053
	[123,667]	[125,091]	[115,843]	[115,554]	[124,269]
Debt to Income $_{t-1}$	2.08	2.09	2.06	1.73	2.20
	[1.78]	[1.75]	[1.90]	[1.87]	[1.73]
Past Due Debt $_{t-1}$	308	237	609	1,129	51
	[1,312]	[1,157]	[1,800]	[2,366]	[483]
Auto Debt Share	0.278	0.270	0.315	0.397	0.241
	[0.311]	[0.306]	[0.329]	[0.372]	[0.279]

Table 7: The Effect of Borrower Race on Auto Loan Interest Rates

The regressions in this table examine the effect of borrower race on auto loan interest rates. The sample is constructed at the auto loan level from the matched dataset of credit bureau records and Home Mortgage Disclosure Act records (see Section 3.3 for details). The sample includes one observation for each new auto loan originated from 2011-2017 (the time period over which interest rates are available), and we require the loan to be the borrower's only outstanding auto loan at origination. The explanatory variables of interest are indicators for the borrower belonging to a racial minority, and the interaction of *Minority* with indicators for living in a state in the top tercile of racial bias (based on Google Search Volume for racial slurs), living in a county in the top tercile of the Herfindahl index for bank deposits (*Low Banking Competition*), living in a ZIP code in the bottom tercile of population density (*Rural*), or living in a county in the top quartile in terms of the share of non-bank auto lending (*High Non-Bank Financing*). These county quartile assignments come from Benmelech et. al. (2017) who compute them as of 2008Q1 using proprietary data. The coefficients are reported in terms of percentage points (i.e. a coefficient of one indicates that a unit increase in the explanatory variable predicts a one percentage point increase in the interest rate). The standard errors are clustered by state-year.

	APR (1)	APR (2)	APR (3)	APR (4)	APR (5)	APR (6)
Demographics and Interaction Terms						
Minority	1.600***	0.704***	0.442***	0.614***	0.648***	0.691***
	(0.169)	(0.117)	(0.084)	(0.110)	(0.137)	(0.120)
Minority X High Racial Bias State			0.805***			
			(0.166)			
Minority X Low Banking Competition				0.293		
				(0.208)		
Low Banking Competition				0.052		
				(0.065)		
Minority X High Non-Bank Financing					0.083	
					(0.175)	
High Non-Bank Financing					0.197**	
					(0.093)	
Minority X Rural						0.056
						(0.223)
Rural						−0.023
						(0.078)
Female	−0.397***	−0.259***	−0.265***	−0.260***	−0.259***	−0.259***
	(0.052)	(0.039)	(0.038)	(0.039)	(0.039)	(0.039)
Age	−0.014***	0.012***	0.012***	0.012***	0.012***	0.012***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Log(Income)	−0.228	0.400***	0.396***	0.396***	0.397***	0.400***
	(0.143)	(0.130)	(0.130)	(0.130)	(0.130)	(0.130)
Auto Loan Characteristics						
Auto Loan Term Indicators	Yes	Yes	Yes	Yes	Yes	Yes
Log(Auto Loan Amount)	−2.922***	−2.674***	−2.674***	−2.669***	−2.677***	−2.674***
	(0.137)	(0.143)	(0.143)	(0.142)	(0.143)	(0.143)
Auto Loan to Income Ratio	−0.326	0.458	0.450	0.443	0.457	0.458
	(0.276)	(0.281)	(0.280)	(0.281)	(0.281)	(0.282)
Credit Characteristics						
Credit Score $_{t-1}$		−0.019***	−0.019***	−0.019***	−0.019***	−0.019***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Log(Total Debt $_{t-1}$)		−0.129***	−0.129***	−0.129***	−0.129***	−0.129***
		(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Debt to Income $_{t-1}$		−0.038*	−0.038*	−0.037*	−0.038*	−0.038*
		(0.019)	(0.019)	(0.020)	(0.020)	(0.019)
Log(Past Due Debt $_{t-1}$)		0.336***	0.335***	0.335***	0.337***	0.336***
		(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Auto Debt Share		0.595***	0.594***	0.593***	0.597***	0.594***
		(0.142)	(0.142)	(0.142)	(0.143)	(0.142)
ZIP Code Characteristics						
Log(Personal Income Per Capita)	0.031	0.071	0.035	0.085	0.034	0.072
	(0.244)	(0.187)	(0.182)	(0.191)	(0.175)	(0.186)
Log(Population Density)	−0.023	0.010	0.007	0.013	−0.003	0.006
	(0.031)	(0.022)	(0.021)	(0.022)	(0.021)	(0.031)
Bachelors Degree	−2.422***	−0.902**	−0.861**	−0.916**	−0.841**	−0.914**
	(0.535)	(0.399)	(0.390)	(0.404)	(0.374)	(0.386)
Commute Using Car	−1.252***	−0.713**	−0.680**	−0.690**	−0.701**	−0.731***
	(0.358)	(0.293)	(0.292)	(0.289)	(0.304)	(0.271)
Origination Month Indicators	Yes	Yes	Yes	Yes	Yes	Yes
State-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Time Relative to Match Indicators	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.255	0.440	0.441	0.441	0.441	0.440
Observations	25,531	25,523	25,523	25,523	25,523	25,523

