Racial Disparities in the U.S. Mortgage Market*

Agustin Hurtado† Jung Sakong‡

AEA Papers & Proceedings, Forthcoming

January 2, 2024

Abstract

We empirically examine the extent and potential drivers of racial disparities in the U.S. mortgage market. Using data newly assembled by Hurtado and Sakong (2024), we present three main findings. First, we document racial disparities in mortgage access between minority and otherwise-identical White borrowers, even within the same bank and loan officer. In contrast, racial disparities in mortgage costs are close to zero. Second, we uncover that the use of purportedly race-blind automated underwriting algorithms is associated with substantially smaller disparities in mortgage access, while individual factors—specifically, loan officers' race and whether borrowers' race is observed at application—do not seem to matter much. Third, we show that the use of automated underwriting algorithms is associated with slightly larger cost disparities, while individual factors make little difference. Our approach and findings represent another step toward understanding the factors driving racial disparities and discriminatory forces in the U.S. mortgage market. Recent research suggests structural or organizational factors may also play a role and have been overlooked by previous studies (Hurtado and Sakong, 2024).

*We thank Tori Healey and Max Jaffe for excellent research assistance and help dealing with confidential data. We are grateful to Pascal Noel, Pablo Slutzky, Liu Yang, and Eric Zwick for helpful comments. This research was funded by the John and Serena Liew Fellowship Fund at the Fama-Miller Center for Research in Finance, the Stigler Center for the Study of the Economy and the State, and the Stevens Doctoral Office at the University of Chicago Booth School of Business. We acknowledge the Bright Initiative, the Community Development Bankers Association, CUCollaborate, the Federal Deposit Insurance Corporation, the Federal Reserve Bank of Chicago, Mighty Deposits, the National Credit Union Administration, the Rustandy Center for Social Sector Innovation, and the U.S. Treasury Department for research support and data access. The views here are ours and do not reflect those of the Federal Reserve System.

†University of Maryland Smith School of Business.

‡Federal Reserve Bank of Chicago.

Racial Disparities in the U.S. Mortgage Market

By Agustin Hurtado and Jung Sakong*

Studying disparities and discriminatory forces in the U.S. mortgage market is central to understanding the racial wealth gap, which features prominently in policy discussions, including those on reparations.[1]

The goal of this study is to empirically examine the extent and potential drivers of disparities in mortgage access and cost. We consider technological and individual factors that might mitigate or exacerbate disparities. The technological factor we examine is the use of purportedly race-blind algorithms known as automated underwriting systems (AUS), which are widely used in the mortgage market. Recent evidence from peer-to-peer and small business credit data suggests that the use of automation, specifically, robo-advising and automatic income verification, might reduce racial disparities (Howell et al., 2023; D'Acunto et al., 2021).

Our investigation of individual factors—specifically, loan officers' race and whether borrowers' race is observed at application—is motivated by work studying financial gatekeepers such as loan officers and investors (Fisman, Paravisini and Vig, 2017; Cook, Marx and Yimford, 2022; Frame et al., 2024).

Empirically studying racial disparities in the mortgage market is challenging. Naive approaches comparing minority and White borrowers using differences in means (henceforth *observed* disparities) typically show large disparities. For example, the average Black applicant is 14.4 percentage points less likely to be approved for a mortgage than the average White applicant (Figure 1, Panel A2).

Since the seminal work of Munnell et al. (1996), much ink has been spilled on the fact that research documenting *observed* disparities does not disentangle the role of race from creditworthiness and other factors that might be correlated with race while also directly impacting mortgage access and cost. Precisely estimating disparities would require an experiment with borrowers identical on every possible dimension except race, which would be randomly assigned.

We resemble this ideal experiment by comparing minority and White borrowers with the same demographic and risk characteristics, with mortgages with the same characteristics, and with the same bank, loan officer, and underwriting method. This approach requires detailed data linking borrowers, banks, and officers. We will discuss these data next.

I. Data

We rely on data developed in Hurtado and Sakong (2024), a study that investigates the economics of minority bank ownership. These data incorporate several innovations, which range from new data sources such as LinkedIn headshots to new tools such as balanced facial attribute recognition used to predict loan officers' race. We refer the reader to Hurtado and Sakong (2024) for more details on the data.

We use the near-universe of nonbrokered mortgage applications submitted under the Home Mortgage Disclosure Act (HMDA) from 2018 to 2019. We access a confidential version of the HMDA data through the Federal Reserve System, which contain information on applicants' credit risk and their loan officers.

We focus on three minority categories combining race and Hispanic ethnicity: non-Hispanic Asian (henceforth Asian), non-Hispanic Black (henceforth Black), and

* Hurtado: University of Maryland, 7621 Mowatt Ln, College Park, MD 20742, hurtado@umd.edu. Sakong: Federal Reserve Bank of Chicago, 230 S La Salle St, Chicago, IL 60604, jung.sakong@chi.frb.org. We thank Tori Healey and Max Jaffe for excellent research assistance. We are grateful to Pascal Noel, Pablo Slutzky, Liu Yang, and Eric Zwick for helpful comments. We acknowledge the Federal Reserve Bank of Chicago for research support and data access. The views here are ours and do not reflect those of the Federal Reserve System.

