Stakeholders' Aversion to Inequality and Bank Lending to Minorities*

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Abstract

We document large and persistent cross-sectional differences in banks' propensity to lend to minorities based on bank stakeholders' aversion to inequality. Using mortgage application data from the Home Mortgage Disclosure Act, we show that banks with more inequality-averse stakeholders are more likely to approve applications in high-minority relative to low-minority areas and, within census tracts, from non-white borrowers relative to white borrowers. These differences (i) are not driven by applicant selection or loan officer assignment, (ii) coincide with stakeholder alignment, reflected in depositor retention and disclosure of initiatives for underserved communities, and (iii) do not predict worse ex-post loan performance.

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1 Introduction

Non-pecuniary preferences increasingly shape economic behavior (Bénabou and Tirole, 2006; Hart and Zingales, 2017). Consumers consider social and ethical values in their purchasing decisions (Conway and Boxell, 2024), firms respond to pressures from stakeholders that extend beyond profit maximization (Iliewa et al., forthcoming; Rajan et al., 2023), and workers choose employers that align with their personal values (Colonnelli et al., 2025). Together, this literature highlights how such preferences influence decisions across households and firms, as well as the market interactions between them. However, *banks* have received relatively little attention in this literature, despite their central role in shaping economic outcomes through credit allocation.

In this paper, we show that banks' inequality aversion affects their propensity to lend to minorities in the residential mortgage market—a setting in which bank credit supply has first-order effects on household debt and house prices (Justiniano et al., 2019). This novel supply-side channel complements the extensive literature documenting discrimination in the residential mortgage market (e.g., Munnell et al., 1996) and aligns with growing anecdotal evidence that stakeholders' non-monetary considerations affect banks' actions.[1]

Our main measure of bank-level inequality aversion is based on the political orientation of the counties to which banks are exposed through their geographic footprint. In line with the literature (e.g., Kuziemko et al., 2015) and survey evidence (Pew Research Center Report, 2020) linking redistribution preferences to political ideology, we assume that Democratic-leaning counties are more averse to inequality than Republican-leaning counties.[2] The higher propensity to lend to minorities by inequality-averse banks is not driven by (i) these

[1]In the wake of the 2020 racial justice protests, Netflix announced that it would permanently shift $100 million of its cash holdings *"into Black banks and other Black-led financial institutions in the U.S."* to support *"more home and small-business loans, resulting in more opportunities for Black communities"* (Netflix, 2021 ESG Report). Around the same time, M&F Bank (the second-oldest Black-owned bank in the U.S.) reported a 20% increase in deposits *"due to all the social unrest happening"* as depositors wanted to *"help recycle dollars into the communities served"* (M&F Bancorp, 2020 Annual Report). Separately, following shareholder pressure related to racial equity and fair-lending concerns, Wells Fargo commissioned in 2022 a racial equity audit to address shareholders' concerns (Wells Fargo, 9/13/2022 Press Release).

[2]Our core result is robust to using an alternative, survey-based measure of inequality aversion.

banks operating in areas with different borrower credit quality, (ii) the selection of applicant quality across banks within geographical areas, (iii) the selection of minority loan officers into inequality-averse banks, (iv) other bank characteristics correlated with banks' inequality aversion (e.g., access to soft information), and (v) changes in banks' borrower base. It is instead consistent with a *"stakeholders' discipline"* channel: inequality-averse banks adjust their lending decisions to attract and retain inequality-averse stakeholders.

Our analysis leverages a dataset of 114.3 million loan applications received by 838 banks from 1995 to 2019, constructed from Home Mortgage Disclosure Act (HMDA), FDIC Summary of Deposits, Federal Reserve Y-9C, and Consolidated Reports of Condition and Income (CALL reports) data. The analysis is structured in six parts. First, we document a few facts about banks' "approval gap," defined as the difference in approval rates for mortgage applications from minority and non-minority borrowers. Approval gaps are typically positive (lower approval rates for minority applicants), markedly different across banks, and persistent within banks over time—i.e., banks with high (low) approval gaps maintain high (low) approval gaps over time.

Second, we show that this correlation is not explained by applicants' selection *across* geographical areas, such as more inequality-averse banks being located in areas of the country with smaller credit quality gaps between minority and non-minority applicant pools. Specifically, we estimate the correlation between banks' inequality aversion and the racial approval gap, controlling for time-census tract-minority status fixed effects, thereby keeping the pool of potential minority and non-minority applicants homogeneous across banks. We also show that this correlation is not explained by selection *within* geographical areas, such as more inequality-averse banks receiving, within the same area, applications from higher-credit-quality minorities and/or lower-credit-quality non-minorities than less inequality-averse banks. In particular, within census tracts, minority (non-minority) borrowers applying to more inequality-averse banks have similar income, credit scores, and debt-to-income ratios to minority (non-minority) borrowers applying to less inequality-averse banks.

Third, the correlation between banks' inequality aversion and their approval gaps is robust when using a survey-based measure of inequality aversion from the General Social Survey, a nationally representative survey conducted since 1972 and widely used in the literature (e.g., Luttmer, 2001). We build a variable capturing banks' racial inequality aversion based on white respondents' degree of agreement with the statement *"we're spending too much money, too little money, or about the right amount of money on assistance to Black individuals"*—which we then aggregate up at the bank level by calculating an average of these responses using, again, banks' geographic footprints as weights.

Fourth, we rule out several explanations for the observed correlation between banks' inequality aversion and approval gaps. Specifically, this correlation is (i) not driven by the selection of loan officers into inequality-averse banks as the *same* loan officer tends to have smaller approval gaps when working at an inequality-averse bank; (ii) robust when we control for lender-borrower distance, suggesting that our results are not driven by banks' differential access to soft information; (iii) not driven by banks' characteristics correlated with banks' inequality aversion, such as bank size and bank mortgage lending expertise; and (iv) not driven by changes in the borrower base that might simultaneously affect banks' inequality aversion and banks' propensity to lend to minorities—as, for example, banks that expand in new Democratic-leaning areas might simultaneously get access to higher credit quality minorities.

Fifth, we present evidence supporting the stakeholders' discipline channel. According to this channel, banks take stakeholders' aversion to inequality into account in their lending decisions. Given that a large fraction of stakeholders are local, banks located in inequality-averse areas of the country are mechanically exposed to stakeholders that share similar values. These banks' higher propensity to lend to minorities helps them attract and retain stakeholders, including depositors and investors. Consistent with this channel, (i) we document a sizable drop in deposits, more pronounced in counties with high inequality aversion, for banks hit by a Department of Justice (DOJ) case for discriminatory lending, redlining, or, more generally, discrimination in their mortgage lending supply; (ii) we show, using a Large Language Model (LLM), that more inequality-averse banks discuss initiatives to support underserved borrowers and communities in shareholder meetings more often compared to less inequality-averse banks.

Sixth, we show that banks with smaller approval gaps do not exhibit worse ex-post loan performance. Specifically, the ex-post performance gap between mortgages extended to minorities and non-minorities is unrelated to whether a more or less inequality-averse bank originates such loans—if anything, this gap tends to be *smaller* for more inequality-averse banks. This result suggests that the higher propensity of inequality-averse banks to lend to minorities is not a manifestation of "costly goodness," i.e., extending loans to "non-deserving" minority borrowers. This result is instead consistent with inequality-averse banks alleviating the well-documented discrimination against minorities by inducing banks to accept some applicants who would otherwise be rejected.

Related literature. Our paper contributes to the literature on (i) social preferences in economic decision making and (ii) discrimination in mortgage markets.

First, our evidence from the stakeholders' discipline channel indicates that *banks* incorporate non-financial considerations into their lending decisions, building on the literature on non-pecuniary motivations in *individual* economic decisions (Bartling et al., 2014; Ottoni-Wilhelm et al., 2017). Within this broader literature, a prominent strand studies individuals in their role as investors, showing that utility-based but non-monetary preferences shape investors' portfolio choices, leading them to favor sustainable assets (Hartzmark and Sussman, 2019) over assets perceived as socially detrimental (Hong and Kacperczyk, 2009). But individuals are not only investors; they are also stakeholders of firms, and their non-pecuniary preferences manifest in corporate behavior affecting executive compensation (Pan et al., 2022), product sales (Meier et al., 2023), shareholders' willingness to pay for stocks (Bonnefon et al., 2025), and worker attraction (Colonnelli et al., 2025).[3] In the context of financial institutions, more closely related to our setting, Homanen (2022) and Chen et al. (2023) document deposit outflows from banks with environmental and social concerns, respectively.[4]

[3]Herpfer et al. (2024) shows that stakeholder influence can meaningfully shape corporate behavior.

[4]Our measure of bank inequality aversion, based on the political orientation of banks' local stakeholders, relates to the literature on political values and corporate socially responsible (CSR) investments. Di Giuli and Kotstovetsky (2014) finds that firms with more Democratic executives and those headquartered in Democratic states have higher CSR ratings than other firms, and Hong and Kotstovetsky (2012) documents that more Democratic-leaning mutual fund managers hold smaller portfolio holdings in socially irresponsible companies. We contribute to this literature in two ways: (i) our analysis of mortgage approval gaps—rather than investments in community activities, employee relations, and environmental records—explores an overlooked aspect of socially responsible investing; (ii) our loan-level data over a long sample period allows

Second, we present a novel supply-side channel explaining why banks differ in their propensity to lend to minorities. There is solid empirical evidence showing that minorities are discriminated against in mortgage lending. In a seminal contribution, Munnell et al. (1996) uses 1990 Boston mortgage application data and finds that, after controlling for applicant characteristics and lender fixed effects, Black and Hispanic applicants are 8% more likely to be denied credit than white applicants. These results are confirmed by subsequent work documenting redlining against minority neighborhoods (Holmes and Horvitz, 1994; Ross and Tootell, 2004), higher probability of high-cost mortgages (Bayer et al., 2018; Bartlett et al., 2022; Ghent et al., 2014; Cheng et al., 2015; Delis and Papadopoulos, 2019), higher mortgage fees and overages (Ambrose et al., 2021; Black et al., 2003; Courchane and Nickerson, 1997), and longer application turnaround times (Wei and Zhao, 2022) for minorities. However, discrimination in the mortgage market appears to have declined in recent years, consistent with progress in fair lending (Bhutta et al., 2025; Bhutta and Hizmo, 2021).[5]

The stakeholders' discipline channel complements recent studies that document how other supply-side forces, such as automation and the minority status of loan officers and bank owners, might reduce disparities in credit access. Evidence from small business lending under the Paycheck Protection Program (PPP) suggests that minority applicants are more likely to borrow from fintech lenders and large banks than from small- and mid-sized banks (Howell et al., 2024; Chernenko and Scharfstein, 2024; Chernenko et al., 2023). Specifically, automation mitigates disparities in application (not approval) rates (Chernenko et al., 2023) by enabling smaller loans, broadening banks' reach, and reducing human bias in decision making (Howell et al., 2024). Finally, Frame et al. (2025) and Hurtado and Sakong (2023) document greater credit access for minorities when paired with minority loan officers or

us, from an identification standpoint, to estimate the effect of *changes* in stakeholders' inequality aversion on mortgage-level approval decisions. For a discussion of how U.S. executives are increasingly segregating by political party, see Fos et al. (2025). Dagostino et al. (2023) shows that bankers whose party coincides with that of the U.S. President charge lower spreads than other bankers.

[5] Bhutta et al. (2025) shows limited discrimination effects in mortgage approval decisions in a sample of FHA loans in 2018–2019. Bhutta and Hizmo (2021) studies prices charged by mortgage lenders in 2014 and 2015 and shows no significant difference in total mortgage prices paid by minorities and non-minorities (the higher interest rates paid by minorities are offset by fewer discount points).

minority-owned banks, those who have an informational advantage with minority borrowers.[6]

Outline. The remainder of the paper is organized as follows. Section 2 presents our data and a set of facts, including the large variation in mortgage approval gaps across banks. Section 3 shows that banks with smaller approval gaps tend to be more inequality averse. Section 4 rules out several channels that might drive this correlation. Section 5 shows that this correlation is consistent with the stakeholders' discipline channel. Section 6 concludes.

2 Facts from raw data

In this section, we present our data and a set of facts on bank-level variation in mortgage approval rates, defined as the number of applications approved divided by the number of applications received. Section 2.1 explains our sample construction and discusses key summary statistics. Section 2.2 documents the large and persistent variation across banks in the mortgage "approval gap," namely, the difference in approval rates for mortgage applications made by minority and non-minority borrowers.

2.1 The sample

Our core dataset comprises 114.3 million loan applications from 838 banks, covering 1995 to 2019.[7] This sample is the result of combining various publicly available or commercially available datasets, such as Home Mortgage Disclosure Act (HMDA) mortgage applications data, FDIC Summary of Deposits data, Federal Reserve Y-9C and CALL reports (Consolidated Reports of Condition and Income) data, and BoardEx.

[6] Using data on loan officers' and borrowers' caste and religion in India, Fisman et al. (2017) finds that cultural proximity improves credit access and relaxes financial constraints. Gong et al. (2023) and Vatsa (2025) analyze "mission-oriented" financial institutions, focusing on Community Development Financial Institutions and Minority Depository Institutions, respectively.

[7] The start of the sample period is explained by the earliest availability of Summary of Deposits data (1994) and the use of lagged deposit data in our analysis. The end is the year before the COVID-19 pandemic, a period characterized by various stimulus programs that affected lending practices and deposit flows.

Sample construction. We construct our core data in three steps. First, we begin with the 1,162 companies (identified by "CompanyID") classified as banks by Boardex from 1999 to 2018. We use tickers and annual report dates in BoardEx to link these CompanyIDs to their PERMCOs in the merged Compustat/CRSP data. Using PERMCOs and annual report dates, we are able to match 673 CompanyIDs to their regulatory identification numbers (RSSD9001) in the CRSP link table made publicly available by New York Fed. We identify RSSD9001s for 450 out of the remaining 489 CompanyIDs from the National Information Center database using a combination of company name, annual report date, and headquarters information. Note that a bank that is delisted yet continues to appear on BoardEx is assigned two separate CompanyIDs, while retaining a unique RSSD9001. Hence, we treat each RSSD9001 as a bank in our analysis. The 1,123 CompanyIDs whose RSSD9001 information is available are associated with 1,090 unique RSSD9001s.

Second, we match banks in this BoardEx sample to the publicly available "HMDA dataset," which provides information on mortgage applications collected under the Home Mortgage Disclosure Act.[8] We identify the RSSDIDs of the lending entity and its bank holding company using the variables *Entity* and *BHC*, respectively, in the "Avery file."[9] We link the RSSD9001 of each bank in our BoardEx sample to the RSSD9001 of the bank holding company in the HMDA data if there is such a match, and the RSSD9001 of the lending entity otherwise. We exclude all financial institutions that are neither bank holding companies nor commercial banks, and we exclude mortgages subsidized by the Federal Housing Administration, the Veterans Administration, and other government programs. We drop applications that are withdrawn, closed for incompleteness, loans purchased by the

[8]The HMDA dataset provides information on loan size, whether the loan was approved, whether the loan was sold (securitized) in the calendar year of origination, the geographical location of the property for which the loan was originated, as well as borrower characteristics. We exclude observations where the primary borrower's race is not reported. This dataset covers all depository institutions that (i) have a home or branch office in a Metropolitan Statistical Area (MSA), (ii) have originated at least one first-lien home purchase loan on a one-to-four family dwelling in the past year, and (iii) have assets above a certain threshold. This threshold is \$10 million before 1997, \$11 million in 1997, and adjusted for annual percentage increase in CPI thereafter. For 2020, the threshold is \$47 million.

[9]The "Avery file," constructed by Robert Avery from the Federal Reserve Board, is available at https://sites.google.com/site/neilbhutta/data.

reporting banks, and applications submitted to lenders acquired during the year.

Third, we determine banks' geographical footprint using the FDIC Summary of Deposits data, available since 1994. For bank holding companies, balance sheet and income statement variables are sourced from Y-9C reports for those filing them. They are aggregated (up to the highest holding company) from CALL reports for those that do not file Y9-C reports. For commercial banks, balance sheet and income statement variables come from CALL reports.

Banks' inequality aversion. We measure banks' inequality aversion by matching their geographical footprints with county-level political orientations.[10] Specifically, for each bank-year, we collect the percentage of votes cast for the Democratic candidate in the most recent presidential election.[11] A bank's inequality aversion is the deposit-weighted average of these percentages. The variable takes higher values when more of the bank's geographic footprint lies in Democratic counties.

Our measure is based on empirical evidence, survey evidence, and extensive literature. At its core, our measure assumes that a county with a more Democratic-leaning population is more averse to inequality. This assumption is backed (i) by the literature linking redistribution preferences and inequality aversion to political ideology (Alesina et al., 2024; Fong, 2001; Fehr et al., forthcoming; Kuziemko et al., 2015) and (ii) a large body of survey evidence. For example, the following results emerge from the Survey of U.S. adults conducted on September 16–29, 2019, by the Pew Research Center: (i) 61% of Democrats say that reducing economic inequality should be a top priority for the government compared to 20% of Republicans; (ii) 78% of Democrats say there is currently too much economic inequality in the U.S. compared to 41% of Republicans (Pew Research Center Report, 2020). Crucially, because a sizable share of stakeholders are *local* (e.g., depositors), bank-level inequality aversion is largely driven by banks' geographical footprint. As discussed later in the paper, we validate and

[10] Di Giuli and Kotstovetsky (2014) and Hong and Kotstovetsky (2012) link political values to corporate social responsibility (CSR).

[11] This data is from the MIT Election Data and Science Lab (from 2000 onward) and Dave Leip's Atlas of U.S. Presidential Elections (before 2000) for every county in which a bank has branches.

complement this measure with an alternative measure of bank racial inequality aversion using data from the General Social Survey (GSS).

Other data sources. We complement our core dataset with other data. First, we use the confidential HMDA data (cHMDA) to analyze applicants' credit scores and debt-to-income ratios, variables that are available only from 2018 onward. We also analyze mortgage ex-post performance by merging cHMDA with ICE, McDash®, a proprietary dataset that tracks the performance and servicing history of mortgages. Second, we use, as control variables, measures of *bank executives'* inequality aversion based on their contributions to political candidates. To this end, we obtain political contribution data from the Federal Election Commission website (individual contributions to federal candidates and political parties dating back to 1979) and match them to executives' identities from BoardEx. Such information includes the contributor's name, employer, zip code, contribution amount, and the candidate's political party. We use executives' names and employment histories from BoardEx to identify their contributions. Finally, we source annual shareholder meeting transcripts from LSEG Workspace for the period 2010–2019.

Summary statistics. Table 1 shows summary statistics for the full sample, reporting application-level variables in Panel A and bank-year-level variables in Panel B. The variable definitions are available in Appendix OA.1. Panel A shows that 74% of all applications are approved and that the average applicant income (in 2012 dollars) is $110,523. We define a loan application (i) as being approved (Approved=1) if the loan is originated or if the application is approved but not accepted, and (ii) as being denied (Approved=0) if the bank denies the application. In terms of demographics, 17% of applicants are non-white, and 7% are from high-minority census tracts. High-minority tracts are defined as tracts where 75% or more of the population is minority according to the Census Bureau's classification.[12]

Panel B presents summary statistics for bank stakeholders' inequality-aversion variables

[12]Minority population is defined as (i) Hispanic population and (ii) non-Hispanic population minus non-Hispanic white population. We use Census Bureau variables to categorize tracts as high-minority.