Table 8: Borrower Race and Auto Loan Default Rates

The regressions in this table test whether borrower race affects the likelihood of auto loan default. The sample is constructed at the auto loan level from the matched dataset of credit bureau records and Home Mortgage Disclosure Act records (see Section 3.3 for details). The sample includes one observation for each new auto loan originated from 2011-2015 (the period over which we can compute both interest rates and our indicator for default). The auto loans are required to be originated after the match between the credit bureau and HMDA records, and the loan must be the borrower's only outstanding auto loan at origination. The outcome variable is an indicator for whether the borrower became 90 or more days delinquent on the loan during the year of origination or the following two calendar years. Column 1 shows the results for the full sample, and Columns 2 and 3 show the results for borrowers with subprime and prime credit scores, respectively. The coefficients are reported in terms of percentage points (i.e. a coefficient of one indicates that a unit increase in the explanatory variable predicts a one percentage point increase in the default rate). The standard errors are clustered by state-year.

	Full Sample	Subprime Borrowers	Prime Borrowers
	Auto Loan Default	Auto Loan Default	Auto Loan Default
	(1)	(2)	(3)
Demographics			
Minority	-0.237	-2.337^{**}	0.288
	(0.397)	(1.125)	(0.345)
Female	0.122	0.619	-0.081
	(0.216)	(1.118)	(0.132)
Age	0.016^{*}	0.020	0.006
	(0.009)	(0.049)	(0.008)
Log(Income)	-0.601	-1.734	-0.514
	(0.450)	(1.847)	(0.378)
Auto Loan Characteristics			
Auto Loan Term Indicators	Yes	Yes	Yes
Log(Auto Loan Amount)	1.653^{***}	4.824^{**}	0.595^{*}
	(0.436)	(2.104)	(0.358)
Auto Loan to Income Ratio	-1.697	-3.826	-0.564
	(1.045)	(4.028)	(0.902)
Auto Loan APR	45.656^{***}	72.553^{***}	16.548^{***}
	(6.616)	(15.369)	(5.820)
Credit Characteristics			
Credit Score $_{t-1}$	-0.014^{***}	-0.060^{***}	-0.005^{**}
	(0.003)	(0.019)	(0.002)
Log(Total Debt $_{t-1}$)	-0.309^{**}	-0.707^{*}	-0.035
	(0.145)	(0.408)	(0.068)
Debt to Income $_{t-1}$	0.261^{*}	0.894^{*}	0.032
	(0.157)	(0.494)	(0.091)
Log(Past Due Debt $_{t-1}$)	0.492^{***}	0.191	0.224^{*}
	(0.117)	(0.168)	(0.118)
Auto Debt Share	2.890^{***}	6.579	0.623
	(1.064)	(4.255)	(0.604)
ZIP Code Characteristics			
Log(Personal Income Per Capita)	-0.568	-3.414	0.085
	(0.802)	(3.807)	(0.511)
Log(Population Density)	-0.001	0.260	-0.049
	(0.099)	(0.431)	(0.054)
Bachelors Degree	0.123	0.086	-0.764
	(1.643)	(8.553)	(0.911)
Commute Using Car	-0.492	13.956	-3.155^{**}
	(2.176)	(8.669)	(1.539)
Origination Month Indicators	Yes	Yes	Yes
State-by-Year FE	Yes	Yes	Yes
Time Relative to Match Indicators	Yes	Yes	Yes
R-Squared	0.096	0.173	0.054
Observations	10,509	2,005	8,480