[1] The mortgage market matters for wealth accumulation because 1) most U.S. households need a mortgage to own housing, 2) having a mortgage likely leads to a 1-to-1 rise in wealth (Bernstein and Koudijs, 2023), and 3) housing is the principal asset held by U.S. households and 4) has the highest risk-adjusted return (Jordà et al., 2019).

Hispanic of any race (henceforth Hispanic).[2] We use three datasets containing Asian–White, Black–White, and Hispanic–White mortgage applicants and discuss results by minority category, from largest to smallest: Hispanic (45 percent of minority applicants), Black (31 percent), and Asian (24 percent). In each dataset, we observe applicants' demographic and risk characteristics, their banks and officers, detailed mortgage and underwriting characteristics, and measures of credit access and cost.

We measure credit access for mortgage applicants as approval conditional on application completion. We quantify the credit cost for borrowers as an interest rate spread conditional on mortgage origination, with the spread calculated as the difference between the mortgage's annual percentage rate (APR) and the average prime offer rate for a comparable transaction. Our APR variable is a single measure of mortgage cost that includes interest rate, points, and fees and does not exhibit the truncation issues highlighted in Bhutta and Hizmo (2021).

II. Estimating Racial Disparities

We mimic the ideal experiment measuring disparities by estimating

$$Y_{ijklt} = \alpha MinorityBorrower_i + X_i'\Theta + \Phi_{jklt} + \varepsilon_{ijklt} \tag{1}$$

where i, j, k, l, and t index applicants or borrowers, property census tracts, banks, loan officers, and application month–year pairs, respectively. Y_{ijklt} is either an indicator for approval (among completed applications) or interest spread (among originated loans), $MinorityBorrower_i$ is a minority indicator, and X_i includes applicant, mortgage, and underwriting characteristics. Applicant characteristics include demographic characteristics (income, gender, co-borrower presence) and creditworthiness (credit score, loan-to-value and debt-to-income ratios). Mortgage characteristics are loan amount, purpose (purchase, improvement, or refinancing), type (conventional, FHA, VA, or FSA/RHS), occupancy (principal, second, or investment), and sold mortgage. Underwriting characteristics include AUS use and observed race of the applicant.[3] $\Phi_{jklt} \equiv \{\phi_j, \phi_k, \phi_l, \phi_t\}$ are census tract, bank, loan officer, and year–month fixed effects. We control for continuous characteristics using percentile fixed effects and cluster standard errors at the bank, loan officer, and census tract levels.

To facilitate interpretations, we estimate specification (1) using the Hispanic–White, Black–White, and Asian–White disparity datasets separately. When we use the Hispanic–White dataset, for example, α measures mortgage disparities between Hispanic and otherwise identical White borrowers with mortgages with the same characteristics and with the same bank, loan officer, and underwriting methods. We refer to α as a *residualized* disparity.

We empirically examine potential drivers of *residualized* disparities by estimating

$$\begin{aligned} Y_{ijklt} =& \beta MinorityBorrower_i + W_{ikl}'\Gamma \\ &+ MinorityBorrower_i \times W_{ikl}'\Lambda \\ &+ X_i'\Theta + \Phi_{jklt} + \xi_{ijklt} \end{aligned} \tag{2}$$

where $W_{ikl} \equiv [AUS_i\ MO_l\ OR_i]'$ and $\Lambda \equiv [\lambda_{AUS}\ \lambda_{MO}\ \lambda_{OR}]'$ are indicator variables and coefficients for AUS, minority officer, and observed race, respectively. Here, β represents a *baseline residualized* disparity that compares minority and White borrowers whose applications were not evaluated by an AUS, with the same non-minority loan officer who did not observe race. We refer to $\beta + \lambda_w$ as the *AUS*, *minority officer*, and *observed race* disparities for $w \in \{AUS, MO, OR\}$. When we use the Hispanic–White dataset, for example, the *minority officer* disparities $\beta + \lambda_{MO}$ compare Hispanic and White borrowers whose applications were not evaluated by an AUS, with the same Hispanic loan officer who did not observe race.