	N	Mean	Median	SD	p25	p75
Panel A. Application-level variables						
Non-White	96,316,648	0.17	0.00	0.38	0.00	0.00
High-Minority Tract	113,966,232	0.07	0.00	0.26	0.00	0.00
Approved	114,303,920	0.74	1.00	0.44	0.00	1.00
Applicant Income	108,785,600	110.52	77.49	1198.45	49.55	121.95
Credit Score	4,383,580	746.36	760.00	61.92	711.00	793.00
DTI Ratio	4,758,127	40.14	37.35	22.23	28.35	44.88
LTI Ratio	108,768,976	1.96	1.68	5.88	0.81	2.65
Jumbo	114,303,896	0.07	0.00	0.25	0.00	0.00
Refinancing	114,303,920	0.57	1.00	0.49	0.00	1.00
Home Improvement	114,303,920	0.13	0.00	0.34	0.00	0.00
Panel B. Bank-year-level variables						
Inequality Aversion	12,185	0.48	0.47	0.12	0.40	0.56
Racial Inequality Aversion	12,191	−1.89	−1.89	0.14	−1.99	−1.83
CEO Experience	6,138	6.48	4.90	5.89	1.90	9.10
CEO Age	5,867	57.15	57.00	6.87	53.00	62.00
Number of Independent Directors	6,306	8.29	8.00	3.34	6.00	10.00
Number of Directors	6,306	11.35	11.00	3.35	9.00	13.00
Female CEO	6,138	0.03	0.00	0.18	0.00	0.00
Assets	12,433	17,204	896	136,841	436	2,643
Log Assets	12,433	7.13	6.80	1.63	6.08	7.88
Deposits/Assets	12,433	0.79	0.81	0.09	0.75	0.86
Cost of Deposits	12,433	0.02	0.02	0.01	0.01	0.03
Liquid Assets/Assets	12,433	0.25	0.24	0.12	0.17	0.32
Tier 1 Capital/Assets	11,765	0.09	0.09	0.03	0.08	0.10
C&I Loans/Assets	12,397	0.11	0.09	0.07	0.06	0.14
Mortgage Loans/Assets	12,433	0.50	0.50	0.15	0.40	0.60
Net Income/Assets	12,433	0.01	0.01	0.01	0.01	0.01
Unused Commitments/Assets	12,390	0.17	0.14	0.26	0.10	0.19
Letters of Credit/Assets	12,433	0.01	0.01	0.02	0.00	0.01
Nonperforming Loans/Loans	12,433	0.01	0.01	0.02	0.00	0.02
CEO Ineq Aversion	6,143	0.37	0.50	0.31	0.00	0.50
IndepDir Ineq Aversion	6,043	0.45	0.45	0.12	0.38	0.51

Table 1: Summary statistics. This table shows summary statistics for our full sample. Panel A shows summary statistics for our application-level variables. Panel B shows summary statistics for our bank-year-level variables. Non-White is an indicator variable equal to one if the applicant is not white. High-Minority Tract is an indicator variable equal to one if the property associated with the mortgage application is in a high-minority census tract. Approved is an indicator variable equal to one if the application is approved. Applicant Income is the gross annual income of the applicant used in making the credit decision, expressed in 2012 dollars. Credit Score is the applicant's credit score that the bank uses to make credit decisions. The DTI Ratio is the applicant's total monthly debt divided by total monthly income, used by the bank in making the credit decision. Credit scores and DTI are only available from 2018. LTI Ratio is the loan amount divided by the borrower's income. Jumbo is an indicator variable equal to 1 if the loan amount exceeds the Federal Housing Finance Agency's limit. Refinancing is an indicator variable equal to one if the loan purpose is refinancing. Home Improvement is an indicator variable equal to 1 if the loan is for home improvement. Inequality Aversion is the deposit-weighted average percentage of votes cast for the Democratic candidate in the most recent presidential election, with weights equal to the percentage of the bank's deposits in counties where the bank has branches. Racial Inequality Aversion is the weighted average racial inequality aversion in GSS survey regions where the bank has deposits, where the weights are fractions of deposits the bank has in these corresponding regions, and each region's racial inequality aversion is minus one times the region's average value of the GSS variable *natrace*. The variable *natrace* records responses to the GSS survey question *"Are we spending too much money, too little money, or about the right amount of money on assistance to Black individuals?"*, with possible responses "Too much" (3), "Too little" (1), and "About the right amount" (2). We include responses from the white population only. See Appendix OA.1 for the definition of other bank-year-level variables.

	Non-White	White	Mean Test
Panel A. Application-level variables			
High-Minority Tract	0.26	0.03	***
Approved	0.65	0.78	***
Applicant Income	95.82	112.29	***
Credit Score	734.21	748.89	***
DTI Ratio	44.08	39.23	***
LTI Ratio	2.11	1.95	***
Jumbo	0.07	0.06	***
Refinancing	0.52	0.57	***
Home Improvement	0.17	0.12	***

	High-Minority Tract	Low-Minority Tract	Mean Test
Panel B. Application-level variables			
Non-White	0.61	0.14	***
Approved	0.58	0.75	***
Applicant Income	80.71	112.96	***
Credit Score	723.63	748.51	***
DTI Ratio	46.42	39.55	***
LTI Ratio	2.17	1.94	***
Jumbo	0.05	0.07	***
Refinancing	0.56	0.57	***
Home Improvement	0.21	0.13	***

Table 2: Summary statistics, minority versus non-minority groups. This table shows sample means of application-level variables for the subsamples of white versus non-white applicants (Panel A) and the subsamples of applicants in high-minority tracts versus low-minority tracts (Panel B). Approved is an indicator variable equal to one if the application is approved. Applicant Income is the applicant's gross annual income used in making the credit decision, expressed in 2012 dollars. Credit Score is the applicant's credit score that the bank uses to make credit decisions. The DTI Ratio is the applicant's total monthly debt divided by total monthly income, used by the bank in making the credit decision. Credit scores and DTI are only available from 2018. LTI Ratio is the loan amount divided by the borrower's income. Jumbo is an indicator equal to 1 if the loan amount exceeds the Federal Housing Finance Agency's limit. Refinancing is an indicator variable equal to one if the loan purpose is refinancing. Home Improvement is an indicator variable equal to 1 if the loan is for home improvement. The last column shows significance for a mean difference test, where ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

and standard balance sheet, income statement, and governance variables. The average bank has approximately $17 billion in assets expressed in 2012 dollars. Table OA.1 shows sample means for the subsamples of more inequality-averse and less inequality-averse banks, defined based on whether the bank has an above (below) median inequality aversion. More inequality-averse banks have more minority applicants than less inequality-averse banks. Their applicants also have higher income and LTI ratios. These observations highlight the endogeneity of banks' borrower pools and, more generally, the endogeneity of bank-borrower matches.

Table 2 shows sample means for the subsamples of white and non-white applicants (Panel A) and applicants from high-minority and low-minority tracts (Panel B). Throughout the rest of the paper, we mostly use these two demographic "cuts" to capture minority and non-minority groups. The table shows that non-white applicants are more likely to reside in high-minority census tracts, are less likely to have their application approved, and have a lower income and a higher LTI ratio compared with white applicants. Panel B documents similar patterns for applicants in high-minority tracts compared with applicants in low-minority tracts. Table OA.2 shows the same comparison of sample means, further differentiating between more inequality-averse banks and less inequality-averse banks.

2.2 Facts about bank-level approval gaps

We now present two facts about bank-level variation in approval gaps. We show that these approval gaps are substantial, persistent, heterogeneous across banks, and strongly correlated with measures of bank inequality aversion in the cross-section.

Fact 1: Substantial and persistent variation in approval gaps across banks. Figure 1 shows substantial variation across banks in approval gaps between non-white and white applicants (left panel) and between applicants in high-minority and low-minority tracts (right panel). For illustrative purposes, this figure focuses on the most recent period (2015–2019) for the top 10 banks by number of applications received. Specifically, the two panels show mean approval rates for minority borrowers (blue bars) and non-minority borrowers (red bars) by bank, with banks ordered on the x-axis by the number of applications received. Note that all top-10 banks (collectively receiving 62% of applications in 2015–2019) have positive approval gaps with substantial cross-sectional variation. Figure OA.1 shows the same bar charts for the period 2010–2014. Figure OA.2 shows density plots for the approval gaps for the top-100 and top-500 banks by number of applications received in the period 2015–2019 and 1995–2019. This figure confirms, in a much larger sample, that approval gaps tend to be positive and largely heterogeneous across banks.

Figure 2 shows that approval gaps are persistent over time; i.e., banks with high (low) approval gaps tend to maintain high (low) approval gaps. The two binscatter plots show the persistence of approval gaps between non-white and white applicants (left figure) and between applicants in high-minority and low-minority tracts (right figure). Each data point

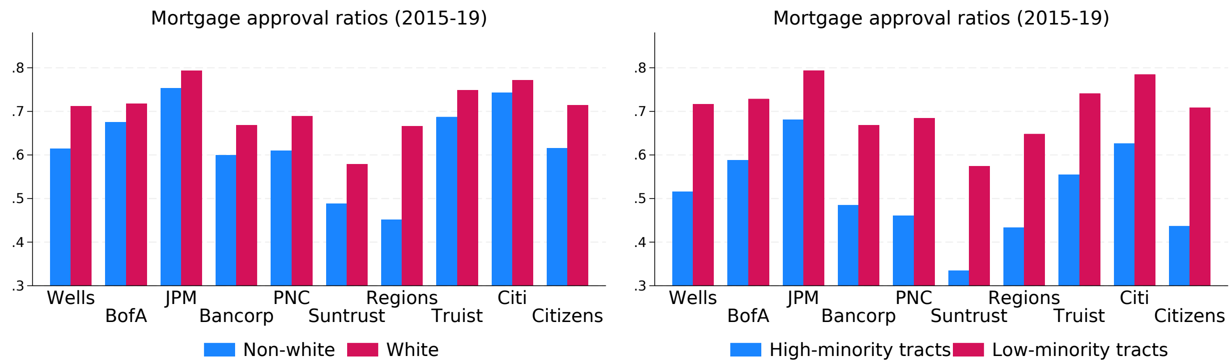

Figure 1: Approval rates across top-10 banks, 2015–2019. This figure shows mortgage approval rates for the top-10 banks by number of applications received in the period 2015–2019. Banks are ranked on the x-axis based on the number of applications received. The blue bars indicate approval rates for non-white applicants (left panel) and applicants in high-minority tracts (right panel). The red bars indicate approval rates for white applicants (left panel) and applicants in low-minority tracts (right panel).

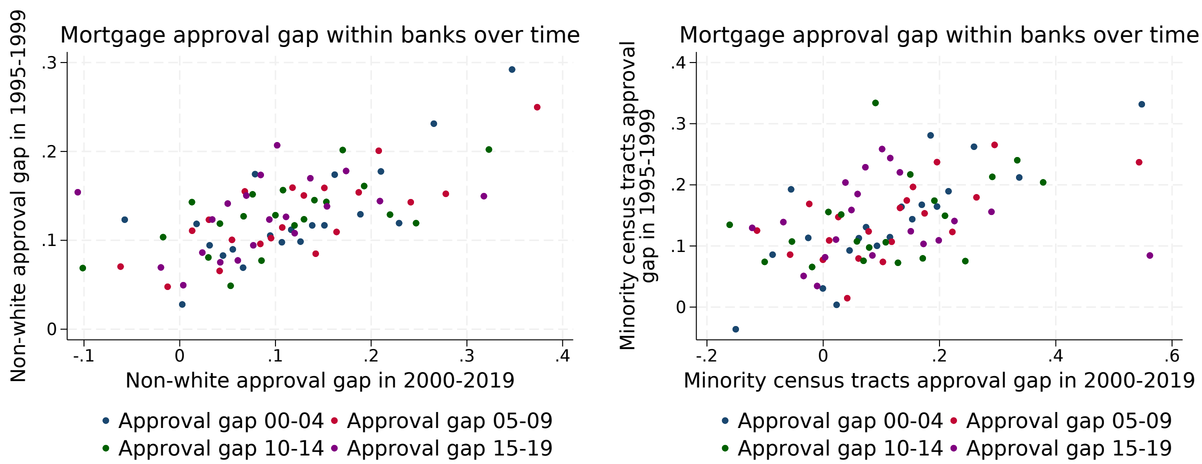

Figure 2: Persistence of bank-level approval gaps. This binscatter plot shows the persistence through time of bank-level approval gaps for non-white versus white applicants (left figure) and applicants in high-minority versus low-minority tracts (right). In each figure, the y-axis shows approval gaps for the period 1995–99, and the x-axis shows approval gaps for the four periods (2000–2004, 2005–2009, 2010–2014, 2015–2019) indicated in the legend.

shows approval gaps for the period 1995–99 (y-axis) and for the period indicated in the legend (x-axis). The data points are spread across the graph and cluster mostly around the 45-degree line, confirming substantial cross-sectional variation and indicating that approval gaps are persistent over time.

Fact 2: Inequality-averse banks tend to have smaller approval gaps. Figure 3 shows that, *within* census tracts, banks with smaller approval gaps tend to have stakeholders that are more averse to inequality. The figure is a binscatter plot run with tract-year fixed effects, thus effectively showing the correlation between stakeholders' inequality aversion and approval gaps *within* census tracts. The left panel focuses on approval gaps between

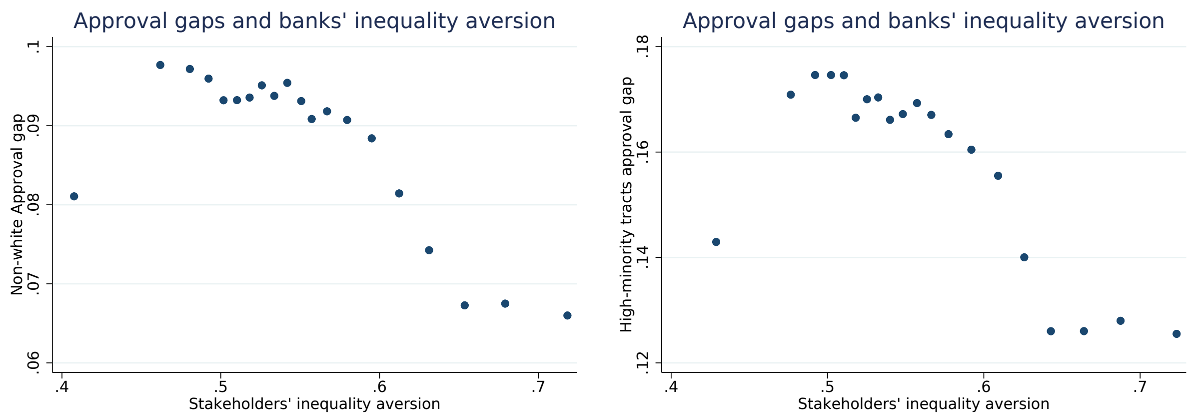

Figure 3: Approval gaps and bank stakeholders' aversion to inequality. This figure shows binscatter plots of approval gaps (y-axis) and measures of bank stakeholders' aversion to inequality (x-axis), controlling for tract-year fixed effects. The left panel focuses on approval gaps for non-white versus white borrowers. The right panel focuses on approval gaps between applicants in high-minority and low-minority tracts. Stakeholders' inequality aversion is the weighted average of the percentage of votes cast for the Democratic presidential candidate in the most recent election across counties where the bank has deposits, with weights equal to the fractions of the bank's deposits in those counties.

non-white and white applicants. The right panel focuses on approval gaps for applicants in high-minority versus low-minority tracts. The two figures show a markedly negative correlation between banks' approval gaps and the inequality aversion of their stakeholders. Figure OA.3 shows a similar pattern using a survey measure of *racial* inequality aversion.

3 Inequality aversion and bank lending

The last fact documented in the previous section shows that banks with smaller approval gaps tend to have more inequality-averse stakeholders than banks with larger approval gaps. In Section 3.1, we show that this correlation is not driven by the selection of applicants, i.e., not driven by higher credit quality minority borrowers and/or lower credit quality non-minority borrowers systematically applying to more inequality-averse banks. In Section 3.2, we show that this correlation is robust to the use of a survey-based measure of inequality aversion.

3.1 Borrower selection

We now present two empirical tests addressing the two main selection concerns in our analysis.

First, selection *across* geographical areas. In this possibility, banks whose stakeholders are more averse to inequality have a bigger presence in areas of the country where the credit quality gap between minority and non-minority borrowers is smaller.[13] For example, high-minority (low-minority) tracts where more inequality-averse banks are located might have a population with higher (lower) average credit quality compared with the high-minority (low-minority) tracts where less inequality-averse banks are located. Alternatively, more inequality-averse banks might be located in areas where non-white residents have higher credit quality and/or where white residents have lower credit quality. Second, selection *within* geographical areas. In this case, *even within the same area*, banks with more inequality-averse stakeholders receive applications from higher-credit-quality minority borrowers and/or lower-credit-quality non-minority borrowers than banks with less inequality-averse stakeholders.

Selection across geographical areas. First, we tackle selection *across* geographical areas. To this end, we run the following specifications separately for different minority attributes, namely $\textit{Non-White}_l$ (specification (1a)) and $\textit{High-Minority Tract}_l$ (specification (1b)):

$$\begin{aligned}\text{Approved}_l = \alpha &+ \beta_1 \text{Non-White}_l \times \text{Inequality Aversion}_{by-1} \qquad (1a)\\ &+ \beta_2 \text{Inequality Aversion}_{by-1} + \boldsymbol{\delta}\mathbf{X}_{by-1} + \boldsymbol{\gamma}\mathbf{Z}_l + \nu_{tyr} + \eta_b + \epsilon_l\end{aligned}$$

$$\begin{aligned}\text{Approved}_l = \alpha &+ \beta_1 \text{High-Minority Tract}_{ty} \times \text{Inequality Aversion}_{by-1} \qquad (1b)\\ &+ \beta_2 \text{Inequality Aversion}_{by-1} + \boldsymbol{\delta}\mathbf{X}_{by-1} + \boldsymbol{\gamma}\mathbf{Z}_l + \nu_{ty} + \eta_b + \epsilon_l\end{aligned}$$

where l is a loan application, b is a bank, t is a census tract, and y is a year. The dependent variable ($\textit{Approved}_l$) is an indicator variable equal to one if loan l is originated (or if the application is approved but not accepted) and equal to zero if the application is denied. Given the large number of fixed effects, we estimate the specification using Ordinary Least Squares (and do so throughout our paper) despite the binary nature of our dependent variable.[14] $\textit{Non-White}_l$ is an indicator variable equal to one if applicant l is non-white. $\textit{High-Minority Tract}_{ty}$ is an indicator variable equal to one if the property associated with the application is

[13]This concern is, in part, justified. Table OA.2 shows that white applicants have an income 17% higher than non-white applicants for more inequality-averse banks. This gap is 27% for less inequality-averse banks.

[14]Probit and Tobit estimations would result in an incidental parameter problem (Greene, 2004).

based in a census tract where 75% or more of the population is minority, according to the Census Bureau's classification. $Inequality\ Aversion_{by-1}$ is the weighted average percentage of votes cast for the Democratic presidential candidate in the most recent election in counties where bank b has deposits.

We saturate the regression specification with several fixed effects and control variables. In terms of fixed effects, we include (i) census tract-year-race fixed effects (ν_{tyr}) in regressions where the minority attribute is $Non\text{-}White_l$ (specification (1a)), and (ii) census tract-year fixed effects (ν_{ty}) in regressions where the minority attribute is $High\text{-}Minority\ Tract_l$ (specification (1b)). These fixed effects address the concern about selection across geographical areas. Specifically, census tract-year-race fixed effects allow us to compare applicants of the same race in the same tract and year across banks with different degrees of inequality aversion, thereby alleviating the concern that more inequality-averse and less inequality-averse banks might operate in different census tracts with different non-white versus white credit quality gaps. Similarly, census tract-year fixed effects allow us to compare applicants in the same tract applying in the same year to banks with different degrees of inequality aversion, thus alleviating the concern that more inequality-averse and less inequality-averse banks might operate in census tracts with systematically different borrower credit quality. In the most stringent regression, we also include bank fixed effects to capture how much *changes* in bank inequality aversion affect banks' approval decisions. Note that the uninteracted variables $Non\text{-}White_l$ and $High\text{-}Minority\ Tract_{ty}$ are excluded from specifications (1a) and (1b), respectively, as the tract-year-race and tract-year fixed effects subsume these variables.

In terms of control variables, we include lagged bank-level controls (both bank and executives' characteristics in the vector $\mathbf{X}_{by-1}$) and loan and borrower characteristics (vector $\mathbf{Z}_l$). The bank characteristics are the natural log of banks' total assets (in million dollars as of 2012), deposits-to-assets ratio, interest on deposits divided by total assets, liquid assets divided by total assets, tier 1 capital divided by total assets, C&I loans divided by total assets, loans secured by real estate divided by total assets, net income divided by total assets, unused commitments divided by total assets, letters of credit divided by total assets, and nonperforming loans divided by total loans. The executives' characteristics are the number of years the CEO has been acting as CEO of the bank, the CEO's age, the number of independent directors, the number of directors, and an indicator variable equal to one for a female CEO.

The loan and borrower characteristics are an indicator variable equal to one for a non-white applicant, an indicator variable equal to one for a female applicant, log of applicant income expressed in thousands of 2012 dollars, loan-to-income ratio (loan amount divided by applicant income), an indicator variable equal to one for a jumbo loan, an indicator variable equal to one for refinancing loans, and an indicator variable equal to one for loans for home improvements. We do not include applicant credit scores as the information is not available for most of the sample period. In the next section, we show that omitting credit scores is unlikely to affect our results. We double cluster standard errors at the bank and tract levels to account for correlation across banks within a tract and across tracts for a particular bank.