Table 9: The 2013 CFPB Intervention and Racial Disparities in Auto Credit

This table examines the effect of the 2013 CFPB Intervention on racial disparities in auto loan interest rates and approval rates. Columns 1-3 examine the interest rates on auto loans from our Credit Bureau/HMDA Matched Panel that were originated from 2011-2017 (the time period over which interest rates are available). The explanatory variables of interest are indicators for the person belonging to a racial minority, and the interaction of *Minority* with indicators for the application occurring in 2014 or later (*Post*), for the person living in a county in the top quartile of non-bank auto lending share (*High Non-Bank Financing*), and for the person living in a state in the top tercile of racial bias based on Google Search Volume for racial slurs (*High Racial Bias State*). Column 1 presents a differences-in-differences test for whether the CFPB intervention affected the additional interest minorities' are charged on auto loans, and Columns 2 and 3 present triple-differences tests for whether the CFPB intervention had a larger effect in certain areas (note that several of the interaction terms are subsumed by the State-by-Year FE). Columns 4-6 present similar tests examining the effect of the CFPB intervention on auto credit approval. In these tests, the outcome variable is an indicator for the person successfully opening a new auto loan, and the sample includes all person-years in our data in which individuals apply for auto loans from 2011-2017. The control variables included in the tests in this table are the same as those reported in previous tables. The coefficients are reported in terms of percentage points (i.e. a coefficient of one indicates that a unit increase in the explanatory variable predicts a one percentage point increase in the APR, or in the probability of credit approval). The standard errors are clustered by state-year.

	Outcome Var = Auto Loan APR			Outcome Var = Credit Approval (Auto)		
	(1)	(2)	(3)	(4)	(5)	(6)
Minority	0.838^{***}	0.614^{***}	0.538^{***}	-1.813^{***}	-2.097^{***}	-1.118^{*}
	(0.132)	(0.205)	(0.135)	(0.491)	(0.544)	(0.605)
Minority X Post	-0.490^{***}	-0.156	-0.401^{**}	0.607	1.451^{*}	0.951
	(0.163)	(0.233)	(0.175)	(0.618)	(0.751)	(0.730)
Minority X Post X High Non-Bank Financing		-0.625^{**}			-1.526	
		(0.293)			(1.073)	
Minority X High Non-Bank Financing		0.401^{*}			0.552	
		(0.242)			(0.811)	
Post X High Non-Bank Financing		0.021			-0.739	
		(0.150)			(0.541)	
High Non-Bank Financing		0.139			-0.269	
		(0.109)			(0.389)	
Minority X Post X High Racial Bias State			-0.312			-1.085
			(0.307)			(1.149)
Minority X High Racial Bias State			0.950^{***}			-2.270^{***}
			(0.238)			(0.862)
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Auto Loan Characteristics	Yes	Yes	Yes			
ZIP Code Controls	Yes	Yes	Yes	Yes	Yes	Yes
Origination Month Indicators	Yes	Yes	Yes			
State-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Time Relative to Match Indicators	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.398	0.398	0.399	0.057	0.057	0.057
Observations	25,523	25,523	25,523	130,867	130,867	130,867