Table 3 shows the estimation results. Panel A shows results from estimating specification (1a) where the minority attribute is $\textit{Non-White}_l$. The estimated coefficient on β_1 indicates that the approval gap is smaller in banks with more inequality-averse stakeholders. In the first three columns, we progressively include control variables: loan and borrower characteristics, bank characteristics, and executives' characteristics. The estimated β_1 coefficient is stable across specifications. In the last column, we include bank fixed effects to control for the possibility that stakeholders' inequality aversion is correlated with time-invariant bank characteristics that may affect banks' propensity to lend. This estimation result shows that, within banks, positive *changes* in bank inequality aversion are associated with decreasing approval gaps. The magnitudes are large. According to the most conservative specification, a one-standard-deviation increase in our measure of inequality aversion reduces the approval gap by 1.6%, which is 12% of the unconditional gap of 12.9%.[15]

Panel B shows the results from estimating specification (1b) where the minority attribute is $\textit{High-Minority Tract}_{ty}$. Consistent with Panel A, banks with more inequality-averse stakeholders have a smaller approval gap than those with less-inequality-averse stakeholders.

[15]The negative coefficient β_2 suggests that more inequality-averse banks may have stricter lending standards than less inequality-averse banks. Investigating this correlation is beyond the scope of this paper.

Panel A	Approved$_l$			
Inequality Aversion$_{by-1}$ × Non-White$_l$	0.176**	0.170**	0.132***	0.131***
	(0.069)	(0.074)	(0.050)	(0.049)
Inequality Aversion$_{by-1}$	−0.730***	−0.598***	−0.288***	−0.163*
	(0.222)	(0.137)	(0.081)	(0.086)
Observations	91,763,321	89,334,860	67,048,747	67,048,745
R-squared	0.176	0.187	0.156	0.162
Fixed Effects				
Tract-Year-Race	✓	✓	✓	✓
Bank				✓

Panel B	Approved$_l$			
Inequality Aversion$_{by-1}$ × High-Minority Tract$_{ty}$	0.220***	0.223***	0.223***	0.199***
	(0.077)	(0.054)	(0.036)	(0.035)
Inequality Aversion$_{by-1}$	−0.720***	−0.586***	−0.285***	−0.155*
	(0.219)	(0.131)	(0.081)	(0.081)
Observations	91,747,125	89,364,553	67,162,494	67,162,492
R-squared	0.162	0.174	0.142	0.147
Fixed Effects				
Tract-Year	✓	✓	✓	✓
Bank				✓

Control Variables				
Loan and Borrower Characteristics ($\mathbf{Z}_l$)	✓	✓	✓	✓
Bank Characteristics ($\mathbf{X}_{by-1}$)		✓	✓	✓
Executives' Characteristics ($\mathbf{X}_{by-1}$)			✓	✓

Table 3: Bank stakeholders' inequality aversion and lending. This table shows estimation results from specifications (1a) and (1b). The dependent variable is Approved$_l$, an indicator variable equal to one if application l is approved and equal to zero if the application is denied. Inequality Aversion$_{by-1}$ is the deposit-weighted average percent of county-level votes cast to the Democratic candidate in the most recent presidential election, where the weights are fractions of the bank's deposits in these counties. The minority attribute is Non-White$_l$ (indicator variable equal to one if the applicant is non-white according to HMDA classification) in Panel A and High-Minority Tract$_{ty}$ (indicator variable equal to one if the property associated with the application is based in a census tract where 75% or more of the population is minority, according to Census Bureau's classification) in Panel B. The loan and borrower characteristics are an indicator variable equal to one for a non-white applicant (the uninteracted variable is omitted from specification (1a)), an indicator variable equal to one for a female applicant, natural log of applicant income expressed in thousands of 2012 dollars, LTI Ratio (loan amount divided by borrower income), an indicator variable equal to one for jumbo loans, an indicator variable equal to one for refinancing loans, and an indicator variable equal to one for loans taken out for home improvements. The (lagged) bank characteristics are the natural log of banks' total assets (in million dollars as of 2012), deposits-to-assets ratio, interest on deposits divided by total assets, liquid assets divided by total assets, tier 1 capital divided by total assets, C&I loans divided by total assets, loans secured by real estate divided by total assets, net income divided by total assets, unused commitments divided by total assets, letters of credit divided by total assets, and nonperforming loans divided by total loans. Executive characteristics include the number of years the CEO has served as CEO of the bank, the CEO's age, the number of independent directors, the number of directors, and an indicator variable equal to one for a female CEO. See Appendix OA.1 for variable definitions. The sample runs annually from 1995 to 2019 for regressions without executive and board control variables and from 1999 to 2019 for regressions with executive and board control variables. Standard errors are double clustered at the bank and tract levels and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

A one-standard-deviation increase in our measure of inequality aversion reduces the approval gap by 2.4%, which is approximately 14% of the unconditional gap of 17%.[16]

Appendix OA.3 provides a set of additional tests. Table OA.3 shows that our results are robust to using *county*-year-race and *county*-year instead of census tract-year-race and census tract-year, fixed effects—addressing the concern that census tracts might be too small to estimate our baseline specification meaningfully. Table OA.4 shows that the effect of inequality aversion on the approval gap between high-minority versus low-minority tracts is separate from the effect of inequality aversion on the approval gap between non-white versus white borrowers. In particular, coefficients on $\textit{Inequality Aversion}_{by-1} \times \textit{Non-White}_l$ and $\textit{Inequality Aversion}_{by-1} \times \textit{High-Minority Tract}_{ty}$ are both positive and statistically significant when both interaction variables are included in the same regression.

Selection within geographical areas. Second, we tackle selection *within* geographical areas by examining whether, within the same census tract and year, credit quality gaps between minority and non-minority applicants are smaller for more inequality-averse banks. To this end, we run specifications (1a) and (1b) with the dependent variable being (i) the applicant's income ($\textit{Income}_l$, measured in 2012 dollars) for the entire sample (our core HMDA data), and the (ii) applicant's credit scores ($\textit{Credit Score}_l$) and debt-to-income ratios (DTI_l) for the 2018–2019 subsample when these variables are reported in cHMDA.[17]

Table 4 shows the estimation results. For brevity, we present only results for the most stringent regression specifications. In the first column, we measure credit quality using income. Panel A shows that, within the same census tract and year, the income gap between non-white and white borrowers is similar for borrowers applying to both more- and less-inequality-

[16]Figure OA.4 shows that the approval gaps of the top-3 banks in the full sample of tracts are similar to those in *shared* tracts, i.e., census tracts with at least one applicant per bank every year—providing non-parametric evidence further suggesting that selection *across* geographical areas is not a first-order concern.

[17]Lenders mostly use FICO scores in making credit decisions, but they can also use Vantage scores or other types of credit scores. In our analyses, we use credit scores reported in the cHMDA dataset without limiting to any type of credit scores. We drop all observations using VantageScore version 2.0, an older version of the Vantage scoring system, which has an uncommon scoring range of 501–990 rather than the industry-standard range of 300–850. These observations account for only 355 of more than 5 million during the 2018–2019 period.

Panel A	Income_l	Credit Score_l	DTI_l
$\text{Inequality Aversion}_{by-1} \times \text{Non-White}_l$	3.364	−0.677	−1.126
	(3.214)	(5.051)	(1.668)
$\text{Inequality Aversion}_{by-1}$	−13.054*	0.540	−4.037
	(6.930)	(32.397)	(8.456)
Observations	67,065,285	3,291,257	3,611,069
R-squared	0.396	0.204	0.343
Fixed Effects			
Tract-Year-Race	✓	✓	✓
Bank	✓	✓	✓

Panel B	Income_l	Credit Score_l	DTI_l
$\text{Inequality Aversion}_{by-1} \times \text{High-Minority Tract}_{ty}$	−5.818*	7.066	−2.826
	(4.791)	(8.943)	(1.739)
$\text{Inequality Aversion}_{by-1}$	−12.461	0.832	−3.956
	(6.993)	(32.359)	(8.447)
Observations	67,178,960	3,287,048	3,607,415
R-squared	0.385	0.204	0.322
Fixed Effects			
Tract-Year	✓	✓	✓
Bank	✓	✓	✓

Sample for Panel A and Panel B			
Sample period	1999–2019	2018–2019	2018–2019
Mortgage applications data	HMDA	cHMDA	cHMDA
Control Variables for Panel A and Panel B			
Loan and Borrower Characteristics ($\mathbf{Z}_l$)	✓	✓	✓
Bank Characteristics ($\mathbf{X}_{by-1}$)	✓	✓	✓
Executives' Characteristics ($\mathbf{X}_{by-1}$)	✓	✓	✓

Table 4: Bank stakeholders' inequality aversion and applicant characteristics. This table shows estimation results from specifications (1a) and (1b). The dependent variable in the first column is Income_l, defined as the applicant income expressed in thousands of 2012 dollars, and is winsorized at the 2^{nd} and 98^{th} percentiles. The dependent variable in the second column is Credit Score_l, which is the applicant's credit score used by the bank to make credit decisions reported in cHMDA. The dependent variable in the third column is DTI_l, which is the ratio of the applicant's total monthly debt to total monthly income used by the bank in making the credit decision, reported in cHMDA. $\text{Inequality Aversion}_{by-1}$ is the deposit-weighted average percent of county-level votes cast to the Democratic candidate in the most recent presidential election, where the weights are fractions of the bank's deposits in these counties. The minority attribute is Non-White_l (indicator variable equal to one if the applicant is non-white according to HMDA classification) in Panel A and $\text{High-Minority Tract}_{ty}$ (indicator variable equal to one if the property associated with the application is based in a census tract where 75% or more of the population is minority, according to Census Bureau's classification) in Panel B. The loan and borrower characteristics are an indicator variable equal to one for a non-white applicant (the uninteracted variable is omitted from specification (1a)), an indicator variable equal to one for jumbo loans, an indicator variable equal to one for refinancing loans, and an indicator variable equal to one for loans taken out for home improvements. Bank characteristics and executives' characteristics are the same variables used in Table 3. See Appendix OA.1 for variable definitions. The sample runs annually from 1999 to 2019 for regressions with Income_l as the dependent variable (HMDA data), and from 2018 to 2019 for regressions with Credit Score_l and DTI_l as the dependent variables (cHMDA data). Standard errors are double clustered at the bank and tract levels and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

averse banks. Similarly, Panel B shows that borrowers applying to more inequality-averse banks have, if anything, a *lower* income compared to those applying to less inequality-averse banks in high-minority census tracts. Overall, these results are consistent with the near-zero correlation between income gaps and approval gaps in the full sample of tracts as well as in the subsample of shared census tracts (i.e., census tracts with at least one applicant per bank every year), documented in Figure OA.5.

In columns (2)-(3), we report results using credit scores and debt-to-income ratios to measure applicants' credit quality, respectively. Panel A shows no difference in the credit scores nor debt-to-income ratios of white and non-white applicants attracted by more inequality-averse compared with less inequality-averse banks in the same census tract and during the same year. Similarly, Panel B shows no difference in credit scores or debt-to-income ratios. between applicants attracted to more inequality-averse banks and those attracted to less inequality-averse banks in high- and low-minority census tracts. While these results are limited by the short time series (2018–2019) for which credit scores and debt-to-income ratios are available, they are consistent with the absence of borrower-income selection within the geographical areas reported earlier for the large sample.

3.2 Survey-based measure of inequality aversion

We now show that the correlation across banks between approval gaps and inequality aversion is robust when using a survey-based measure of inequality aversion.

While political orientation is widely used in the literature (Kuziemko et al., 2015) to capture inequality aversion, it is an imperfect measure. First, differences in these preferences between Democrats and Republicans may change over time. The Voter Study Group Report published in 2021 documents a remarkable increase in the disparity between Democrats and Republicans with respect to their attitude toward racial inequality from 2011 to 2020.[18]

[18] In 2011, 32% of Democrats agreed with the statement that Black individuals have gotten less than they deserved, while the corresponding statistic in 2020 is 73%. In contrast, 7% of Republicans agreed that Black individuals have gotten less than they deserved in 2011 compared to 12% in 2020. The 25-point gap between Democrats and Republicans in 2011 has grown to 51 points in 2020 (Voter Study Group, 2017).

Second, significant diversity of views exists within each partisan coalition. For example, research released in 2021 by the Pew Research Center finds that while Democrats generally agree with the goal of fighting racial inequality, they disagree on whether systemic measures should be taken to achieve it (Pew Research Center, 2021). Progressive Left supports the social safety net and far-reaching measures to combat racial inequity, while Establishment Liberals are less likely to support these measures. With respect to income inequality, the Populist Right is very similar to the majority of Democrats in favoring tax increases on high-income households.

To address these concerns, we use a survey question from the GSS asking whether *"we are spending too much money, too little money, or about the right amount of money on assistance to Black individuals."*[19] Survey respondents can choose one of the following three options, which are coded with the values 3 (too much), 1 (too little), and 2 (about the right amount).[20] For each survey year, we select responses from white individuals following Chernenko and Scharfstein (2024), multiply the values of these responses by -1 such that a higher value indicates higher racial inequality aversion, and use the average value for each region as the region's racial inequality aversion. We then compute the deposit-weighted average of racial inequality aversion for each bank, with weights equal to the fractions of deposits held in each region. Given the ordinal nature of the coded survey responses, we construct a dummy variable ($\textit{Racial Inequality Aversion}_{by-1}$) equal to one if the weighted average is above the median, calculated each year across banks.

[19]The GSS is a nationally representative survey of adults in the U.S. conducted since 1972 with the goal of *"monitoring and explaining trends in opinions, attitudes, and behaviors."* The GSS data is publicly available at `https://gss.norc.org/`. This data has been used, among many others, in Luttmer (2001). The American National Election Studies (ANES) survey also provides survey responses capturing inequality aversion. This survey runs every four years and provides responses at the county level. However, the number of responses is typically smaller than the number of counties in the U.S., making a match between county-level branches and survey responses not representative of the inequality aversion of bank local stakeholders. Hence, we use only the GSS-based measure of racial inequality aversion for robustness checks.

[20]We observe each response and the region of the survey respondent, where the U.S. is partitioned into nine regions. This coarse geographical partition further explains why our preferred measure of bank inequality aversion is based on county-level voting data. The nine GSS regions are (i) New England, (ii) Rhode Island Middle Atlantic, (iii) Pennsylvania East North Central, (iv) Michigan, Ohio West North Central, (v) Kansas South Atlantic, (vi) District of Columbia East South Central, (vii) Mississippi West South Central, (viii) Louisiana, Texas Mountain, and (ix) New Mexico Pacific.

	Approved$_l$			
Racial Inequality Aversion$_{by-1}$ × Non-White$_l$	0.012*	0.011*		
	(0.007)	(0.006)		
Racial Inequality Aversion$_{by-1}$ × High-Minority Tract$_{ty}$			0.021**	0.017**
			(0.008)	(0.008)
Racial Inequality Aversion$_{by-1}$	0.004	0.001	0.004	0.001
	(0.005)	(0.006)	(0.005)	(0.006)
Observations	67,048,747	67,048,745	67,162,494	67,162,492
R-squared	0.155	0.161	0.141	0.148
Specification	(1a)	(1a)	(1b)	(1b)
Fixed Effects				
Tract-Year-Race	✓	✓		
Tract-Year			✓	✓
Bank		✓		✓
Control Variables				
Loan and Borrower Characteristics ($\mathbf{Z}_l$)	✓	✓	✓	✓
Bank Characteristics ($\mathbf{X}_{by-1}$)	✓	✓	✓	✓
Executives' Characteristics ($\mathbf{X}_{by-1}$)	✓	✓	✓	✓

Table 5: Bank stakeholders' racial inequality aversion and lending, survey-based measure of inequality aversion. This table shows estimation results from specifications (1a) and (1b), with the variable Inequality Aversion being replaced by the variable Racial Inequality Aversion. Racial Inequality Aversion, measured at the bank-year level, is the weighted average racial inequality aversion in GSS survey regions, where the weights are fractions of deposits the bank has in these corresponding regions, and each region's racial inequality aversion is minus one times the average value of the GSS variable *natrace*. Variable *natrace* records responses to the survey question *"Are we spending too much, too little, or about the right amount on improving the conditions of Black individuals"*, with possible responses "Too much" (3), "Too little" (1), and "About the right amount" (2). The dependent variable is Approved$_l$, an indicator variable equal to one if the application is approved and equal to zero if the application is denied. Non-White$_l$ is an indicator variable equal to one if the applicant is non-white according to HMDA classification. High-Minority Tract$_{ty}$ is an indicator variable equal to one if the property associated with the application is based in a census tract where 75% or more of the population is minority, according to the Census Bureau's classification. The loan and borrower characteristics are an indicator variable equal to one for a non-white applicant (the uninteracted variable is omitted from specification (1a)), an indicator variable equal to one for a female applicant, the natural log of applicant income expressed in thousands of 2012 dollars, LTI Ratio (loan amount divided by borrower income), an indicator variable equal to one for jumbo loans, an indicator variable equal to one for refinancing loans, and an indicator variable equal to one for loans taken out for home improvements. The (lagged) bank characteristics are the natural log of banks' total assets (in million dollars as of 2012), deposits-to-assets ratio, interest on deposits divided by total assets, liquid assets divided by total assets, tier 1 capital divided by total assets, C&I loans divided by total assets, loans secured by real estate divided by total assets, net income divided by total assets, unused commitments divided by total assets, letters of credit divided by total assets, and nonperforming loans divided by total loans. Executive characteristics include the number of years the CEO has served as CEO of the bank, the CEO's age, the number of independent directors, the number of directors, and an indicator variable equal to one for a female CEO. See Appendix OA.1 for variable definitions. The sample runs annually from 1999 to 2019. Standard errors are double clustered at the bank and tract levels and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5 shows the estimation results using this survey-based variable in the most stringent specifications (1a) and (1b). Minority applicants are defined as non-white applicants in the first two columns and as applicants in high-minority tracts in the last two columns. The estimation results based on survey data confirm that banks with more inequality-averse stakeholders are more likely to lend to minority borrowers than those with less inequality-averse stakeholders.

4 Ruling out a few potential explanations

In the previous section, we have shown that the correlation between bank stakeholders' inequality aversion and bank-level approval gaps (i) is not driven by the selection of applicants and (ii) is robust to using a survey-based measure of inequality aversion. We now rule out a set of potential explanations before discussing, in Section 5, the stakeholders' discipline channel that, we argue, drives this correlation.

Specifically, we now show that this correlation is not driven by (i) loan officers selection into inequality-averse banks (Section 4.1), (ii) banks' differential access to soft information (Section 4.2), (iii) banks' differential mortgage lending expertise nor other banks' characteristics that might be correlated with stakeholders' inequality aversion (Section 4.3), nor (iv) changes in the bank borrower base (Section 4.4).

4.1 Loan officers selection into inequality-averse banks

We now show that the correlation between bank stakeholders' inequality aversion and bank-level approval gaps is not explained by the endogenous matching between banks and loan officers. Frame et al. (2025) shows that, although banks are less likely to approve an application from minority borrowers than from non-minority borrowers, this gap is smaller—and default rates lower—when minority borrowers are matched with minority loan officers, consistent with an informational advantage of such pairings. Fisman et al. (2017) shows that borrowers who are culturally closer to their loan officer are more likely to receive credit and obtain better loan terms, consistent with cultural proximity improving the use of soft information. If, within a census tract, inequality-averse banks employ more minority loan officers, our results could reflect cross-bank differences in loan officer composition rather than differences in stakeholders' inequality aversion.

In this section, we show that our results are robust to this alternative explanation in the sample period for which loan officer identifiers are available. We identify the loan officers for all mortgage applications between 2018 and 2019 from cHMDA and estimate specifications (1a) and (1b) with the following modifications. First, in terms of fixed effects, we replace tract-year-race and tract-year fixed effects in specifications (1a) and (1b) with *county*-year-race-*officer* and *county*-year-minority tract-*officer* fixed effects, respectively. With these fixed effects, we identify the effect of bank-level variation in inequality aversion on approval rates for borrowers of the same type (minority or non-minority) in the same year and the same geographical area by the *same loan officer* who processes applications for different banks. These are cases in which loan officers switch banks, or in which contractors work as loan officers for more than one bank simultaneously. Because these cases are few within a census tract, we use counties and states rather than census tracts in the fixed effects. We also omit bank fixed effects, as they are largely subsumed by the time-varying bank-level inequality aversion variable, given the short time span of our sample. We exclude other time-varying bank characteristics because of the tight identification from the quadruple fixed effects (there are relatively few banks within each fixed-effects cluster, which limits the power of the test when multiple bank-level controls are included). Finally, we control for applicant credit scores, which are available in cHMDA for the same sample period.