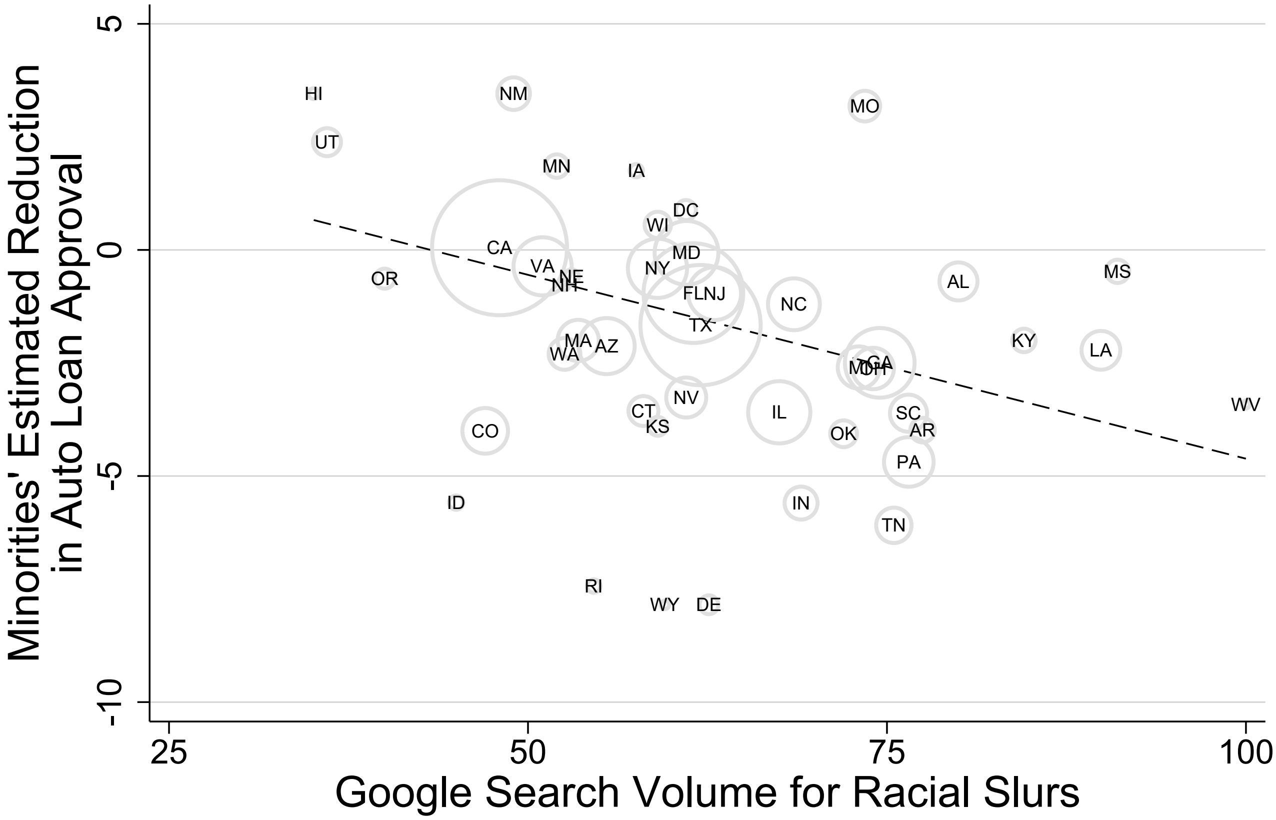

Figure 1
Auto Lending Discrimination and Racial Biases
This figure plots our point estimates of the reduction in auto loan approval rates that minorities face in each U.S. state against the prevalence of racial biases in the state measured using the Google Search Volume for racial slurs (following Stephens-Davidowitz (2014)). The point estimates come from a regression of auto loan approval on controls, similar to the regression reported in Column 2 of Table 4, except that the *Minority* indicator is interacted with indicators for each state and the District of Columbia. We require that our sample contains at least 25 minority applications in a state in order to report the *State$_i$ X Minority* coefficient estimate (excludes 6 states with small minority populations). The size of the circle plotted for each state is proportional to the number of minority applications in the state. Each state is weighted by the number of minority applications when computing the best fit line in the plot, and the correlation between the *State$_i$ X Minority* coefficient and the *Racial Slur GSV*, which is -0.49 (p-value = 0.001).