We present the results in Table 6. The first (last) two columns present results where the geographical area in the fixed effects is defined as a county (state). Our main results are qualitatively unchanged—approval gaps from the same loan officer are smaller when the loan officer works for a more inequality-averse bank.

4.2 Banks' differential access to soft information

We now show that our results are not driven by the distance between lenders and borrowers, which might affect banks' access to, and production of, soft information.

Broeckner (1990), Petersen and Rajan (2002), Boot and Thakor (2000), and Dell'Ariccia and Marquez (2004), among others, show that physical branches give banks greater *access* to soft information on borrowers with low-quality hard information (likely to be defined as minorities in our context) in the surrounding neighborhood, allowing these banks to "cream-skim" the best borrowers. By doing so, these lenders would likely lower the credit quality of the low-quality hard-information borrower pool for competing lenders without branches in the same area. Similarly, Agarwal and Hauswald (2010) shows that physical proximity facilitates the *production* of soft information, and Mayer (2024) finds that mortgage approval rates decline with the distance from borrowers to the lenders' nearest branch,

	Approved$_l$			
Inequality Aversion × Non-White	0.250***		0.207***	
	(0.075)		(0.045)	
Inequality Aversion × High-Minority Tract		0.289**		0.284***
		(0.117)		(0.063)
Inequality Aversion	−0.122**	−0.103**	−0.113**	−0.098*
	(0.048)	(0.048)	(0.051)	(0.049)
Non-White		−0.046***		−0.046***
		(0.003)		(0.003)
High-Minority Tract	−0.015***		−0.018***	
	(0.003)		(0.005)	
Credit Score	0.002***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	2,725,117	2,802,282	3,154,493	3,196,545
R-Squared	0.459	0.453	0.411	0.404
Specification	(1a)	(1a)	(1b)	(1b)
Fixed Effects				
County-Year-Race-Officer	✓			
County-Year-MinorityTract-Officer		✓		
State-Year-Race-Officer			✓	
State-Year-MinorityTract-Officer				✓
Control Variables				
Loan and Borrower Characteristics	✓	✓	✓	✓

Table 6: Bank stakeholders' inequality aversion and loan officer fixed effects. This table shows estimation results from modified versions of specifications (1a) and (1b), run with County-Year-Race-Officer (State-Year-Race-Officer) fixed effects and County-Year-MinorityTract-Officer (State-Year-MinorityTract-Officer) fixed effects, respectively. The dependent variable is Approved$_l$, an indicator variable equal to one if application l is approved and equal to zero if the application is denied. Inequality Aversion$_{by-1}$ is the deposit-weighted average percent of county-level votes cast to the Democratic candidate in the most recent presidential election, where the weights are fractions of the bank's deposits in these counties. The minority attribute is Non-White$_l$ (indicator variable equal to one if the applicant is non-white according to HMDA classification) in columns 1 and 3 and High-Minority Tract$_{ty}$ (indicator variable equal to one if the property associated with the application is based in a census tract where 75% or more of the population is minority, according to Census Bureau's classification) in columns 2 and 4. The loan and borrower characteristics are an indicator variable equal to one for a non-white applicant, an indicator variable equal to one for an applicant residing in a high minority census tract, an indicator variable equal to one for a female applicant, natural log of applicant income expressed in thousands of 2012 dollars, LTI Ratio (loan amount divided by borrower income), an indicator variable equal to one for jumbo loans, an indicator variable equal to one for refinancing loans, and an indicator variable equal to one for loans taken out for home improvements. See Appendix OA.1 for variable definitions. The sample runs annually from 2018 to 2019. Standard errors are double clustered at the bank and county/state levels and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

especially for low-income borrowers. In our context, the association between inequality aversion and approval gaps might thus result from more inequality-averse banks operating in close proximity to minority borrowers, collecting more soft information, and subsequently granting more credit to these borrowers.

To address this identification concern, we estimate our baseline specifications (1a) and (1b) with all control variables, in the subsample of mortgage applications to banks with branches in the applicants' counties. The results are presented in Table 7. The first two columns focus on the approval gap between non-white and white applicants, and the last two columns focus

	Approved$_l$			
Inequality Aversion$_{by-1}$ × Non-White$_l$	0.127***	0.091***		
	(0.030)	(0.032)		
Inequality Aversion$_{by-1}$ × High-Minority Tract$_{ty}$			0.220***	0.180***
			(0.059)	(0.053)
Inequality Aversion$_{by-1}$	−0.187***	−0.123	−0.189***	−0.133
	(0.070)	(0.104)	(0.070)	(0.102)
Observations	43,738,091	43,738,089	43,905,696	43,905,694
R-squared	0.174	0.178	0.156	0.161
Specification	(1a)	(1a)	(1b)	(1b)
Fixed Effects				
Tract-Year-Race	✓	✓		
Tract-Year			✓	✓
Bank		✓		✓
Control Variables				
Loan and Borrower Characteristics ($\mathbf{Z}_l$)	✓	✓	✓	✓
Bank Characteristics ($\mathbf{X}_{by-1}$)	✓	✓	✓	✓
Executives' Characteristics ($\mathbf{X}_{by-1}$)	✓	✓	✓	✓

Table 7: Bank stakeholders' inequality aversion and lending in the sample of banks with branches in applicants' counties. This table shows estimation results from specifications (1a) and (1b) run in the subsample of applications made to banks that have branches in the applicants' counties. The dependent variable is Approved$_l$, an indicator variable equal to one if the application is approved and equal to zero if the application is denied. Inequality Aversion$_{by-1}$ is the deposit-weighted average county-level percent of votes cast to the Democratic candidate in the most recent presidential election, where the weights are fractions of the bank's deposits in these counties. Non-White$_l$ is an indicator variable equal to one if applicant l is non-white according to HMDA classification. High-Minority Tract$_{ty}$ is an indicator variable equal to one if applicant l is based in a census tract where 75% or more of the population is minority, according to the Census Bureau's classification. The loan and borrower characteristics are an indicator variable equal to one for a non-white applicant (the uninteracted variable is omitted from specification (1a)), an indicator variable equal to one for a female applicant, the natural log of applicant income expressed in thousands of 2012 dollars, loan-to-income ratio (loan amount divided by borrower income), an indicator variable equal to one for jumbo loans, an indicator variable equal to one for refinancing loans, and an indicator variable equal to one for loans taken out for home improvements. The (lagged) bank characteristics are the natural log of banks' total assets (in million dollars as of 2012), deposits-to-assets ratio, interest on deposits divided by total assets, liquid assets divided by total assets, tier 1 capital divided by total assets, C&I loans divided by total assets, loans secured by real estate divided by total assets, net income divided by total assets, unused commitments divided by total assets, letters of credit divided by total assets, and nonperforming loans divided by total loans. Executive characteristics include the number of years the CEO has served as CEO of the bank, the CEO's age, the number of independent directors, the number of directors, and an indicator variable equal to one for a female CEO. See Appendix OA.1 for variable definitions. The sample runs annually from 1999 to 2019. Standard errors are double clustered at the bank and tract levels and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

on the approval gap between applicants in high-minority tracts and those in low-minority tracts, respectively. The correlation between bank stakeholders' inequality aversion and approval gaps is robust in this subsample, where banks arguably have similar access to soft information on borrowers. As an additional test, we proxy for lender–borrower proximity using the bank's branch share in the borrower's county. Table OA.5 shows that controlling for proximity leaves the effects of bank stakeholders' inequality aversion on approval gaps qualitatively unchanged.

4.3 Banks' characteristics correlated with inequality aversion

We now address the concern that our results might be driven by banks' differential mortgage-lending expertise or other bank characteristics correlated with stakeholders' inequality aversion. Table OA.1 shows some examples of such correlations: more inequality-averse banks are larger, engage in more C&I lending, and have more inequality-averse executives (as measured by their campaign contributions) compared with less inequality-averse banks.

The literature documents four types of omitted-variable bias relevant to our analysis. First, Howell et al. (2024) shows that *larger* banks use more automation in the application and approval process, potentially reducing taste-based discrimination. Second, Blanchard et al. (2008) finds that discrimination in small business loans mostly arises for banks whose *primary activity* is not small business lending, and thus are unlikely to use formal underwriting models. Third, Di Giuli and Kotstovetsky (2014) shows that firms with *Democratic-leaning executives* have higher Corporate Social Responsibility scores than those with *Republican-leaning executives*. Fourth, inequality-averse banks might operate in *competitive markets*, where reduced economic rents can lead to less discrimination (Becker, 1957).

To test the importance of these channels, we augment the most stringent version of our baseline specifications (1a) and (1b) with a set of bank-level and county-level characteristics *interacted* with either the $\textit{Non-White}_l$ dummy or the $\textit{High-Minority Tract}_{ty}$ dummy. Driven by both theory and the differences in observables documented in Table OA.1, these variables are lagged values of $\textit{Log(Assets)}_{by-1}$, $\textit{Mortgage Loans/Assets}_{by-1}$, $\textit{CEO Ineq Aversion}_{by-1}$, $\textit{IndepDir Ineq Aversion}_{by-1}$, and $\textit{Competition}_{cy-1}$.[21] Table 8 shows the estimation results. Panel A and Panel B extend the estimations in the last column of Panel A and Panel B in Table 3, respectively. Each row is a different estimation. For brevity, we report only

[21] $\textit{Competition}_{cy-1}$ is calculated as the Herfindal-Hirschman index of deposits in a county for each year, and is a proxy for the level of deposit and loan competition. $\textit{CEO Ineq Aversion}_{by-1}$ and $\textit{IndepDir Ineq Aversion}_{by-1}$ are defined as the fraction of CEO's and independent directors' campaign contributions made to Democrats between 1979 and 2018, respectively. If a CEO makes no political contributions, the measure is set to 0.5. If a bank has more than one CEO (independent director), $\textit{CEO Ineq Aversion}_{by-1}$ ($\textit{IndepDir Ineq Aversion}_{by-1}$) is the average measure across the bank's CEOs (independent directors).

Panel A. White vs. Non-White Applicants — Specification (1a) — Table 3, Panel A, Column (4)				
Non-White$_l$ × Inequality Aversion$_{by-1}$		**Non-White$_l$ × K**		
Estimated coefficient	SD	Estimated coefficient	SD	**K**
0.176***	(0.049)	−0.005***	(0.001)	Log(Assets)$_{by-1}$
0.225***	(0.039)	0.079***	(0.026)	Mortgage Loans/Assets$_{by-1}$
0.187***	(0.061)	−0.022**	(0.011)	CEO Ineq Aversion$_{by-1}$
0.111**	(0.046)	0.029	(0.038)	IndepDir Ineq Aversion$_{by-1}$
0.167***	(0.043)	−0.107***	(0.011)	Competition$_{cy-1}$

Panel B. High-Minority vs. Low-Minority Tracts — Specification (1b) — Table 3, Panel B, Column (4)				
High-Minority Tract$_{ty}$ × Inequality Aversion$_{by-1}$		**High-Minority Tract$_{ty}$ × K**		
Estimated coefficient	SD	Estimated coefficient	SD	**K**
0.266***	(0.027)	−0.007***	(0.002)	Log(Assets)$_{by-1}$
0.274***	(0.028)	0.061*	(0.031)	Mortgage Loans/Assets$_{by-1}$
0.187***	(0.047)	0.007	(0.012)	CEO Ineq Aversion$_{by-1}$
0.168***	(0.036)	0.050	(0.049)	IndepDir Ineq Aversion$_{by-1}$
0.169***	(0.066)	−0.010	(0.029)	Competition$_{cy-1}$

Table 8: Bank stakeholders' inequality aversion and lending to non-white applicants and applicants in high-minority census tracts, robustness with respect to bank and county characteristics. This table shows estimation results from the most stringent version (Table 3, column (4)) of specifications (1a) (Panel A) and specification (1b) (Panel B) augmented with a set of bank-level and county-level characteristics interacted with either the Non-White$_l$ dummy (Panel A) or the High-Minority Tract$_{ty}$ dummy (Panel B). For brevity, we report only the estimated coefficients for the interaction terms. Table OA.6 and Table OA.7 show the full estimation results. The dependent variable is Approved$_l$, an indicator variable equal to one if the application is approved and equal to zero if the application is denied. Non-White$_l$ is an indicator variable equal to one if the applicant is non-white according to HMDA classification. The loan-level and county-level variables used in the interaction terms are Log(Assets)$_{by-1}$, Mortgage Loans/Assets$_{by-1}$, CEO Ineq Aversion$_{by-1}$, IndepDir Ineq Aversion$_{by-1}$, and Competition$_{cy-1}$. See Appendix OA.1 for variable definitions. Every regression in Panel A includes tract-year-race fixed effects and bank fixed effects, with the exception of the last row (interaction with Competition$_{cy-1}$) that includes tract-year and bank fixed effects. Every regression in Panel B includes tract-year and bank fixed effects, except for the last row (interaction with Competition$_{cy-1}$) that includes tract, bank, and year fixed effects. The sample runs annually from 1999 to 2019. Standard errors are double clustered at the bank and tract levels and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

the estimated coefficients for the interaction terms.[22] In sum, the correlation between bank stakeholders' inequality aversion and the minority vs. non-minority approval gap is robust to the inclusion of—and therefore does not seem to be driven by—this set of bank-level and county-level characteristics.

4.4 Changes in borrower base

We now show that our results are not driven by changes in the borrower base that might simultaneously affect banks' inequality aversion and their propensity to lend to minorities. Suppose, for example, a bank opens several new branches in Democratic-leaning states. This

[22] Table OA.6 and Table OA.7 show the full estimation results.

geographical expansion would mechanically increase both the bank's inequality aversion and its pool of minority borrowers.[23] This change in the borrower base might drive the correlation between banks' inequality aversion and their propensity to lend to minorities, as, for example, the bank might develop more expertise in serving a minority clientele.

To test whether our results are robust to this alternative explanation, we analyze the effects of changes in a bank's stakeholders' inequality aversion that are not driven by changes in the bank's geographical footprint. Specifically, we examine how approval gaps between minority and non-minority applicants are affected by changes in the political leaning of banks' *existing* stakeholders around presidential elections, where a bank's existing stakeholders are identified from the location of its deposits three years before an election. Specifically, we run the following two specifications:

$$\Delta\text{Approval Gap}_{bte}^{\text{Non-White}} = \alpha + \beta\Delta\text{Inequality Aversion}_{be} + \gamma\mathbf{X}_{be} + \nu_{te} + \epsilon_{bte} \tag{2a}$$

$$\begin{aligned}\Delta\text{Approval Rate}_{bte} = \alpha &+ \beta\Delta\text{Inequality Aversion}_{be} \times \text{High-Minority Tract}_{te} \\ &+ \gamma_1\Delta\text{Inequality Aversion}_{be} + \gamma_2\mathbf{X}_{be} + \nu_{te} + \epsilon_{bte}\end{aligned} \tag{2b}$$

where b is a bank, t is a census tract, and e is an election. The first specification analyzes changes in approval gaps between non-white and white applicants. The second specification analyzes changes in approval gaps between applicants in high-minority and low-minority tracts. The first dependent variable ($\Delta Approval\ Gap_{bte}^{\text{Non-White}}$) is the post-election versus pre-election change in the *unexplained* approval gap between non-white and white applicants for bank b in census tract t around election e, where the unexplained approval gap is the unexplained approval rate for non-white minus the same ratio for white applicants. The second dependent variable ($\Delta Approval\ Rate_{bte}$) is the post-election versus pre-election change

[23]Using Census Bureau tract-level data covering our sample period, we find that Democratic states (where 50% or more of the votes go to the Democratic presidential candidate) have higher minority populations and more residents in high-minority census tracts than Republican states (where 50% or fewer of the votes go to the Democratic presidential candidate). Specifically, minorities—defined as individuals other than non-Hispanic white—account for 29.5% of the population in Democratic states versus 22.6% in Republican states, and 15.0% of residents live in high-minority tracts in Democratic states compared with 8.8% in Republican states.

	ΔApproval Gap$_{bte}^{Non\text{-}White}$	ΔApproval Ratio$_{bte}$
ΔInequality Aversion$_{be}$	0.237**	−0.594***
	(0.104)	(0.163)
ΔInequality Aversion$_{be}$ × High-Minority Tract$_{te}$		1.098**
		(0.481)
Bank Controls ($\mathbf{X}_{be}$)	✓	✓
Tract-election FE	✓	✓
Specification	(2a)	(2b)
Observations	302,071	615,793
R-squared	0.193	0.173

Table 9: Bank stakeholders' inequality aversion and lending, holding borrower base constant. This table shows estimation results from specifications (2a) and (2b) in the first column and second column, respectively. The dependent variable in the first column is the post-election versus pre-election change in the *unexplained* non-white versus white approval gap for bank b in census tract t around election e. The dependent variable in the second column is the post-election versus pre-election change in the *unexplained* approval rate for bank b in census tract t around election e. Pre-election refers to years -2 and -1, and post-election refers to years 0 (the election year) and $+1$. ΔInequality Aversion$_{be}$ is the deposit-weighted average change in the fraction of votes cast at the county level for the Democratic presidential candidate from election $e-1$ to election e, where the weights are bank b's fractions of deposits in its branch counties in year -3. We exclude bank-tract-elections where the average annual number of applications over years -2 through +1 is fewer than 10, and winsorize the dependent variables at the 2^{nd} and 98^{th} percentiles. Bank control variables are measured the year before the election and are defined in Appendix OA.1. Standard errors are clustered at the bank and tract levels and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

in the *unexplained* approval rate for bank b in census tract t around election e.[24] The *unexplained* approval rates for a type of applicant (non-white, white, high-minority tract, low-minority tract) are the portion of the approval rates not explained by the observable characteristics described in Section 3.1, other than bank inequality aversion.[25]

The variable *Inequality Aversion$_{be}$* is defined as follows. For each election and each county where a bank has deposits in the year -3 relative to the election year, we compute the change in the fraction of votes cast for the Democratic presidential candidate relative to the previous

[24]Pre-election years are defined as years -2 and -1 and post-election years are defined as years 0 (the election year) and $+1$. We restrict our sample to bank–tract–election observations with an average of at least 10 applications per year to avoid distortions from banks with limited lending activity.

[25]The unexplained approval rates are calculated in two steps. In the first step, for any application l, we compute the unexplained probability of approval as the residual of the following regression, run separately for non-white and white applicants, and for applicants from high-minority and low-minority census tracts:

$$\text{Approved}_l = \alpha + \delta \mathbf{X}_{by-1} + \gamma \mathbf{Z}_l + \nu_{ty} + \eta_b + \epsilon_l,$$

where $\mathbf{Z}_l$ is a vector of borrower and loan characteristics and $\mathbf{X}_{by-1}$ is a vector of bank characteristics (we exclude the *Non-White$_l$* dummy for regressions focusing on non-white or white applicants). In the second step, the unexplained approval rate for a particular type of applicant at a bank over a period of time is simply the average residual for that bank and that type of applicant during that period.

election. We then use the bank's county-level deposit fractions in year -3 as weights to compute the independent variable $\Delta \textit{Inequality Aversion}_{be}$, which is the deposit-weighted average of these changes. The coefficient β in specifications (2a) and (2b) thus captures how these changes affect the approval gaps. Finally, $\mathbf{X}_{be}$ are bank b's characteristics measured one year before election e. As in previous analyses, tract-election fixed effects allow us to compare changes in approval gaps for borrowers within the same census tract around the same election between banks whose existing stakeholders lean more Democratic and banks whose existing stakeholders lean more Republican.

Table 9 shows the estimation results. The first column presents the results of estimating specification (2a). The second column presents the results of estimating specification (2b). The table shows that the estimated coefficient of interest, β, is positive and statistically significant, confirming our main results that banks with more inequality-averse stakeholders increase their approval rate for non-white relative to white borrowers, and for borrowers from high-minority tracts relative to borrowers in low-minority tracts, in a setting where changes in stakeholder political orientation are independent of changes in a bank's borrower base. In terms of economic magnitude, banks with a one-standard-deviation higher value of $\Delta \textit{Inequality Aversion}_{by}$ are associated with (i) a 0.79% greater change in the unexplained non-white versus white approval gap, compared to a mean change in the unexplained non-white versus white approval gap of -0.15%, and (ii) a 3.64% higher unexplained high-minority versus low-minority approval gap, compared to the average change of 0.25%.

5 The stakeholders' discipline channel

We have documented that banks with smaller approval gaps tend to have more inequality-averse stakeholders, and that this correlation is not driven by applicant selection (Section 3). We have also ruled out a few potential explanations for this correlation (Section 4). In this section, we present evidence supporting a "stakeholders' discipline" channel as a mechanism underlying this correlation.

According to the stakeholders' discipline channel, banks take stakeholders' inequality aversion into account when making decisions, including in their lending practices. Hence, banks with more inequality-averse stakeholders are more likely to lend to minorities than banks with less inequality-averse stakeholders. In turn, these inequality-averse banks attract and retain stakeholders (e.g., depositors) who share their values. Given that a sizable share of stakeholders are local, the strength of stakeholders' discipline depends heavily on banks' geographical footprint: banks located in more inequality-averse areas of the country are mechanically exposed to stakeholders who share similar values.

We now provide evidence supporting the stakeholders' discipline channel. Section 5.1 shows that inequality-averse stakeholders respond to a perceived decline in their bank's propensity to lend to minorities by exiting the bank. Section 5.2 shows that banks with more inequality-averse stakeholders actively communicate their relatively stronger commitment to lending to minorities. Section 5.3 shows that a higher propensity to lend to minority borrowers does not lead to a worse ex-post performance.

5.1 Depositors' discipline and lending discrimination

We now show that depositors react to events signaling a deterioration in banks' propensity to lend to minorities. Specifically, we hand collect cases filed against banks by the DOJ for potential breaches of the Equal Credit Opportunity Act, which includes discriminatory pricing, redlining, and discrimination in the loan approval process.[26] Appendix OA.4 shows the details about the 16 cases filed against our sample banks from October 1995 (first case in our sample period) to September 2020 (most recent), which we match with county-level deposit data from the Summary of Deposit dataset.[27] Since the last case is in September

[26]The Equal Credit Opportunity Act *"prohibits creditors from discriminating against credit applicants on the basis of race, color, religion, national origin, sex, marital status, age, because an applicant receives income from a public assistance program, or because an applicant has in good faith exercised any right under the Consumer Credit Protection Act."* These cases are publicly available at `www.justice.gov`.

[27]Given the difference-in-differences nature of this test, we drop two DOJ cases that happen right after another DOJ case for the same bank, namely (i) United States v. Bank of America Home Loans (October 2012, right after a DOJ case in December 2011 for the same bank) and (ii) United States v. Fifth Third Bank (October 2015, right after a DOJ case in August 2014 for the same bank). This filter leaves us with 14 DOJ cases filed against 12 unique banks. The only two banks that have faced repeated DOJ cases are Bank of America (one case in December 2011 and one in September 2020) and Fifth Third Mortgage (one case in May 2004 and one in August 2014). We keep these cases in the sample as they are several years apart.

	$\Delta\text{Deposit}_{bcy}$		
DOJ Case_{by}	-0.024^{**}	-0.011	0.012
	(0.009)	(0.011)	(0.010)
DOJ Case_{by} × High Inequality Aversion_{cy-1}		-0.029^{***}	-0.023^{***}
		(0.008)	(0.007)
<u>Fixed Effects</u>			
County-Year	✓	✓	✓
Bank			✓
Observations	179,701	163,532	163,532
R-squared	0.223	0.226	0.251

Table 10: Bank deposit flows and DOJ Housing and Civil Enforcements. The first column of this table shows the estimation results from specification (3). The dependent variable is the percentage change in deposits from year $y-1$ to year y, winsorized at the 2 percent level (i.e., at the 1st and 99th percentiles). DOJ Case_{by} is an indicator variable (i) equal to one in the June 30-to-June 30 year of the DOJ case and the following two years, and (ii) equal to one in the June 30-to-June 30 year after the DOJ case and the following two years for cases filed in June and May. In the second and third columns, the same specification is estimated with the addition of the interaction variable formed between DOJ Case_{by} and an indicator variable High Inequality Aversion_{cy-1}. High Inequality Aversion_{cy-1} is equal to one if county c has above the median percent of votes to the Democratic candidate in the most recent presidential election by year y, and 0 otherwise. See Appendix OA.1 for variable definitions. See Appendix OA.4 for a list of DOJ cases. Standard errors are double-clustered at the county and year levels and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

2020, we obtain county-bank-level deposits at an annual frequency from 1994 to 2022.

We then estimate the following specification:

$$\Delta\text{Deposit}_{bcy} = \alpha + \beta\text{DOJ Case}_{by} + \nu_{cy} + \eta_b + \epsilon_{bcy} \tag{3}$$

where the unit of observation is bank b, county c, and year y. The dependent variable is the percentage change in deposits from year $y-1$ to year y. The main independent variable DOJ Case_{by} is an indicator variable equal to one in the year of the DOJ case and in the two following years and equal to zero in the two years before the DOJ case.[28] The control group is made up of observations of never-treated bank-county pairs. The specification also includes bank fixed effects and county-year fixed effects to compare deposit flows within the same county-year for banks affected and unaffected by a DOJ case.

Table 10 shows the estimation results. The first column documents that, following a

[28]The deposit data is from the FDIC Summary of Deposits, which provides deposits at the bank-county level as of June 30 every year. Hence, more precisely, the DOJ Case_{by} variable is set (i) equal to one in the June 30-to-June 30 year of the DOJ case and the following two years, and (ii) equal to one in the June 30-to-June 30 year after the DOJ case and the following two years for cases filed in June and May.

DOJ case, banks tend to lose deposits. Specifically, banks' deposit growth declines by about 2.4 percentage points following a DOJ case, compared with a median growth rate of 3.9 percent. The second and third columns show that the reduction in deposits is driven by counties with high inequality aversion, where the High Inequality Aversion$_{cy-1}$ dummy is equal to one for counties with above median inequality aversion (the uninteracted term High Inequality Aversion$_{cy-1}$ is absorbed by the county-year fixed effects).

5.2 Banks' communication of lending practices

The evidence so far suggests that, consistent with the stakeholders' discipline channel, inequality-averse depositors punish banks facing DOJ lawsuits for discriminatory practices. Such "voting-with-their-feet" behavior can constitute a credible threat, thereby aligning bank lending practices with stakeholders' preferences for equality. Because DOJ lawsuits are relatively rare and salient events, we now show that annual shareholder meetings provide an important, more regular channel through which banks *communicate* their lending practices to stakeholders. Specifically, we find that banks with more inequality-averse stakeholders place greater emphasis on initiatives supporting minorities during these meetings.

Annual shareholder meetings typically include an "Agenda & Presentation" section, a business presentation by management, and a Q&A segment in which shareholders can ask questions (Brochet et al., 2024). Although only the agenda and voting are legally required, the presentation and Q&A provide an avenue for banks to frame their strategies and respond to stakeholders. We obtain presentation transcripts for all covered financial companies from LSEG Workspace for the period 2010–2019. We match these transcripts to the banks in our main sample at the year level, resulting in 94 transcripts from 28 unique banks.[29]

We then use a large language model (LLM) to classify the extent to which banks discuss initiatives to support underserved communities. Each transcript is segmented by speaker to reduce the model's input length and ensure that different topics are analyzed separately.

[29]The limited sample size reflects the coverage of LSEG's transcript data.

```
You are an economic analyst specializing in extracting nuanced insights from textual
data. Your task is to determine the extent to which a bank describes initiatives that
support underserved communities in the provided text.

Definitions
    - Underserved communities:
        - Racial or ethnic minorities, and/or
        - Individuals living in high-minority neighborhoods.
    - Initiatives to support underserved communities:
        - Lending targeted to underserved communities,
        - Support for affordable housing programs,
        - Charitable donations or contributions directed toward underserved communities.

You will be given a section of a bank’s presentation to investors where the dialogue is
segmented by speaker. Based only on this text, rate how central initiatives supporting
underserved communities are within the speaker’s remarks using the following scale:
    - 0 = Absent: No discussion.
    - 1 = Peripheral: Brief or passing mention.
    - 2 = Substantive: Sustained attention but not prioritized.
    - 3 = Emphasized: Clearly prioritized.

Return a JSON object that matches the schema.
```

Figure 4: Prompt given to the LLM.

LLMs are particularly well-suited for this task because they can process large volumes of text while preserving context and capturing relationships within the text (Vaswani et al., 2017).[30] Specifically, we use OpenAI's GPT-4.1 model through the Responses API endpoint. We set the temperature to 0 so that the model deterministically selects the most probable next token in its output, which is preferred in a classification task such as ours. To standardize outputs, we use a structured JavaScript Object Notation (JSON) schema that enforces consistent response formatting. Each API request includes the prompt in Figure 4 followed by a speaker section of a presentation.

From the model output, we construct a transcript-level score that measures how prominently a bank discusses initiatives supporting underserved communities. We sum the scores across all speaker sections and divide by the total number of words in the transcript to account for length. Scores are multiplied by 10,000 for readability. Table OA.8 shows summary statistics for the LLM-based measure. There is substantial heterogeneity across

[30]Traditional text analysis techniques such as keyword extraction, word counts, and sentiment analysis struggle to preserve context over long sequences and to capture the complex relationships between words.

	LLM Score$_{by}$	
Inequality Aversion$_{by-1}$	10.204***	10.394***
	(2.989)	(3.111)
Year FE		✓
Observations	94	94
R-squared	0.15	0.22

Table 11: Bank stakeholders' inequality aversion and LLM Score. This table shows estimation results from specification (4). The dependent variable is LLM Score$_{by}$, an LLM-based measure of how prominently bank b discusses initiatives supporting underserved communities in its shareholder meeting in year y. The score is constructed by summing the section-level scores in the transcript, dividing by the transcript's word count, and multiplying by 10,000 for readability. Inequality Aversion$_{by-1}$ is the deposit-weighted average percent of county-level votes cast to the Democratic candidate in the most recent presidential election, where the weights are fractions of the bank's deposits in these counties. Standard errors are reported in parentheses and clustered at the year level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

transcripts: the average score is 2.77, the minimum is 0, and the maximum reaches 12.08 in 2017, indicating that some banks devote meaningful attention to these topics while others do not mention them at all.

To examine whether more inequality-averse banks focus more on initiatives supporting minorities in their presentations to shareholders, we run the following specification:

$$\text{LLM Score}_{by} = \alpha + \beta \text{Inequality Aversion}_{by-1} + \nu_y + \epsilon_{by} \tag{4}$$

where LLM Score$_{by}$ is the LLM-derived measure of emphasis on initiatives supporting underserved communities for bank b in year y.

Table 11 shows the estimation results. Across specifications, the estimated coefficient on inequality aversion is positive and statistically significant. Banks with more inequality-averse stakeholders place greater emphasis on initiatives supporting underserved communities in their annual shareholder meetings. This pattern suggests that (i) stakeholders can observe bank lending practices and (ii) banks with more inequality-averse stakeholders highlight these initiatives to align with stakeholders' preferences.

5.3 No negative effect on loan performance

Having shown that stakeholders' inequality aversion shapes banks' approval gaps, we now explore how these gaps relate to loan performance. The results presented in the previous sections suggest (i) that approval gaps do not seem to be driven by observable differences in borrower characteristics or in borrower bases across banks and (ii) that approval gaps might capture the possibility of banks treating applicants differently based on their minority status.

On the one hand, smaller gaps might reflect a higher propensity to lend to risky minorities (and/or a lower propensity to lend to safe non-minorities), suggesting that the desire for equality could lead to worse loan performance consistent with existing evidence of "goodness being costly" (Hong et al., 2012; Di Giuli and Kotstovetsky, 2014). In this case, more inequality-averse banks are associated with *larger* gaps in ex-post performance between mortgages extended to minorities and non-minority borrowers. On the other hand, smaller gaps might reflect inequality-averse banks alleviating existing discrimination while catering to stakeholders' preferences. In this case, more inequality-averse banks are associated with *smaller* gaps in ex-post performance between mortgages extended to minorities and non-minority borrowers.

To test these hypotheses, we analyze ex-post loan performance by merging cHMDA with ICE, McDash®, a mortgage loan dataset that includes detailed performance metrics.[31] Specifically, we estimate specifications (1a) and (1b) in the subsample of approved mortgages using the following dependent variables aimed at capturing ex-post loan performance: (i) $\textit{Ever Delinquent}_l$, defined as a dummy equal to one if the loan is reported as delinquent, in foreclosure, or in REO (owned by lender) status in any month during the observed life of the loan, (ii) $\textit{Ever Foreclosed}_l$, defined as a dummy equal to one if the loan is reported as being in foreclosure in any month during the observed life of the loan.

Table 12 shows the estimation results. In Panel A, the minority attribute is $\textit{Non-White}_l$. In Panel B, the minority attribute is $\textit{High-Minority Tract}_{ty}$. We find that the gap in ex-post performance between mortgages extended to minorities and non-minorities is unrelated to

[31] Intercontinental Exchange (ICE), McDash® contains servicing data from the largest U.S. residential mortgage servicers with detailed information on loan performance. We merge cHMDA to ICE, McDash® at the loan level using the matching algorithm developed by Rosen (2011) (and later applied in studies such as Fuster et al. (2022) and Frame et al. (2025)), which relies on origination date, loan amount, ZIP code, lien status, and occupancy type. To retain bank characteristics while maintaining confidentiality, we implement an anonymized hashing procedure that links banks to their loans. The final merged dataset includes loans originated from 1995 to 2019 and includes ex-post outcomes such as delinquency, foreclosure, and REO (owned by lender) status.

Panel A	Ever Delinquent$_l$		Ever Foreclosed$_l$	
Inequality Aversion$_{by-1}$ × Non-White$_l$	−0.064*	−0.046	−0.073**	−0.059*
	(0.038)	(0.034)	(0.034)	(0.033)
Inequality Aversion$_{by-1}$	0.073**	−0.101***	−0.001	−0.142***
	(0.037)	(0.039)	(0.033)	(0.018)
Observations	18,535,643	18,535,626	18,535,643	18,535,626
R-squared	0.187	0.190	0.183	0.185
Fixed Effects				
Tract-Year-Race	✓	✓	✓	✓
Bank		✓		✓

Panel B	Ever Delinquent$_l$		Ever Foreclosed$_l$	
Inequality Aversion$_{by-1}$ × High-Minority Tract$_{ty}$	−0.046	−0.038	−0.100	−0.082
	(0.081)	(0.077)	(0.068)	(0.063)
Inequality Aversion$_{by-1}$	0.068*	−0.108***	−0.005	−0.146***
	(0.038)	(0.041)	(0.034)	(0.019)
Observations	18,772,854	18,772,836	18,772,854	18,772,836
R-squared	0.167	0.170	0.162	0.164
Fixed Effects				
Tract-Year	✓	✓	✓	✓
Bank		✓		✓

Control Variables				
Loan and Borrower Characteristics ($\mathbf{Z}_l$)	✓	✓	✓	✓
Bank Characteristics ($\mathbf{X}_{by-1}$)	✓	✓	✓	✓
Executives' Characteristics ($\mathbf{X}_{by-1}$)	✓	✓	✓	✓

Table 12: Bank stakeholders' inequality aversion and lending. This table shows estimation results from specifications (1a) and (1b), where the dependent variables are Ever Delinquent$_l$ in columns (1)-(2), an indicator variable equal to one if loan l is reported as delinquent, in foreclosure, or in REO status in any month during the observed life of the loan, and Ever Foreclosed$_l$ in columns (3)-(4), an indicator variable equal to one if loan l is reported as being in foreclosure in any month during the oberved life of the loan. Inequality Aversion$_{by-1}$ is the deposit-weighted average percent of county-level votes cast to the Democratic candidate in the most recent presidential election, where the weights are fractions of the bank's deposits in these counties. The minority attribute is Non-White$_l$ (indicator variable equal to one if the applicant is non-white according to HMDA classification) in Panel A and High-Minority Tract$_{ty}$ (indicator variable equal to one if the property associated with the application is based in a census tract where 75% or more of the population is minority, according to Census Bureau's classification) in Panel B. The loan and borrower characteristics are an indicator variable equal to one for a non-white applicant (the uninteracted variable is omitted from specification (1a)), an indicator variable equal to one for a female applicant, natural log of applicant income expressed in thousands of 2012 dollars, LTI Ratio (loan amount divided by borrower income), an indicator variable equal to one for jumbo loans, an indicator variable equal to one for refinancing loans, and an indicator variable equal to one for loans taken out for home improvements. The (lagged) bank characteristics are the natural log of banks' total assets (in million dollars as of 2012), deposits-to-assets ratio, interest on deposits divided by total assets, liquid assets divided by total assets, tier 1 capital divided by total assets, C&I loans divided by total assets, loans secured by real estate divided by total assets, net income divided by total assets, unused commitments divided by total assets, letters of credit divided by total assets, and nonperforming loans divided by total loans. Executives' characteristics are the number of years the CEO has been acting as CEO of the bank, CEO age, the number of independent directors, the number of directors, and an indicator variable equal to one for a female CEO. See Appendix OA.1 for variable definitions. The sample comprises only approved mortgages and is derived from the intersection of the ICE, McDash® and HMDA datasets. The sample runs annually from 1995 to 2019 for regressions without executive and board control variables and from 1999 to 2019 for regressions with executive and board control variables. Standard errors are double clustered at the bank and tract levels and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

whether a more or less inequality-averse bank originates such loans. If anything, the gap in ex-post performance between mortgages extended to *non-white* and *white* applicants is smaller for more inequality-averse banks. In sum, our results suggest that smaller approval gaps by more inequality-averse banks are unlikely to result from these banks lending to "non-deserving" minority borrowers. The magnitudes are economically meaningful. Using column (1), a one-standard-deviation increase in inequality aversion reduces the delinquency gap between nonwhite and white borrowers by 1.24%, about 18% of the unconditional gap of 7.02%. Using column (3), the same increase reduces the foreclosure gap by 1.42%, about 46% of the unconditional gap of 3.1%. Appendix OA.5 shows consistent results analyzing banks' overall real estate portfolio.

6 Conclusion

Our analysis documents substantial and persistent cross-sectional variation in banks' propensity to lend to minorities. Banks' approval gaps, defined as the difference in approval rates between mortgage applications from minorities and non-minorities, vary substantially across banks, even within the same geographical areas. Banks with more inequality-averse stakeholders have smaller approval gaps compared to banks with less inequality-averse stakeholders. Applicants' selection does not explain this correlation, which is instead consistent with a stakeholders' discipline channel. According to this channel, banks take stakeholders' aversion to inequality into account in their lending decisions to attract and retain their stakeholders, such as depositors and shareholders. Finally, we show that a higher propensity to lend to minorities does not lead to worse ex-post performance, suggesting that the stakeholders' discipline channel may drive banks' specialization and/or alleviate lending discrimination.

Our paper opens up several avenues for future research. Our measure of inequality aversion reflects the preferences of local stakeholders, but this group encompasses heterogeneous actors, including lenders, executives, and employees. Identifying which stakeholders play the most important role in disciplining banks and through which channels is a key direction for future work. Our analysis also suggests that credit access for minorities may vary across geographic areas, depending on the composition of local banks. Understanding this mechanism and its equilibrium implications represents another promising avenue for future research.

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Online Appendix

This appendix is structured as follows. Appendix OA.1 presents the variable definitions. Appendix OA.2 presents additional figures. Appendix OA.3 presents additional tables. Appendix OA.4 presents the list of cases by the DOJ against our sample banks for potential breaches of the Equal Credit Opportunity Act. Appendix OA.5 presents an analysis of how approval gaps relate to bank performance.

OA.1 Variable definition

This section presents the definitions of the main variables used in our empirical analysis. As per the subscripts, l is a loan application, b is a bank, t is a census tract, and y is a year.

Variables proxying for minority applicants' characteristics

- **Non-White**$_l$. Dummy variable equal to one if the applicant's race code is 1 (American Indian or Alaska Native), 2 (Asian), 3 (Black or African American), or 4 (Native Hawaiian or other Pacific Islander) according to HMDA classification; and 0 if the borrower's race code is 5 (White). *Source:* HMDA.

- **High-Minority Tract**$_{ty}$. Dummy variable equal to one if the property associated with the application is in a census tract where 75% or more of the population is minority, according Census Bureau's classification. The minority population is defined as (i) the total Hispanic population and (ii) the non-Hispanic population minus the non-Hispanic white alone population. The data variables used to categorize census tracts as high-minority are from the Census Bureau. *Sources:* HMDA, Census Bureau.

Inequality aversion variables

- **Inequality Aversion**$_{by}$. Calculated at the bank-year level, this variable is the weighted average percentage of votes cast for the Democratic candidate in the most recent presidential election in counties where the bank has deposits. The weights are fractions of the deposits the bank has in those counties. *Sources:* FDIC Summary of Deposits, MIT Election Data and Science Lab, Dave Leip's Atlas of U.S. Presidential Elections.