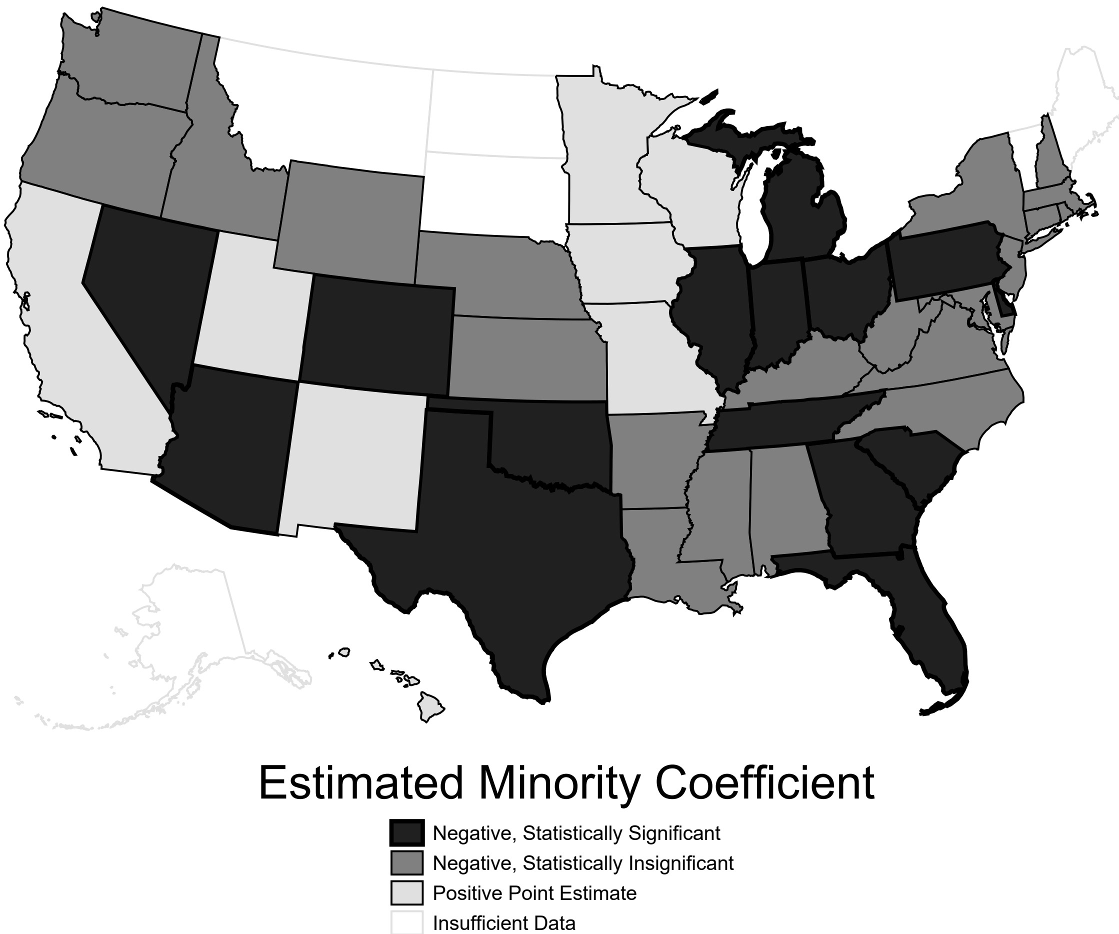

Figure 2
Where is the Evidence of Auto Lending Discrimination Strongest?
This figure presents a map categorizing U.S. states based on whether we find statistically significant evidence that minorities face reduced access to auto credit in the state. Our estimates of whether minorities face reduced access to credit come from a regression of auto loan approval on controls, similar to the regression reported in Column 2 of Table 4, except that the *Minority* indicator is interacted with indicators for each state and the District of Columbia. We require that our sample contains at least 25 minority applications in a state in order to make any inferences about discrimination in the state based on the $State_i$ *X Minority* coefficient (this excludes 6 states with small minority populations). In the states shaded black, we find statistically significant evidence (p-value ≤ 0.1) that minorities face a reduced auto loan approval rate. In the dark gray states, we find negative but statistically insignificant $State_i$ *X Minority* coefficients, and in the light gray states we find positive coefficients.