- **Racial Inequality Aversion**$_{by}$. This variable is constructed using a GSS survey question that asks whether *"we're spending too much money, too little money, or about the right amount of money on assistance to Black individuals."* Survey respondents can choose one of these three options, which are coded with the values 3, 1, and 2, respectively. We observe each response and the "region" of the survey respondent, where the U.S. is partitioned into nine regions: (i) New England, (ii) Rhode Island Middle Atlantic, (iii) Pennsylvania East North Central, (iv) Michigan, Ohio West North Central, (v) Kansas South Atlantic, (vi) District of Columbia East South Central, (vii) Mississippi West South Central, (viii) Louisiana, Texas Mountain, and (ix) New Mexico Pacific. For each survey year, we select responses from white individuals, multiply the values by -1 so that higher values indicate greater racial inequality aversion, and use the average value for each region as that region's racial inequality aversion. We then calculate the deposit-weighted average of racial inequality aversion for each bank using the fraction of deposits the bank has in each region as weights. Our Racial Inequality Aversion$_{by}$ variable is an indicator variable that takes a value of one if the weighted average exceeds the median, calculated each year across the cross-section of banks. *Sources:* FDIC Summary of Deposits, the General Social Survey.

Loan and borrower characteristics. *Source:* HMDA

- **Female**$_l$. Dummy variable equal to one if the borrower is female, and 0 otherwise.

- **LTI**$_l$. Loan amount divided by applicant income.

- **Log of Applicant Income**$_l$. The natural log of (the gross of) annual applicant income, relied on in making the credit decision or in processing the application. Annual applicant income is expressed in 2012 thousand dollars.

- **Jumbo**$_l$. Dummy variable equal to one if the loan amount exceeds the conforming loan limits. We use the Federal Housing Finance Agency (FHFA)'s conforming loan limits for one-unit properties. Prior to 2019, we apply nation-wide loan limits which were $187,450 in 1990 and increasing to $417,500 in 2006–2008. This algorithm follows Bayer et al. (2018).

- **Refinancing**$_l$. Dummy variable equal to one if the loan is a refinancing.

- **Home Improvement**$_l$. Dummy variable equal to one if the loan is for loan improvement purposes.

- **Officer**$_l$. Identifier for the mortgage loan originator responsible for the loan, based on the Nationwide Multistate Licensing System (NMLS) unique originator ID. The variable is only available in the confidential version of HMDA from 2018.

Bank Characteristics. *Sources:* FR Y-9C reports, CALL reports

- **Log Assets**$_{by}$: The natural log of the bank's total assets. Bank assets are in millions of 2012 dollars.

- **Deposits/Assets**$_{by}$. Total deposits divided by total assets.

- **Cost of Deposits**$_{by}$. Interest on deposits divided by total deposits.

- **Liquid Assets/Assets**$_{by}$. Liquid assets divided by total assets. Liquid Assets is the sum of cash, Federal funds sold and securities excluding MBS/ABS securities.

- **Tier 1 Capital/Assets**$_{by}$. Tier 1 capital divided by total assets.

- **C&I Loans/Assets**$_{by}$. Consumer and industrial (C&I) loans, divided by total assets.

- **Mortgage Loans/Assets**$_{by}$. Total loans secured by real estate divided by total assets.

- **Net Income/Assets**$_{by}$. Net income divided by total assets.

- **Unused Commitments/Assets**$_{by}$. Total unused commitments divided by total assets.

- **Letters of Credit/Assets**$_{by}$. Letters of credit divided by total assets. Letters of credit are the sum of financial standby letters of credit and foreign office guarantees, performance standby letters of credit, and commercial and similar letters of credit.

- **Nonperforming Loans/Loans**$_{by}$. Total loans and lease financing receivables that are past due 90 days or more and still accruing, plus total loans and lease financing that are non-accrual, divided by total loans.

- **DOJ Case**$_{by}$. A dummy equal to one in the year of the DOJ case and in the two following years, and equal to 0 in the two years before the DOJ case. *Source:* U.S. Department of Justice.

Bank executives' characteristics

- **CEO Experience**$_{by}$. The number of years the CEO has been acting as CEO of the bank. If there are more than one CEO, this is the average across the CEOs. *Source:* Execucomp.

- **CEO Age**$_{by}$. The age of the CEO. If there are more than one CEO, this is the average across the CEOs. *Source:* Execucomp.

- **Number of Independent Directors**$_{by}$. The number of independent directors on the board. *Source:* Execucomp.

- **Number of Directors**$_{by}$. The number of directors on the board. *Source:* Execucomp.

- **Female CEO**$_{by}$. This variable is an indicator variable equal to one if the bank's CEO is female, and 0 otherwise. If there is more than one CEO, this variable equals one if at least one CEO is female. *Source:* Execucomp.

- **CEO Ineq Aversion**$_{by}$. The political orientation of the bank CEO for a particular bank-year. This variable is calculated as the CEO's campaign contributions to Democrats, divided by her total campaign contributions between 1979 and 2018. If a CEO makes no political contributions, the measure is set to 0.5. If a bank has more than one CEO, this variable is the average political orientation across the bank's CEOs. If no contribution is found, the measure is set to 0.5. If there are multiple executives for a particular title, we take the average across them. *Sources:* Execucomp, Federal Election Commission.

- **IndepDir Ineq Aversion**$_{by}$**.** The average political orientation of the bank's independent directors for a particular bank-year. Political orientation for each independent director is measured in the same way as that used for the CEO. *Sources:* Execucomp, Federal Election Commission.

Dependent Variables.

- **Approved**$_{l}$. Dummy variable equal to one if the loan is approved, and 0 otherwise. *Source:* HMDA.

- **Income**$_{l}$. The (the gross of) annual applicant income, relied on in making the credit decision or in processing the application. Annual applicant income is expressed in 2012 thousand dollars. *Source:* HMDA.

- **Credit Score**$_{l}$. The credit score relied on in making the credit decision. Lenders usually use FICO scores, but they may also use other scores such as Vantage and Equifax. The variable is only available in the confidential version of HMDA from 2018. *Source:* HMDA.

- **DTI**$_{l}$. The ratio of the applicant's total monthly debt to total monthly income used by the bank in making the credit decision. The variable is only available in the confidential version of HMDA from 2018.

- Δ**Approval Gap**$_{bte}^{\textbf{\textit{Non-White}}}$. The change around a presidential election in the unexplained approval rate difference between non-white and white applicants for a given bank and census tract.

- Δ**Approval Rate**$_{bte}$. The change around a presidential election in the unexplained loan approval rate for a given bank and census tract.

- Δ**Deposit**$_{bcy}$. The percentage change in deposits for a bank around a DOJ case.

- **LLM Score**$_{by}$. The LLM-derived score measures how predominantly the bank discusses initiatives supporting underserved communities in that year's shareholder meeting. *Source:* LSEG Workspace.

- **Ever Delinquent**$_l$. Dummy variable equal to one if the loan is reported as delinquent, in foreclosure, or in REO status in any month during the observed life of the loan, and 0 otherwise. *Source:* ICE, McDash®.

- **Ever Foreclosed**$_l$. Dummy variable equal to one if the loan is reported as being in foreclosure in any month during the observed life of the loan, and 0 otherwise. *Source:* ICE, McDash®.

OA.2 Additional figures

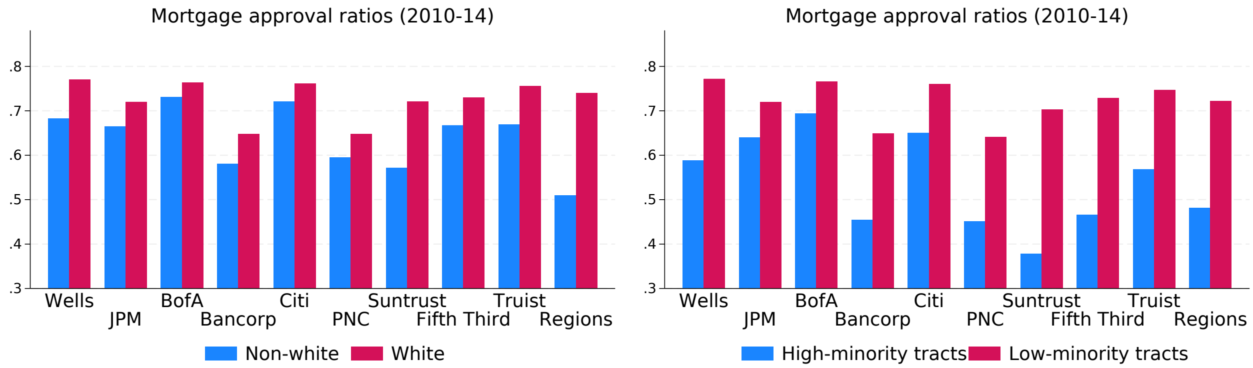

Figure OA.1: Approval rates across top-10 banks, 2010–2014. This figure shows mortgage approval rates for the top-10 banks by number of applications received in the period from 2010–2014. Banks are ranked on the x-axis based on the number of applications received. The blue bars indicate approval rates for non-white applicants (left panel) and applicants in high-minority tracts (right panel). The red bars indicate approval rates for white applicants (left panel) and applicants in low-minority tracts (right panel).

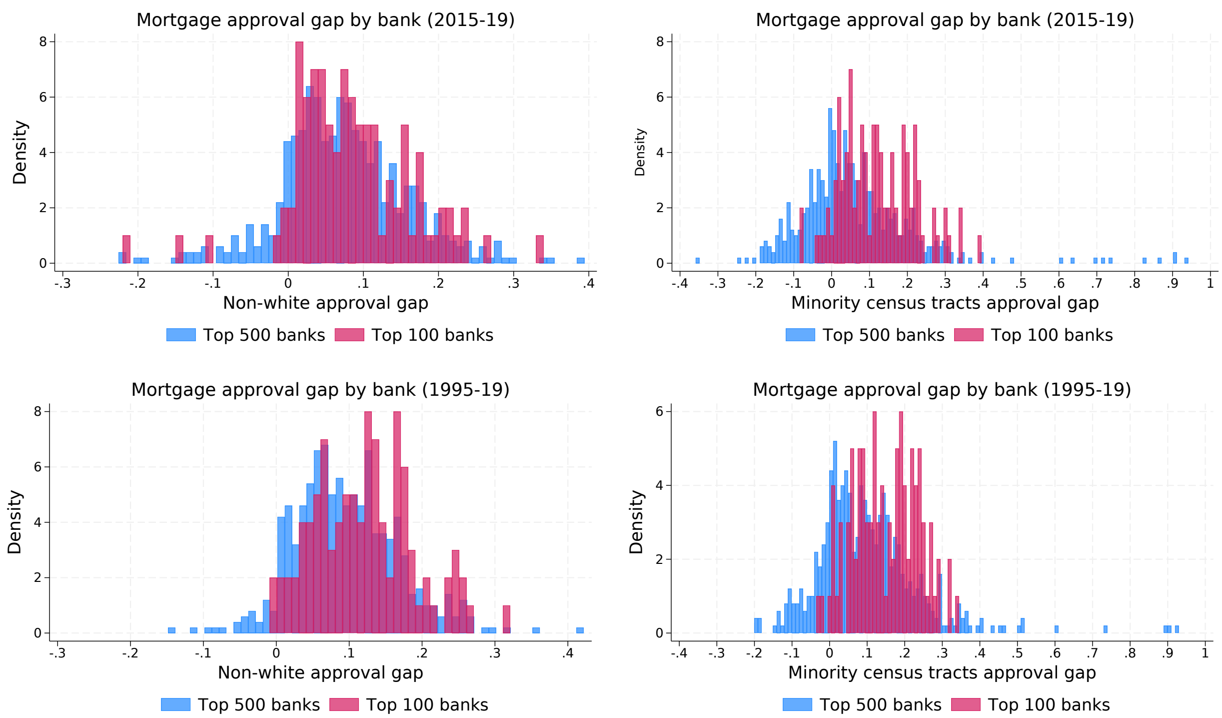

Figure OA.2: Distribution of approval gaps across banks. This figure shows the distribution of approval gaps across the top-100 banks (red bars) and top-500 banks (blue bars) by number of mortgage applications received. The top panel shows the distributions for the period 2015–2019. The bottom panel shows the distributions for the full period (1995–2019). The figures on the left show the distribution of approval gaps between non-white and white applicants. The figures on the right show the distribution of approval gaps between applicants in high-minority and low-minority tracts.

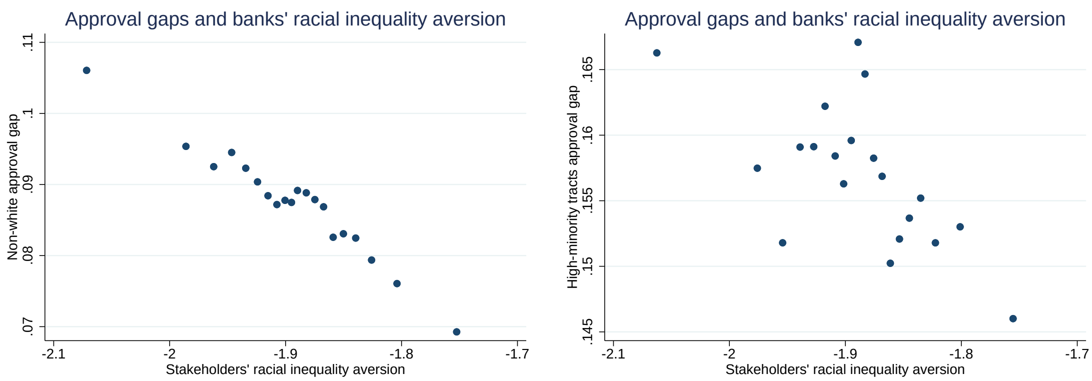

Figure OA.3: Approval gaps and bank stakeholders' aversion to racial inequality from survey data. This figure shows binscatter plots of approval gaps (y-axis) and measures of bank stakeholders' aversion to inequality (x-axis), controlling for tract-year fixed effects. The left panel focuses on approval gaps for non-white versus white borrowers. The right panel focuses on approval gaps between applicants in high-minority and low-minority tracts. The measure of racial inequality aversion is defined as the weighted average racial inequality aversion in GSS survey regions where the bank has deposits. The weights are fractions of the bank's deposits in these survey regions, and each region's racial inequality aversion is minus one times the average value of the GSS variable *natrace*. Variable *natrace* records responses to the GSS survey question *"Are we spending too much money, too little money, or about the right amount of money on assistance to Black individuals?"*, with possible responses "Too much" (3), "Too little" (1), and "About the right amount" (2).

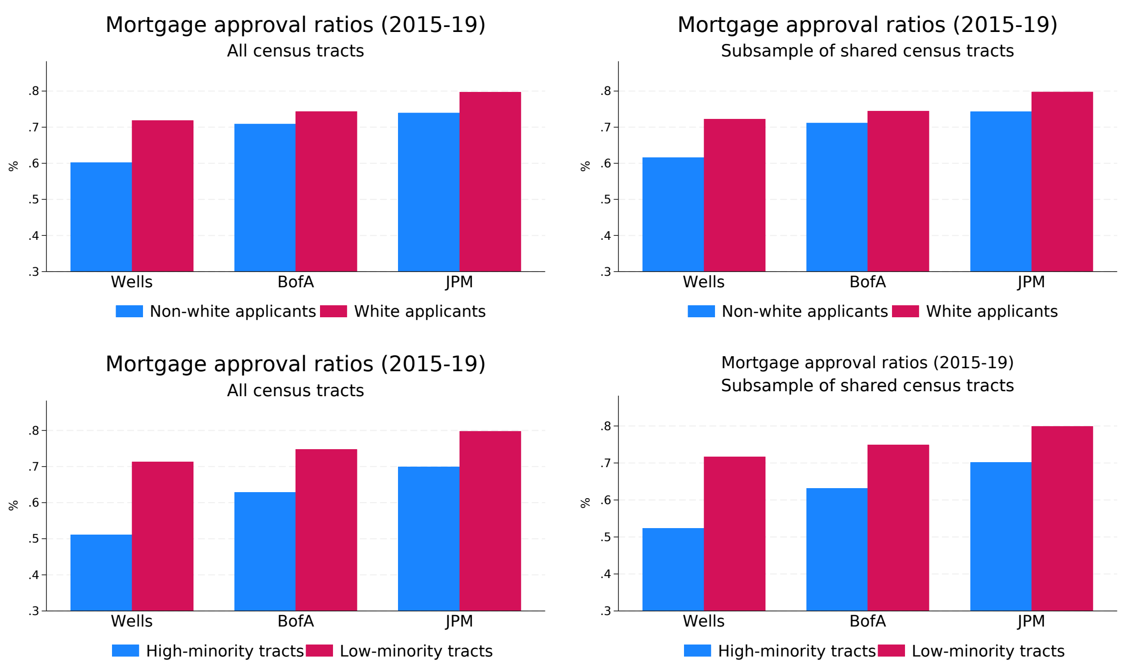

Figure OA.4: Approval rates across top-3 banks, 2015–2019, shared census tracts. This figure shows mortgage approval rates for the top-3 banks by number of applications received in the period from 2015 to 2019. The top figures show approval rates for non-white (blue bars) versus white applicants (red bars). The bottom figures show approval rates for applicants in high-minority tracts (blue bars) and low-minority tracts (red bars). The left figures show approval rates in the full sample of census tracts. The right figures show approval rates for the subsample of census tracts with at least one application per bank each year from 2015 to 2019. Banks are ranked on the x-axis based on the number of applications received.

Figure OA.5: Approval gaps and income gaps. This figure shows the correlation between the mortgage approval gaps and income gaps (defined as the difference in mean income between non-minority and minority borrowers in 2012 dollars) for all banks that receive mortgage applications in at least 500 census tracts during the entire sample period (143 unique banks). Given that there are no census tracts in which all 143 of these banks received an application, we narrow the criterion of shared census tracts to those in which 70% (or 100) of the 143 banks received an application. The top figures show the correlation between the income gap and the approval gap for non-white versus white applicants. The bottom figures show the correlation between the income gap and the approval gap for applicants in high-minority versus low-minority tracts. The left figures show the correlation in the full sample of census tracts. The right figures show the correlation in the sub-sample of census tracts in which at least 70% of the 143 banks received an application between 1995 to 2019. The figure covers 822 shared tracts in the analysis of non-white versus white applicants and 898 shared tracts in the analysis of high-minority versus low-minority tracts.

OA.3 Additional tables

	Less inequality-averse banks	More inequality-averse banks	Mean test
Panel A. Application-level variables			
Non-White	0.11	0.18	***
High-Minority Tract	0.04	0.08	***
Approved	0.81	0.73	***
Applicant Income	99.70	112.27	***
Credit Score	741.82	747.24	***
DTI	36.33	40.88	***
LTI Ratio	1.64	2.01	***
Jumbo	0.04	0.07	***
Refinancing	0.47	0.59	***
Home Improvement	0.18	0.13	***
Panel B. Bank-year-level variables			
Inequality Aversion	0.40	0.57	***
Racial Inequality Aversion	−1.90	−1.85	***
CEO Experience	6.28	5.80	
CEO Age	56.74	57.45	
Number of Independent Directors	7.28	7.28	
Number of Directors	10.89	10.91	
Female CEO	0.02	0.05	***
Assets	2742.00	22669.00	***
Log Assets	6.73	7.25	***
Deposits/Assets	0.81	0.78	***
Cost of Deposits	0.02	0.02	
Liquid Assets/Assets	0.24	0.24	
Tier 1 Capital/Assets	0.09	0.10	
C&I loans/Assets	0.10	0.11	**
Mortgage Loans/Assets	0.52	0.51	
Net Income/Assets	0.01	0.01	
Unused Commitments/Assets	0.15	0.19	*
Letters of Credit/Assets	0.01	0.01	***
Nonperforming Loans/Loans	0.01	0.01	
CEO Ineq Aversion	0.33	0.43	***
IndepDir Ineq Aversion	0.43	0.49	***

Table OA.1: Summary statistics, by more inequality-averse and less inequality-averse banks. This table shows sample means for the subsamples of more inequality-averse and less inequality-averse banks, defined based on whether they have an above (below) median Inequality Aversion, where medians are calculated each year in the cross-section of banks. Panel A shows summary statistics for our application-level variables. Panel B shows summary statistics for our bank-year-level variables. Non-White is an indicator variable equal to one if the applicant is not white. High-Minority Tract is an indicator variable equal to one if the property associated with the mortgage application is in a high-minority census tract. Inequality Aversion is the deposit-weighted average percentage of votes cast for the Democratic candidate in the most recent presidential election, with weights equal to the percentage of the bank's deposits in counties where the bank has branches. Racial Inequality Aversion is the deposit-weighted average value of GSS survey regions' racial inequality aversion, where each survey region's racial inequality aversion is the average of minus one times the values of GSS variable *natrace* in that particular region. The weights are the percentage of the bank's deposits in the nine regions where the GSS survey is conducted. See Appendix OA.1 for the definition of other variables.