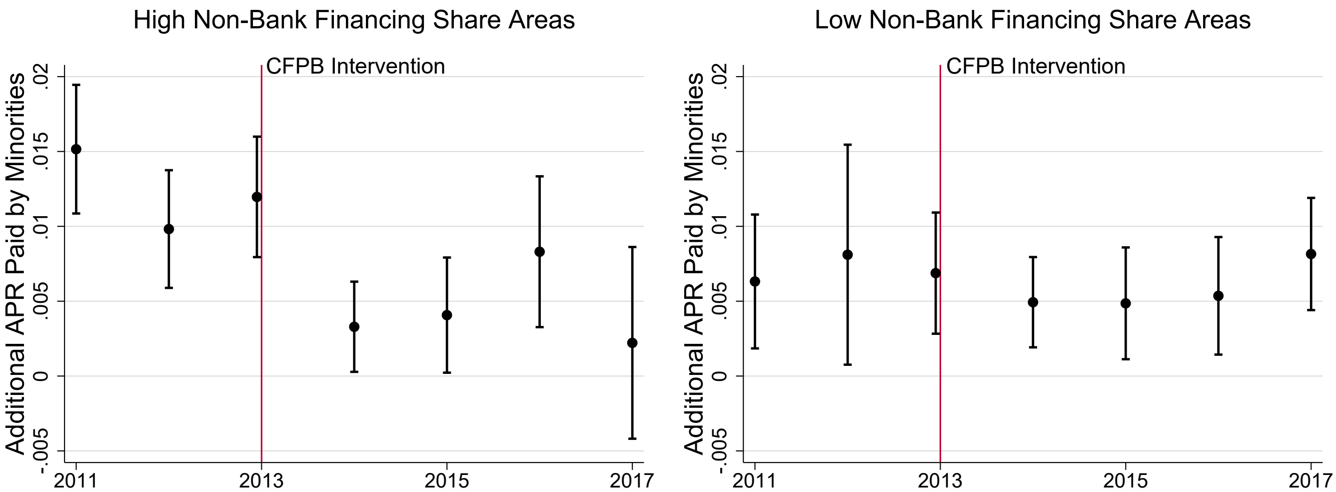

Figure 3
The 2013 CFPB Intervention and Racial Disparities in Auto Loan Interest Rates
This figure shows estimates of the additional interest (APR) minorities pay on auto loans each year from 2011-2017. The left (right) plot shows estimates for minorities living in areas where a high (low) share of loans are financed by non-bank lenders. Each set of point estimates comes from a regression of interest rates on the full set of individual, loan, and ZIP code level controls, similar to the regression in Column 2 of Table 7, except that the *Minority* indicator is interacted with indicators for each year. The plots show these *Minority X Year* coefficient estimates and 90% confidence intervals. Over the course of 2013, the Consumer Financial Protection Bureau signaled to indirect auto lenders (primarily non-bank lenders) that it would increase its efforts to hold them accountable for discrimination in the interest rates they charge. The CFPB signaled this intent with a Bulletin in March of 2013, and especially with its first major enforcement action against a large indirect auto lender (Ally Financial) in December of 2013. The vertical line in the plots denotes the cutoff between the pre (2011-2013) and post (2014-2017) periods we use to examine the effect of heightened CFPB scrutiny on lending discrimination.

Table A.3: Borrower Race and Auto Loan Interest Rates – Quantile Regressions

The quantile regressions in this table estimate the effect of borrower race at the 75th percentile of auto loan interest rates. The sample of auto loans is constructed from the Credit Bureau/HMDA Matched Panel, and has an observation for each new auto loan originated from 2011-2017 (the time period over which interest rates are available). We require the loan to be the borrower's only auto loan at origination, so that loan characteristics can be accurately measured. To make our sample more similar to Charles, Hurst, and Stephens (2008), these tests focus on only White and Black borrowers. The coefficients are reported in terms of percentage points (i.e. a coefficient of one indicates that a unit increase in the explanatory variable predicts a one percentage point increase in the interest rate).

	APR 75th Percentile	APR 75th Percentile	APR 75th Percentile
	(1)	(2)	(3)
Demographics			
Black	1.004^{***}	1.387^{***}	2.785^{***}
	(0.164)	(0.183)	(0.234)
Female	-0.281^{***}	-0.307^{***}	-0.515^{***}
	(0.063)	(0.056)	(0.087)
Age	0.012^{***}	-0.006^{**}	-0.013^{***}
	(0.002)	(0.002)	(0.003)
Log(Income)	0.594^{***}	0.667^{***}	0.114
	(0.149)	(0.159)	(0.169)
Auto Loan Characteristics			
Auto Loan Term Indicators	Yes	Yes	Yes
Log(Auto Loan Amount)	-2.622^{***}	-2.870^{***}	-3.118^{***}
	(0.157)	(0.157)	(0.162)
Auto Loan to Income Ratio	0.739^{**}	0.550^{**}	0.488
	(0.300)	(0.269)	(0.367)
Credit Characteristics			
Credit Score $_{t-1}$	-0.019^{***}		
	(0.000)		
Log(Total Debt $_{t-1}$)	-0.186^{***}	-0.310^{***}	
	(0.027)	(0.023)	
Debt to Income $_{t-1}$	-0.000	0.144^{***}	
	(0.029)	(0.022)	
Log(Past Due Debt $_{t-1}$)	0.598^{***}	0.943^{***}	
	(0.030)	(0.022)	
Auto Debt Share	0.647^{***}	0.648^{***}	
	(0.103)	(0.164)	
ZIP Code Characteristics			
Log(Personal Income Per Capita)	0.545^{**}	0.617^{***}	0.431^{***}
	(0.217)	(0.129)	(0.155)
Log(Population Density)	0.020	0.018	-0.017
	(0.021)	(0.018)	(0.034)
Bachelors Degree	-1.360^{***}	-2.234^{***}	-2.608^{***}
	(0.409)	(0.342)	(0.348)
Commute Using Car	-0.826	-0.556	-0.974^{**}
	(0.528)	(0.654)	(0.383)
Origination Month Indicators	Yes	Yes	Yes
State-by-Year FE	Yes	Yes	Yes
Time Relative to Match Indicators	Yes	Yes	Yes
Pseudo R-Squared	0.308	0.273	0.177
Observations	22,850	22,850	22,850

Appendix B — Back-of-the-Envelope Calculations

In this Appendix, we use two approaches to estimate the total number of minority auto loan applicants who fail to secure loans each year, that they would have received if they were White (*MinoritiesDeniedPerYear*). In each approach, we estimate this number by multiplying an estimate of the total number of minorities applying for auto loans per year (*YearlyMinorityApps*) by the reduction in their probability of approval due to discrimination. This reduction in credit approval rates is already estimated by the coefficient on *Minority* in Column 2 of Table 4, which we refer to as *MinorityCoefficient*. The two approaches differ only in how they estimate *YearlyMinorityApps*. The first approach is simple and naive, whereas the second approach is data-driven and produces the estimates we reference in the paper. Below we describe the two approaches, and how they may over or underestimate *MinoritiesDeniedPerYear*.

B.1 Naive Estimate of the Number of Applicants Denied Credit Each Year Due to Discrimination

In this approach, we take the average number of borrowers applying for auto loans each year in our 1% sample of credit bureau data, and multiply it by 100 to estimate the number of U.S. residents with a credit history that apply for auto loans each year. We then make the naive assumption that Black and Hispanic borrowers apply for auto loans exactly as often as other borrowers. Using this assumption, we estimate *YearlyMinorityApps* by multiplying the number of auto loan applications per year by the fraction of the U.S. population that is Black and/or Hispanic (approximately 29% according to the 2010 Census). We then obtain an estimate of the number of minority applicants denied auto loans each year due to discrimination, by multiplying *YearlyMinorityApps* by the 1.5 percentage point *MinorityCoefficient* from Table 4.

On average, there are 338,972 borrowers applying for auto loans each year in our credit bureau data. Therefore,

Estimate of $\textit{YearlyMinorityApps} = 338,972 \times 100 \times 0.29 = 9,830,188$

Estimate of *MinoritiesDeniedPerYear* $= 9,830,188 \times 0.015 =$ **147,453**

B.2 Data-Driven Estimate of the Number of Applicants Denied Credit Each Year Due to Discrimination

B.2.1 Estimate the Number of Minority Auto Loan Applicants Per Year

First, note that we only observe auto loan applicants race in our final dataset, the Credit Bureau/HMDA Matched Panel. Therefore, we need to walk through the filtering process that determines which auto loan applications end up in our final dataset. Understanding the filters allows us to estimate the percentage of all auto loan applications by minorities in the United States that end up in our final dataset (call this fraction F_{Final}).

Let us consider the filtering process for a randomly selected minority borrower-year from 2005-2017 during which the borrower applied for auto credit (call this borrower-year *TargetApp*). To make it into our final dataset, *TargetApp* must make it through three sequential filters: making it into our 1% credit bureau sample, belonging to a borrower who is a candidate to be matched to the HMDA data, and being successfully matched to the HMDA data. We refer to the probabilities that *TargetApp* makes it through these three filters as $F_{CreditBureau}$, $F_{MatchCandidate}$, and $F_{Matched}$, respectively. Therefore, the probability that *TargetApp* makes it into our matched dataset is:

$F_{Final} = F_{CreditBureau} \times F_{MatchCandidate} \times F_{Matched}$.