Panel A.	**Non-White**	**White**	**Non-White**	**White**
Application-level variables	More inequality-averse banks		Less inequality-averse banks	
High-Minority Tract	0.26	0.04	0.20	0.01
Approved	0.65	0.76	0.65	0.84
Applicant Income	97.56	114.41	79.62	101.07
Credit Score	715.43	744.37	736.11	749.91
DTI	41.02	35.81	44.39	40.01
LTI Ratio	2.17	2.01	1.54	1.67
Jumbo	0.07	0.07	0.03	0.04
Refinancing	0.54	0.59	0.38	0.48
Home Improvement	0.15	0.12	0.26	0.16

Panel B.	**High-Min. Tract**	**Low-Min. Tract**	**High-Min. Tract**	**Low-Min. Tract**
Application-level variables	More inequality-averse banks		Less inequality-averse banks	
Non-White	0.61	0.15	0.64	0.09
Approved	0.58	0.74	0.60	0.82
Applicant Income	81.32	115.01	72.90	100.76
Credit Score	713.71	743.00	724.29	749.65
DTI	41.04	36.15	46.86	40.26
LTI Ratio	2.22	1.99	1.39	1.65
Jumbo	0.05	0.07	0.02	0.04
Refinancing	0.58	0.59	0.40	0.47
Home Improvement	0.20	0.12	0.32	0.17

Table OA.2: Summary statistics, minority versus non-minority groups, by bank inequality aversion. This table shows sample means of application-level variables for the subsamples of white versus non-white applicants (Panel A) and applicants in high-minority tracts versus applicants in low-minority tracts (Panel B). Each panel further compares the subsamples of more inequality-averse and less inequality-averse banks, defined based on whether they have an above (below) median Inequality Aversion, where medians are calculated each year in the cross-section of banks. Non-White is an indicator variable equal to one if the applicant is not white. High-Minority Tract is an indicator variable equal to one if the property associated with the mortgage application is in a high-minority census tract. Approved is an indicator variable equal to one if the application is approved. Applicant income is the income of the applicant expressed in 2012 dollars. Credit Score is the applicant's credit score used by the bank to make credit decisions. DTI is the ratio of the applicant's total monthly debt to total monthly income used by the bank in making the credit decision. Credit scores and DTI are only available from 2018. LTI is the loan-to-income ratio, defined as the loan amount divided by borrower income. *Jumbo* is an indicator variable equal to one if the loan amount exceeds the limit set by the Federal Housing Finance Agency. *Refinancing* is an indicator variable equal to one if the loan purpose is refinancing. and *Home Improvement* is an indicator variable equal to one if the loan is for home improvement purposes. Variable definitions are available in Appendix OA.1. The last column shows significance for a mean difference test, where ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A	Approved$_l$			
Inequality Aversion$_{by-1}$ × Non-White$_l$	0.165**	0.163**	0.155***	0.158***
	(0.067)	(0.070)	(0.041)	(0.043)
Inequality Aversion$_{by-1}$	−0.721***	−0.563***	−0.253***	−0.174*
	(0.205)	(0.135)	(0.089)	(0.098)
Observations	92,041,476	89,618,745	67,283,058	67,283,056
R-squared	0.122	0.135	0.101	0.108
Fixed Effects				
County-Year-Race	✓	✓	✓	✓
Bank				✓

Panel B	Approved$_l$			
Inequality Aversion$_{by-1}$ × High-Minority Tract$_{ty}$	0.229***	0.237***	0.250***	0.228***
	(0.068)	(0.060)	(0.044)	(0.046)
Inequality Aversion$_{by-1}$	−0.702***	−0.544***	−0.236***	−0.156*
	(0.205)	(0.131)	(0.089)	(0.093)
High-Minority Tract$_{ty}$	−0.186***	−0.193***	−0.208***	−0.198***
	(0.042)	(0.033)	(0.024)	(0.026)
Observations	91,770,425	89,397,703	67,182,335	67,182,333
R-squared	0.121	0.134	0.101	0.108
Fixed Effects				
County-Year	✓	✓	✓	✓
Bank				✓

Control Variables for Panel A and Panel B				
Loan and Borrower Characteristics ($\mathbf{Z}_l$)	✓	✓	✓	✓
Bank Characteristics ($\mathbf{X}_{by-1}$)		✓	✓	✓
Executives Characteristics ($\mathbf{X}_{by-1}$)			✓	✓

Table OA.3: Bank stakeholders' inequality aversion and lending, County-Year-Race and County-Year fixed effects. This table shows estimation results from specifications (1a) and (1b), with County-Year-Race and County-Year fixed effects instead of Tract-Year-Race and Tract-Year fixed effects, respectively. The dependent variable is Approved$_l$, an indicator variable equal to one if application l is approved and equal to zero if the application is denied. The minority attribute is Non-White$_l$ (indicator variable equal to one if the applicant is non-white according to HMDA classification) in Panel A and High-Minority Tract$_{ty}$ (indicator variable equal to one if application l is for a property based in a census tract where 75% or more of the population is minority, according to Census Bureau's classification) in Panel B. The loan and borrower characteristics are an indicator variable equal to one for a non-white applicant (omitted in specifications including County-Year-Race fixed effects), an indicator variable equal to one for a female applicant, applicant income expressed in thousands of 2012 dollars, loan-to-income ratio (loan amount divided by borrower income), an indicator variable equal to one for a jumbo loan, an indicator variable equal to one for refinancing loans, and an indicator variable equal to one for loans taken out for home improvements. The (lagged) bank characteristics are the natural log of banks' total assets (in million dollars as of 2012), deposits-to-assets ratio, interest on deposits divided by total assets, liquid assets divided by total assets, tier 1 capital divided by total assets, C&I loans divided by total assets, loans secured by real estate divided by total assets, net income divided by total assets, unused commitments divided by total assets, letters of credit divided by total assets, and nonperforming loans divided by total loans. The executives' characteristics are the number of years the CEO has served as CEO of the bank, the CEO's age, the number of independent directors, the number of directors, and an indicator variable equal to one for a female CEO. The sample runs annually from 1999 to 2019. See Appendix OA.1 for variable definitions. Standard errors are double clustered at the bank and tract levels and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Approved$_l$			
Inequality Aversion$_{by-1}$ × Non-White$_l$	0.143**	0.136*	0.090*	0.096**
	(0.065)	(0.071)	(0.048)	(0.047)
Inequality Aversion$_{by-1}$	−0.734***	−0.602***	−0.293***	−0.171**
	(0.221)	(0.138)	(0.081)	(0.086)
Inequality Aversion$_{by-1}$ × High-Minority Tract$_{ty}$	0.145**	0.154***	0.183***	0.158***
	(0.065)	(0.029)	(0.028)	(0.023)
Observations	91,499,920	89,120,059	66,950,033	66,950,031
R-squared	0.176	0.187	0.156	0.161

Fixed Effects				
Tract-Year-Race	✓	✓	✓	✓
Bank				✓
Control Variables				
Loan and Borrower Characteristics ($\mathbf{Z}_l$)	✓	✓	✓	✓
Bank Characteristics ($\mathbf{X}_{by-1}$)		✓	✓	✓
Executives Characteristics ($\mathbf{X}_{by-1}$)			✓	✓

Table OA.4: Bank stakeholders' inequality aversion and lending - Simultaneous inclusion of both minority attributes. This table shows estimation results from a version of specification (1a) that relates bank inequality aversion to both the Non-White vs. White and High-minority vs. Low-minority approval gaps. The dependent variable is Approved$_l$, an indicator variable equal to one if application l is approved and equal to zero if the application is denied. Non-White$_l$ is an indicator variable equal to one if the applicant is non-white according to HMDA classification, and High-Minority Tract$_{ty}$ is an indicator variable equal to one if application l is based in a census tract where 75% or more of the population is minority, according to the Census Bureau's classification. The loan and borrower characteristics are an indicator variable equal to one for a non-white applicant (the non-interacted term is omitted as the tract-year-race fixed effects subsume it), an indicator variable equal to one for a female applicant, applicant income expressed in thousands of 2012 dollars, loan-to-income ratio (loan amount divided by borrower income), an indicator variable equal to one for a jumbo loan, an indicator variable equal to one for refinancing loans, and an indicator variable equal to one for loans taken out for home improvements. The (lagged) bank characteristics are the natural log of banks' total assets (in million dollars as of 2012), deposits-to-assets ratio, interest on deposits divided by total assets, liquid assets divided by total assets, tier 1 capital divided by total assets, C&I loans divided by total assets, loans secured by real estate divided by total assets, net income divided by total assets, unused commitments divided by total assets, letters of credit divided by total assets, and nonperforming loans divided by total loans. Executives' characteristics include the number of years the CEO has been acting as CEO of the bank, CEO age, the number of independent directors, the number of directors, and an indicator variable equal to one for a female CEO. The sample runs annually from 1999 to 2019. See Appendix OA.1 for variable definitions. Standard errors are double clustered at the bank and census tract levels and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Approved$_l$			
Inequality Aversion$_{by-1}$ × Non-White$_l$	0.099**	0.097**		
	(0.045)	(0.041)		
Branch Share$_{bcy-1}$ × Non-White$_l$	−0.126***	−0.141***		
	(0.032)	(0.032)		
Inequality Aversion$_{by-1}$ × High-Minority Tract$_{ty}$			0.191***	0.168***
			(0.035)	(0.030)
Branch share$_{bcy-1}$ × High-Minority Tract$_{ty}$			−0.133***	−0.149***
			(0.039)	(0.041)
Inequality Aversion$_{by-1}$	−0.265***	−0.154*	−0.263***	−0.149*
	(0.082)	(0.086)	(0.082)	(0.081)
Branch Share$_{bcy-1}$	0.112***	0.091	0.103***	0.081***
	(0.018)	(0.019)	(0.019)	(0.019)
Observations	67,037,894	67,037,892	67,151,560	67,151,558
R-squared	0.156	0.162	0.142	0.148

Fixed Effects				
Tract-Year-Race	✓	✓		
Tract-Year			✓	✓
Bank		✓		✓
Control Variables				
Loan and Borrower Characteristics ($\mathbf{Z}_l$)	✓	✓	✓	✓
Bank Characteristics ($\mathbf{X}_{by-1}$)	✓	✓	✓	✓
Executives' Characteristics ($\mathbf{X}_{by-1}$)	✓	✓	✓	✓

Table OA.5: Bank stakeholders' inequality aversion and lending: Controlling for lender-borrower proximity. This table shows estimation results from specifications (1a) and (1b), controlling for effects of lender-borrower proximity. For each bank b and in each applicant county c, lender-borrower proximity (Branch Share$_{bcy}$) for year y is the number of bank b's branches divided by the total number of branches for all banks in the county. The dependent variable is Approved$_l$, an indicator variable equal to one if application l is approved and equal to zero if the application is denied. Inequality Aversion$_{by}$ is the deposit-weighted average county-level percent of votes cast to the Democratic candidate in the most recent presidential election, where the weights are fractions of the bank's deposits in these counties. Non-White$_l$ is an indicator variable equal to one if the applicant is non-white according to HMDA classification. High-Minority Tract$_{ty}$ is an indicator variable equal to one if the property associated with the application is based in a census tract where 75% or more of the population is minority, according to the Census Bureau's classification. The loan and borrower characteristics include an indicator variable equal to one for a non-white applicant (the uninteracted variable is omitted from specification (1a)), an indicator variable equal to one for a female applicant, the natural log of applicant income expressed in thousands of 2012 dollars, LTI Ratio (loan amount divided by borrower income), an indicator variable equal to one for jumbo loans, an indicator variable equal to one for refinancing loans, and an indicator variable equal to one for loans taken out for home improvements. The (lagged) bank characteristics are the natural log of banks' total assets (in million dollars as of 2012), deposits-to-assets ratio, interest on deposits divided by total assets, liquid assets divided by total assets, tier 1 capital divided by total assets, C&I loans divided by total assets, loans secured by real estate divided by total assets, net income divided by total assets, unused commitments divided by total assets, letters of credit divided by total assets, and nonperforming loans divided by total loans. Executives' characteristics are the number of years the CEO has been acting as CEO of the bank, the CEO's age, the number of independent directors, the number of directors, and an indicator variable equal to one for a female CEO. See Appendix OA.1 for variable definitions. The sample runs annually from 1999 to 2019. Standard errors are double clustered at the bank and tract levels and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Approved$_l$				
Non-White$_l$ × Inequality Aversion$_{by-1}$	0.176***	0.225***	0.187***	0.111**	0.167***
	(0.049)	(0.039)	(0.061)	(0.046)	(0.043)
Non-White$_l$ × Log(Assets)$_{by-1}$	−0.005***				
	(0.001)				
Non-White$_l$ × Mortgage Loans/Assets$_{by-1}$		0.079***			
		(0.026)			
Non-White$_l$ × CEO Ineq Aversion$_{by-1}$			−0.022**		
			(0.011)		
Non-White$_l$ × IndepDir Ineq Aversion$_{by-1}$				0.029	
				(0.038)	
Non-White$_l$ × Competition$_{cy-1}$					−0.107***
					(0.011)
Observations	67,048,745	67,048,745	67,048,512	64,848,043	67,251,056
R-squared	0.162	0.162	0.162	0.164	0.148

Fixed Effects					
Tract-Year					✓
Bank	✓	✓	✓	✓	✓
Tract-Year-Race	✓	✓	✓	✓	
Control Variables					
Loan Characteristics ($\mathbf{Z}_l$)	✓	✓	✓	✓	✓
Bank Characteristics ($\mathbf{X}_{by-1}$)	✓	✓	✓	✓	✓
Executives' Characteristics ($\mathbf{X}_{by-1}$)	✓	✓	✓	✓	✓

Table OA.6: Bank stakeholders' inequality aversion and lending to non-white applicants, robustness with respect to bank characteristics. This table shows estimation results from specification (1a). The dependent variable is Approved$_l$, an indicator variable equal to one if the application is approved and equal to zero if the application is denied. Non-White$_l$ is an indicator variable equal to one if the applicant is non-white according to HMDA classification. Relevant uninteracted terms are estimated but not shown in this table for brevity. Loan and borrower characteristics are an indicator variable equal to one for a non-white applicant (the uninteracted variable is omitted from specification (1a)), an indicator variable equal to one for a female applicant, the natural log of the applicant's income expressed in thousands of 2012 dollars, LTI Ratio (loan amount divided by borrower income), an indicator variable equal to one for a jumbo loan, an indicator variable equal to one for refinancing loans, and an indicator variable equal to one for loans taken out for home improvements. The (lagged) bank characteristics are the natural log of banks' total assets (in million dollars as of 2012), deposits-to-assets ratio, interest on deposits divided by total assets, liquid assets divided by total assets, tier 1 capital divided by total assets, C&I loans divided by total assets, loans secured by real estate divided by total assets, net income divided by total assets, unused commitments divided by total assets, letters of credit divided by total assets, and nonperforming loans divided by total loans. Executives' characteristics are the number of years the CEO has been acting as CEO of the bank, CEO age, the number of independent directors, the number of directors, and an indicator variable equal to one for a female CEO. The county characteristic Competition$_{cy}$ is the deposit HHI of county c in year y. See Appendix OA.1 for variable definitions. The sample runs annually from 1999 to 2019. Standard errors are double clustered at the bank and tract levels and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Approved$_l$				
High-Minority Tract$_{ty}$ × Inequality Aversion$_{by-1}$	0.266***	0.274***	0.187***	0.168***	0.169***
	(0.027)	(0.028)	(0.047)	(0.036)	(0.066)
High-Minority Tract$_{ty}$ × Log(Assets)$_{by-1}$	−0.007***				
	(0.002)				
High-Minority Tract$_{ty}$ × Mortgage Loans/Assets$_{by-1}$		0.061*			
		(0.031)			
High-Minority Tract$_{ty}$ × CEO Ineq Aversion$_{by-1}$			0.007		
			(0.012)		
High-Minority Tract$_{ty}$ × IndepDir Ineq Aversion$_{by-1}$				0.050	
				(0.049)	
High-Minority Tract$_{ty}$ × Competition$_{cy-1}$					−0.010
					(0.029)
Observations	67,162,492	67,162,492	67,162,266	64,971,713	67,171,091
R-squared	0.147	0.147	0.147	0.150	0.123

Fixed Effects					
Tract-Year	✓	✓	✓	✓	
Bank	✓	✓	✓	✓	✓
Tract					✓
Year					✓
Control Variables					
Loan Characteristics ($\mathbf{Z}_l$)	✓	✓	✓	✓	✓
Bank Characteristics ($\mathbf{X}_{by-1}$)	✓	✓	✓	✓	✓
Executives Characteristics ($\mathbf{X}_{by-1}$)	✓	✓	✓	✓	✓

Table OA.7: Bank stakeholders' inequality aversion and lending to applicants in high-minority tracts, robustness with respect to bank characteristics. This table shows estimation results from specification (1b). The dependent variable is Approved$_l$, an indicator variable equal to one if the application is approved and equal to zero if the application is denied. High-Minority Tract$_{ty}$ is an indicator variable equal to one if the property associated with the application is based in a census tract where 75% or more of the population is minority, according to the Census Bureau's classification. The loan and borrower characteristics include an indicator variable equal to one for a non-white applicant, an indicator variable equal to one for a female applicant, the natural log of the applicant's gross annual income expressed in thousands of 2012 dollars, LTI Ratio (loan amount divided by borrower income), an indicator variable equal to one for a jumbo loan, an indicator variable equal to one for refinancing loans, and an indicator variable equal to one for loans taken out for home improvements. The (lagged) bank characteristics include the natural log of total assets (in million dollars as of 2012), deposits-to-assets ratio, interest on deposits divided by total assets, liquid assets divided by total assets, tier 1 capital divided by total assets, C&I loans divided by total assets, loans secured by real estate divided by total assets, net income divided by total assets, unused commitments divided by total assets, letters of credit divided by total assets, and nonperforming loans divided by total loans. Executive characteristics include the number of years the CEO has served as CEO of the bank, the CEO's age, the number of independent directors, the number of directors, and an indicator variable equal to one for a female CEO. The county characteristic Competition$_{cy}$ is the deposit HHI of county c in year y. The sample runs annually from 1999 to 2019. See Appendix OA.1 for variable definitions. Standard errors are double clustered at the bank and tract levels and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	N	Avg	SD	p50	Min	Max
2010	5	5.01	4.61	7.58	0.00	9.35
2011	5	4.49	6.17	0.00	0.00	12.04
2012	5	3.83	4.68	3.52	0.00	11.44
2013	2	2.93	4.14	2.93	0.00	5.85
2014	4	1.00	1.20	0.78	0.00	2.42
2015	3	3.51	3.08	4.74	0.00	5.79
2016	3	0.93	1.61	0.00	0.00	2.79
2017	21	3.03	3.84	1.61	0.00	12.08
2018	22	2.00	2.28	1.43	0.00	7.47
2019	24	2.63	2.87	1.88	0.00	8.86
Total	94	2.77	3.36	1.59	0.00	12.08

Table OA.8: Summary statistics, LLM score by year. This table shows summary statistics for the LLM Score by year. The LLM score is calculated by summing the scores across all speaker sections in a presentation transcript and dividing by the total number of words in the transcript. All scores are multiplied by 10,000 for readability. Each observation represents a transcript-year.