Filter 1: Credit Bureau Sample

The probability that *TargetApp* appears in our credit bureau sample ($F_{CreditBureau}$) should be 1%, because these data are a 1% sample of all U.S. Residents with a credit history and Social Security number.

Filter 2: Must Belong to a Candidate for the Match to HMDA

In order to be a candidate for the match to HMDA, the borrower from *TargetApp* must take out a mortgage between 2010 and 2016, and the mortgage must fit the following requirements:

1) Must be borrowers only first lien mortgage at the time of origination.

2) Person must live in an MSA directly following the mortgage origination.

3) Person must be the only applicant on the mortgage loan.

Fortunately, because we have the 1% sample of credit bureau data, we can calculate the probability that a randomly selected borrower-year during which the borrower applies for auto credit, belongs to a borrower who takes out this type of mortgage between 2010 and 2016. Using the credit bureau data, we calculate this probability (based on all auto loan applicants) to be 8.77%, which we use as our estimate of $F_{MatchCandidate}$ (the probability for minority applicants).

It is important to note that this approach assumes that minority auto loan applicants are just as likely as White applicants to take out a home purchase or refinance loan on their own (no co-applicant), for their primary residence located in an MSA. Based on our summary statistics showing that, even within the matched sample of homeowners, minorities have lower credit scores on average, we would expect minority auto loan applicants to be less likely to become this type of homeowner than White applicants. Therefore, $F_{MatchCandidate}$ likely overstates the probability that the minority borrower from *TargetApp* is a candidate for the match to HMDA. This overstatement of $F_{MatchCandidate}$ would bias our estimate of F_{Final} upwards, which would in turn bias our final estimate of the total number of minority applicants denied credit downwards (making it conservative).

Filter 3: Candidate Must be Successfully Matched to HMDA

For the borrower from *TargetApp* to be in the final matched dataset, a mortgage they take out fitting the match criteria must actually be successfully matched to HMDA. The probability of a credit bureau mortgage that fits the match criteria being successfully matched to HMDA is calculated in the summary statistics describing the match in Table 1, and is 68.82%. This approach assumes that minorities mortgages are just as likely to be matched as White borrowers, and this assumption is supported by the results in Table 2 showing that race does not affect the likelihood of being matched. Therefore, 68.82% should be an accurate estimate of $F_{Matched}$.

<u>Estimate *YearlyMinorityApps*</u>

Based on the filters described above, the probability that *TargetApp* makes it into our final matched dataset is:

$$\begin{aligned} F_{Final} &= F_{CreditBureau} \cdot F_{MatchCandidate} \cdot F_{Matched} \\ &= 0.01 \times 0.0877 \times 0.6882 \\ &= 0.0006036 \end{aligned}$$

Therefore, we can estimate the total number of minority auto loan applications per year as the number of them in our sample per year, multiplied by $1/F_{Final}$. Based on the summary statistics in Table 3, our sample contains 42,565 minority auto loan applicant-years from 2005-2017, i.e. 3,274 applications per year. Therefore,

Estimate of *YearlyMinorityApps* $= \frac{3{,}274}{0.0006036} = 5,424,122$

B.2.2 Calculate the Final Estimate

We use the data-driven estimate of the number of minorities applying for auto credit each year, and the reduction in loan approval rates that minorities face, to estimate the number of minority applicants denied auto credit each year due to discrimination.

Estimate of *MinoritiesDeniedPerYear* $= 5,424,122 \times 0.015 =$ **81,362**

It is important to note that we are assuming that *MinorityCoefficient* is based on a representative sample of minority auto loan applicants. However, the sample of applicants from our matched dataset are homeowners (or soon-to-be homeowners), and are likely of higher credit quality than the average minority auto loan applicant. Because we find evidence that lower credit quality borrowers face stronger discrimination, this suggests that our estimate of *MinorityCoefficient* likely understates the true effect for the population of minority auto loan applicants. Therefore, our estimate of the total number of minorities denied credit due to discrimination each year is likely conservative.