OA.4 DOJ discriminatory lending cases

Case	Summary	Date
United States v. JPMorgan Chase Bank, N.A. (S.D.N.Y.)	On January 20, 2017, the court entered a consent order in United States v. JPMorgan Chase Bank, N.A. (S.D.N.Y.). The complaint, which was filed on January 18, 2017, by the United States Attorney's Office alleged that the defendant violated the Fair Housing Act and the Equal Credit Opportunity Act when African American and Hispanic borrowers paid higher rates and fees for wholesale mortgage loans than similarly situated white borrowers. The consent order includes monetary relief of $53 million which includes a civil penalty of $55,000.	1/18/2017
United States v. Huntington Mortgage Company (N.D. Ohio)	In our complaint we claimed that the bank charged African Americans higher up-front fees on home mortgages, known as overages. Under the agreement that we signed on October 18, 1995, with Huntington, the company agreed to create a $420,000 fund to compensate victims and change its policies to ensure uniform pricing.	10/18/1995
Consumer Financial Protection Bureau and United States v. National City Bank (W.D. Pa.)	On January 9, 2014, the court entered a consent order in Consumer Financial Protection Bureau & United States v. National City Bank (W.D. Pa.), an Equal Credit Opportunity Act and Fair Housing Act case that resulted from a joint investigation by the Division and the CFPB. PNC Bank is the successor in interest to National City Bank. The complaint, filed on December 23, 2013, alleged a pattern or practice of discrimination based on race and national origin in residential mortgage lending. The consent order requires PNC Bank to pay $35 million to African-American and Hispanic victims of National City Bank's discriminatory conduct.	1/9/2014
United States v. Old Kent Financial Corporation and Old Kent Bank (E.D. Mich.)	On May 19, 2004, the U.S. simultaneously filed a complaint and settlement agreement in U.S. v. Old Kent Financial Corporation and Old Kent Bank (E.D. Mich.), a Fair Housing Act and Equal Credit Opportunity Act case. The complaint alleges that Old Kent Financial Corporation and Old Kent Bank of Detroit unlawfully avoided making business and residential loans in predominantly African-American neighborhoods, a practice commonly referred to as redlining. The complaint alleges that Old Kent intentionally refused to issue loans and open branches in Detroit because of the city's African-American population. Specifically, the complaint alleges that while Old Kent served largely white suburbs, it opened a branch in Detroit only after the Justice Department opened its investigation. The complaint also alleges that of the 15,473 small business and residential real estate related loans Old Kent made between 1996 and 2000 in the Detroit metropolitan area, only 335, or 2.2%, were made in majority African-American neighborhoods. The complaint further alleges that while capturing most of the greater Detroit area, Old Kent defined its Community Reinvestment Act service area to exclude certain majority African-American areas. The enforceable settlement agreement requires the defendants to provide three million dollars for a loan subsidy program to provide Detroit businesses and residents small business loans and residential real estate-related loan products on favorable terms; open three new full-service branches in Detroit; advertise its products so as to generate loan applications from qualified businesses and residents in Detroit; invest $200,000 to develop and implement consumer education programs for residents and small businesses in Detroit; and, relocate its team of business banking lenders responsible for developing business in Detroit, the "Detroit Business Group Team," to the city of Detroit by the end of 2004.	5/19/2004
United States v. Fifth Third Bank (S.D. Ohio)	On September 28, 2015, the United States filed a complaint and consent order in United States v. Fifth Third Bank (S.D. Ohio), alleging that the bank engaged in a pattern or practice of discrimination on the basis of race and national origin in its indirect auto lending business in violation of the Equal Credit and Opportunity Act (ECOA). The consent order includes $18 million in restitution for harmed African American and Hispanic borrowers, and requires the bank to change the way it prices its loans by limiting dealer markup to 125 basis points (or 1.25%) for loans of 60 months or less, and to 100 basis points (or 1%) for loans greater than 60 months. This matter was investigated and settled jointly with the Consumer Financial Protection Bureau. The court entered the consent order on October 1, 2015.	10/1/2015
United States v. Fifth Third Mortgage (M.D. Ga.)	On August 11, 2014, the court entered a consent order in United States v. Fifth Third Mortgage Co.(M.D. Ga.). The complaint, filed on August 7, 2014, alleges that Fifth Third Mortgage Company and Cranbrook Mortgage Corporation violated the FHA and the ECOA by requiring recipients of disability income to provide a letter from a doctor to substantiate their income, and that Fifth Third Mortgage Company engaged in a pattern or practice of discrimination. The consent order provides for a $1.5 million fund to compensate victims who had been asked to provide medical documentation to prove the income they received from Social Security Disability Insurance. The bank also agreed to other injunctive relief, including employee training and the implementation of new policies.	8/11/2014

Table OA.9. Continues on next page. See the end of the table for the caption.

Case	Summary	Date
United States v. Countrywide Financial Corporation (C.D. Cal.)	On December 28, 2011, the court entered a consent order in United States v. Countrywide Financial Corporation (C.D. Cal.). The complaint and consent order, both filed on December 21, 2011 against Countrywide Financial Corporation and its subsidiaries Countrywide Home Loans and Countrywide Bank, alleged that between 2004 and 2008, Countrywide engaged in a nationwide pattern or practice of discrimination in its residential lending activities in violation of both the Fair Housing Act and the Equal Credit Opportunity Act. The alleged violations by Countrywide include: (a) discrimination against African-American and Hispanic borrowers in the pricing of retail home loans; (b) discrimination against African-American and Hispanic borrowers in the pricing of wholesale home loans; (c) discrimination against African-American and Hispanic wholesale borrowers by placing them in subprime loan products when it placed white wholesale borrowers with similar credit qualifications in prime loan products; and (d) discrimination on the basis of marital status by following policies and practices that encouraged the non-applicant spouse of a married borrower applying for credit in his/her own name to execute documents transferring his/her rights in the property securing the loan to the applicant spouse. The consent order includes the establishment of a $335 million Settlement Fund to compensate victims of Countrywide's discrimination, which is being administered by an independent Administrator, Rust Consulting, Inc., and injunctive relief to prevent the recurrence of the alleged unlawful lending practices in the event Countrywide re-enters the residential mortgage lending business.	12/28/2011
United Stats v. Bank of America N.A. (E.D. N.Y.)	On July 23, 2020 the United States filed a complaint and proposed order in United States v. Bank of America (E.D.N.Y.). The complaint alleges that Bank of America discriminated on the basis of disability, in violation of the FHA, through implementation of a policy that prohibited the issuance of mortgage loans to adults who had legal guardians or conservators. The requires the bank to maintain new policies that permit loans to adults with guardians or conservators, to ensure that employees are trained on the new policies, and to pay damages of $4,000 for each loan application that was denied as a result of the bank's prior unlawful policy. The court approved the entry of the settlement agreement and order on September 11, 2020	9/11/2020
United States v. Bank of America N.A., d/b/a Bank of America Home Loans (W.D.N.C. 2012)	On September 13, 2012, the United States filed a complaint and consent order in United States v. Bank of America, N.A., d/b/a Banlk of America Home Loans (W.D.N.C.). The complaint, based on a HUD election referral, alleges that Bank of America discriminated on the basis of disability and receipt of public assistance in underwriting and originating loans, by requiring loan applicants who receive Social Security Disability Insurance (SSDI) income to provide a letter from their doctor as part of the loan application. The consent order requires the Bank to maintain revised policies, conduct employee training and pay compensation to victims. Bank of America will pay $1,000, $2,500 or $5,000 to eligible mortgage loan applicants who were asked to provide a letter from their doctor to document the income they received from SSDI. Applicants who were asked to provide more detailed medical information to document their income may be paid more than those who were asked to have a doctor verify their source of income. In addition, the HUD complainants who initiated this suit received a total of $125,000. The consent order was entered on October 10, 2012, and later amended on December 6, 2012.	10/10/2012
United States v. Compass Bank (N.D. Ala.)	On February 21, 2007, the court entered the consent order in United States v. Compass Bank (N.D. Ala.), resolving claims that Compass Bank violated the Equal Credit Opportunity Act by engaging in a pattern of discrimination on the basis of marital status in thousands of automobile loans that it made through hundreds of different car dealerships in the South and Southwest between May 2001 and May 2003. Specifically, the complaint, which was filed on January 12, 2007, alleged that the bank charged non-spousal co-applicants higher interest rates than similarly-situated married co-applicants. To remedy the alleged discrimination, Compass Bank will pay up to $1.75 million to compensate several thousand non-spousal co-applicants whom the United States alleges were charged higher rates as a result of their marital status. This case resulted from a referral by the Federal Reserve Board.	2/21/2007

Table OA.9. Continues on next page. See the end of the table for the caption.

Case	Summary	Date
United States v. Wells Fargo Bank, NA (D.D.C.)	On December 19, 2012, the Division notified the court in United States v. Wells Fargo Bank (D.D.C.) that the bank will provide $59.3 million in compensation to African-American and Hispanic retail subprime borrowers. Under the consent order, entered on September 21, 2012, Wells Fargo agreed to undertake an internal review to determine whether there were African-American and/or Hispanic borrowers who received subprime Wells Fargo loans from the bank's retail channel who might have qualified for prime loans from the retail channel. The consent order provided that any borrowers identified pursuant to the review would be compensated in an amount commensurate with the amounts paid to borrowers who received subprime loans from the bank's wholesale division. As a result of its review, Wells Fargo identified nearly 4,000 retail subprime borrowers who are eligible for compensation. With the additional compensation to retail subprime borrowers, the Division's settlement with Wells Fargo totals $234.3 million. The complaint, filed on July 12, 2012, alleged that Wells Fargo engaged in a pattern or practice of discrimination against qualified African-American and Hispanic borrowers in its mortgage lending from 2004 through 2009. The complaint alleged that Wells Fargo discriminated by steering approximately 4,000 African-American and Hispanic wholesale borrowers, as well as additional retail borrowers, into subprime mortgages when non-Hispanic white borrowers with similar credit profiles received prime loans. All the borrowers who were allegedly discriminated against were qualified for Wells Fargo mortgage loans according to Well Fargo's own underwriting criteria. The United States also alleged that, between 2004 and 2009, Wells Fargo discriminated by charging approximately 30,000 African-American and Hispanic wholesale borrowers higher fees and rates than non-Hispanic white borrowers because of their race or national origin rather than the borrowers' credit worthiness or other objective criteria related to borrower risk. The consent order provided $125 million in compensation for wholesale borrowers who were allegedly steered into subprime mortgages or who allegedly paid higher fees and rates than white borrowers because of their race or national origin. Wells Fargo was also required to pay $50 million in direct down payment assistance to borrowers in communities around the country where the Department identified large numbers of discrimination victims and which were hard hit by the housing crisis.	9/21/2012
United States v. SunTrust Mortgage, Inc. (E.D. Va.)	On September 14, 2012, the court entered a consent order resolving United States v. SunTrust Mortgage, Inc. (E.D. Va.). The complaint, wich was filed simultaneoulsy with the consent order on May 31, 2012, alleged that from 2005 to 2009, SunTrust Mortgage discriminated against at least 20,000 African-American and Hispanic borrowers across the country by systematically charging higher discretionary broker fees and retail loan markups to those borrowers than to white borrowers in violation of the Fair Housing Act and Equal Credit Opportunity Act. The consent order provides for a $21 million settlement fund and for injunctive relief specifying that SunTrust Mortgage must maintain for at least three years specific improved pricing policies and fair lending monitoring that it has adopted since the conduct at issue in the complaint occurred. The case was referred to the Division by the Federal Reserve Board.	9/13/2012
United States v. Citizens Republic Bancorp, Inc. and Citizens Bank (E.D. Mich.)	On May 5, 2011, the United States filed a complaint in United States v. Citizens Republic Bancorp, Inc. and Citizens Bank (E.D. Mich.), a Fair Housing Act and Equal Credit Opportunity Act pattern or practice case that was referred by the Board of Governors of the Federal Reserve System. The complaint alleged that Citizens Republic Bancorp, Inc. (CRBC), as the successor to Republic Bank, and Citizens Bank failed to provide their home mortgage lending services to the residents of majority African-American neighborhoods on an equal basis as those services are provided to residents of predominantly white neighborhoods in the Detroit metropolitan area, a practice commonly known as "redlining." On May 24, 2011, the court declined to enter a proposed consent order, and on June 23, 2011, the United States and defendants filed a stipulated notice of dismissal based on the settlement agreement reached by the parties and attached to that notice. On June 28, 2011, the court dismissed the case. Under the settlement agreement, defendants will open a loan production office in an African-American neighborhood in the City of Detroit and hire two community lenders; and invest in the formerly redlined majority African-American areas of Wayne County by providing $1.5 million in a special financing program to increase the amount of credit the bank extends in those areas, by partnering with the City of Detroit to provide $1.625 million in matching grants of up to $5,000 to existing homeowners for exterior improvements, and by conducting $500,000 in advertising, marketing, and consumer financial education targeted to those areas.	6/23/2011

Table OA.9. Continues on next page. See the end of the table for the caption.

Case	Summary	Date
United States v. First Merchants Bank (S.D. Ind.)	On August 12, 2019, the court approved the entry of settlement agreement and agreed order resolving United States v. First Merchants Bank (S.D. Ind.). On June 13, 2019, the United States filed the complaint and proposed settlement. The complaint alleged that from 2011 to at least 2017, First Merchants violated the Fair Housing Act and Equal Credit Opportunity Act on the basis of race by engaging in unlawful redlining in Indianapolis by intentionally avoiding predominantly African-American neighborhoods. The Department's complaint also alleges that First Merchants adopted a residential mortgage lending policy that had the effect of denying residents of predominantly African-American neighborhoods equal access to credit in violation of federal law. Under the settlement, the Bank will invest $1.12 million in a loan subsidy fund to increase credit opportunities to residents of predominantly African-American neighborhoods, and will devote $500,000 toward advertising, community outreach, and credit repair and education. First Merchants will also open a branch and loan production office to serve the banking and credit needs of residents in predominantly African-American neighborhoods in Indianapolis.	8/12/2019
United States v. C & F Corporation (E.D. Va.)	On October 4, 2011, the court entered a consent order in United States v. C&F Mortgage Corporation (E.D. Va.), a pattern or practice case under the Fair Housing Act and the Equal Credit Opportunity Act that was referred by the Federal Deposit Insurance Corporation. The complaint, filed on September 30, 2011, alleged that C&F charged greater interest rate markups (overages) and gave lesser discounts (underages) on home mortgage loans made to African-American and Hispanic borrowers by giving its employees wide discretion in overages and underages without having in place objective criteria for setting the overages and underages. The complaint alleged that this policy had a disparate impact on African-American and Hispanic borrowers. The consent order resolves the case by requiring C&F to develop uniform policies for all aspects of its loan pricing and to phase out the practice of charging overages to home mortgage borrowers. The settlement also requires the bank to pay $140,000 to black and Hispanic victims of discrimination, monitor its loans for potential disparities based on race or national origin, and provide equal credit opportunity training to its employees.	10/4/2011
United States and Consumer Financial Protection Bureau v. BancorpSouth Bank (N.D. Miss.)	On June 29, 2016, the United States filed a complaint and a consent order in United States and Consumer Financial Protection Bureau v. BancorpSouth Bank (N.D. Miss.). The joint complaint with the Consumer Financial Protection Bureau (CFPB) alleges that the bank failed to provide its home mortgage lending services to majority-minority neighborhoods on an equal basis as it provided those services to predominantly white neighborhoods, a practice commonly known as "redlining," throughout its major market areas in the Memphis Metropolitan Statistical Area; discriminated on the basis of race in the pricing and underwriting of mortgage loans originated by its Community Banking Department; and implemented a discriminatory loan policy or practice of denying applications from minorities more quickly than similarly-situated white applicants in its Mortgage Department, in violation of ECOA and FHA. The consent order requires the bank to amend its pricing and underwriting policies, establish a monitoring program, have employees undergo fair housing and fair lending training, extend credit offers to unlawfully denied applicants, and open a new full-service branch or Loan Processing Office (LPO) in a high-minority neighborhood, among other injunctive relief. The consent order also includes a $2.78 million settlement fund to remediate harmed borrowers for pricing and underwriting discrimination; a $4 million loan subsidy program to extend mortgage loans to qualified applicants in the Memphis MSA; at least $800,000 in advertising, outreach, and community partnerships; and a $3 million civil money penalty to the CFPB. The court entered the consent order on July 25, 2016.	7/25/2016

Table OA.9: DOJ Equal Credit Opportunity Act cases. This table shows the list of cases by the DOJ against our sample banks for potential breaches of the Equal Credit Opportunity Act, which *"prohibits creditors from discriminating against credit applicants on the basis of race, color, religion, national origin, sex, marital status, age, because an applicant receives income from a public assistance program, or because an applicant has in good faith exercised any right under the Consumer Credit Protection Act."* These cases are publicly available at www.justice.gov.

OA.5 No negative effect on *bank* performance

We now explore how approval gaps relate to *bank* performance. To this end, we estimate the following specification:

$$\begin{aligned}\text{Loan Performance}_{by} = \alpha + \sum_{\tau}^{3} \beta_{1\tau} \text{ApprGap}_{by-\tau}^{\text{Non-White}} \\ + \sum_{\tau}^{3} \beta_{2\tau} \text{ApprGap}_{by-\tau}^{\text{HighMinTract}} + \gamma \mathbf{X}_{by-1} + \nu_y + \eta_b + \epsilon_{by}\end{aligned} \tag{OA.1}$$

where the dependent variable is bank b's performance in year y. We use two measures of performance directly related to real estate loans, namely *Real Estate NPL*$_{by}$ (nonperforming real estate loans divided by lagged real estate loans) and *Real Estate Charge-Off*$_{by}$ (charge-offs minus recoveries on real estate loans divided by lagged real estate loans). We also use a more general bank performance measure, only partially influenced by real estate loan performance, namely *Net Income/Assets*$_{by}$ (net income to lagged assets ratio). Finally, the specification also includes year and bank fixed effects. We cluster standard errors at the bank level.

The main explanatory variables are (i) three lags of the variable $\text{ApprGap}_{by}^{Non-White}$, which measures the difference in *unexplained* approval rates between white and non-white applicants for bank b in year y and (ii) three lags of the variable $\text{ApprGap}_{by}^{HighMinTract}$, which measures the difference in *unexplained* approval rates between applicants in low-minority tracts and high-minority tracts for bank b in year y. The construction of these unexplained approval rates is described in Section 4.4. $\mathbf{X}_{by-1}$ is a vector of control variables for bank b measured in year $y-1$.

Table OA.10 shows the estimation results. Overall, consistent with the results presented in Section 5.3, we find no evidence consistent with a weaker real estate loan performance or overall bank performance for banks with smaller unexplained approval gaps, indicating that smaller gaps do not proxy for higher propensity to lend to non-deserving minority borrowers. If anything, banks with larger unexplained approval gaps between white and non-white applicants perform slightly worse. These effects are small in magnitude. A one-standard-deviation increase in the first lag of the white versus non-white unexplained approval gap is associated with (i) a 0.047% increase in the real estate nonperforming loans ratio, compared to a mean ratio of 1.9%; (ii) a 0.021% increase in the real estate charge-off ratio, compared to a mean real estate charge-off ratio of 0.39%; and (iii) a 0.02% decrease in net income to assets ratio, compared to a mean net income to assets ratio of 0.77%.

	Real Estate NPL_{by}	Real Estate Charge-Off_{by}	Net $\text{Income/Assets}_{by}$
$\text{ApprGap}_{y-1}^{\text{Non-White}}$	0.558**	0.249***	−0.219**
	(0.259)	(0.082)	(0.094)
$\text{ApprGap}_{y-2}^{\text{Non-White}}$	0.150	0.096	−0.080
	(0.247)	(0.079)	(0.100)
$\text{ApprGap}_{y-3}^{\text{Non-White}}$	0.159	0.093	−0.065
	(0.207)	(0.088)	(0.078)
$\text{ApprGap}_{y-1}^{\text{HighMinTract}}$	0.028	−0.016	0.053
	(0.136)	(0.045)	(0.041)
$\text{ApprGap}_{y-2}^{\text{HighMinTract}}$	−0.185	−0.048	−0.064
	(0.130)	(0.049)	(0.049)
$\text{ApprGap}_{y-3}^{\text{HighMinTract}}$	−0.109	−0.054	−0.001
	(0.134)	(0.043)	(0.036)
Bank Controls ($\mathbf{X}_{by-1}$)	✓	✓	✓
Fixed Effects			
Year	✓	✓	✓
Bank	✓	✓	✓
Observations	2,573	2,573	2,573
R-squared	0.815	0.796	0.739

Table OA.10: Bank unexplained approval gaps and loan performance. This table shows estimation results from specification (OA.1). The dependent variable in the first column is nonperforming real estate loans divided by lagged real estate loans. The dependent variable in the second column is charge-offs minus recoveries on real estate loans divided by lag real estate loans. The dependent variable in the third column is the net income to asset ratio. We multiply all dependent variables by 100 for readability. The independent variables include three lags of the bank's *unexplained* approval gaps between non-white and white borrowers and between borrowers in high-minority and low-minority census tracts. The (lagged) bank characteristics are the natural log of banks' total assets (in million dollars as of 2012), deposits-to-assets ratio, interest on deposits divided by total assets, liquid assets divided by total assets, tier 1 capital divided by total assets, C&I loans divided by total assets, loans secured by real estate divided by total assets, net income divided by total assets, unused commitments divided by total assets, letters of credit divided by total assets, and nonperforming loans divided by total loans. The sample runs annually from 2002 to 2019 (to accommodate the three lags of approval gaps as independent variables). See Appendix OA.1 for variable definitions. All dependent variables are winsorized at the 5^{th} and 95^{th} percentiles, to limit effects of outliers in performance especially during the Global Financial Crisis. Standard errors are clustered at the bank level and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.