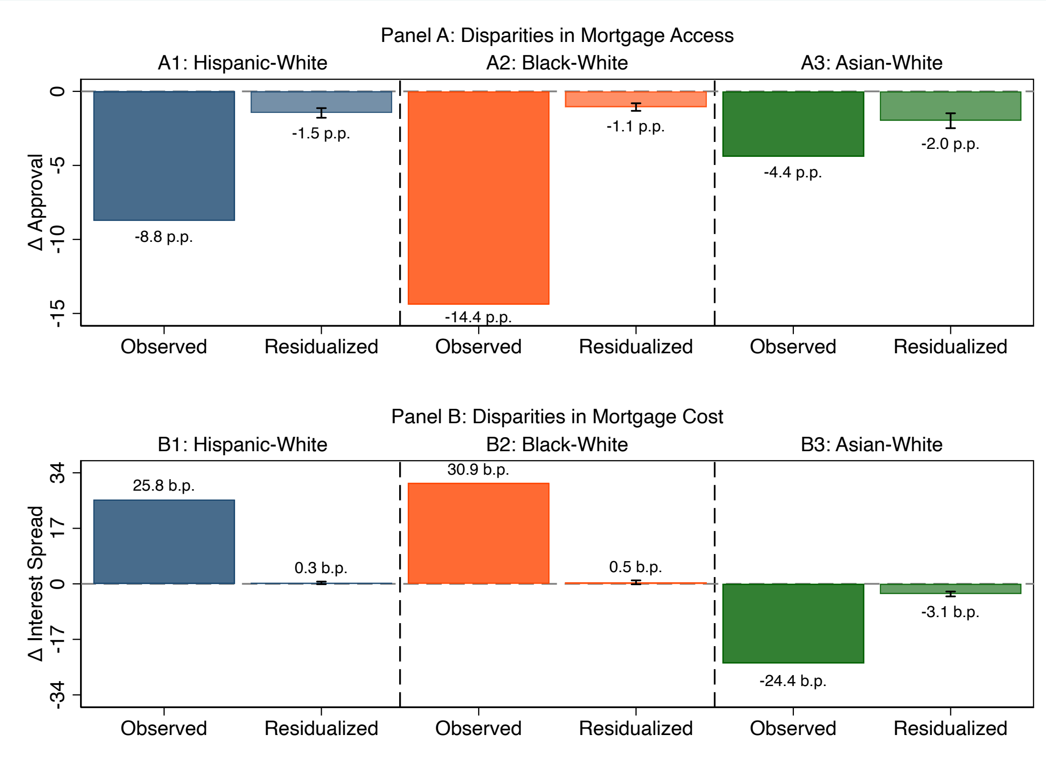
III. Findings

Our first set of results shows that the *residualized* disparities in mortgage access are smaller

[2] These categories are based on the Office of Management and Budget's Directive 15 and provide well-defined standards that we can consistently use when linking records. We exclude the Native category because its small size, unique laws, and geographies might threaten inference and external validity.

[3] The confidential HMDA data contain information on whether an applicant's race or ethnicity was collected on the basis of visual observation or surname, which we use as a proxy for whether officers observed an applicant's race.

FIGURE 1. OBSERVED AND RESIDUALIZED RACIAL DISPARITIES IN THE MORTGAGE MARKET



Note: The first bar in each sub-panel reports *observed* disparities, which compare minority and White borrowers using differences in means. The second bar in each sub-panel depicts *residualized* disparities $\hat{\alpha}$ and 95% confidence intervals from specification (1). Percentage points are designated by p.p., and basis points are designated by b.p.

TABLE 1—POTENTIAL DRIVERS OF RACIAL DISPARITIES IN THE MORTGAGE MARKET

Race	Base	AUS	MO	OR
A. Mortgage Access: Approval (p.p)				
Hispanic	-5.4	-0.2	-5.9	-6.5
	(0.4)	(0.2)	(0.5)	(0.5)
Black	-5.2	0.1	-5.8	-5.9
	(0.7)	(0.2)	(0.6)	(0.7)
Asian	-4.4	-1.1	-3.8	-5.7
	(0.6)	(0.2)	(0.5)	(0.5)
B. Mortgage Cost: Spread (b.p)				
Hispanic	-8.9	1.2	-7.7	-4.6
	(3.7)	(0.5)	(3.8)	(3.3)
Black	-6.3	1.4	-6.1	0.7
	(3.4)	(0.4)	(3.3)	(3.3)
Asian	-8.6	-2.8	-8.3	-5.7
	(1.5)	(0.3)	(1.5)	(1.5)

Note: The second column reports *baseline* disparities $\hat{\beta}$ from specification (2). The last three columns depict *AUS*, *minority officer* (*MO*), and *observed race* (*OR*) disparities $\hat{\beta}+\hat{\lambda}_w$ from (2), with $w \in \{AUS, MO, OR\}$. Clustered standard errors are reported in parentheses. Percentage points are designated by p.p., and basis points are designated by b.p.

than the *observed* disparities but still exist. Panels A1–A3 in Figure 1 show that Hispanic, Black, and Asian mortgage applicants are 1.5, 1.1, and 2.0 percentage points (p.p.) less likely to be approved than White applicants with the same demographic and risk characteristics applying for mortgages with the same characteristics at the same bank and with the same loan officer and underwriting method.

In contrast, the Hispanic–White and Black–White *residualized* disparities in mortgage cost are not only substantially smaller than the *observed* disparities but also statistically indistinguishable from zero, consistent with the results of Bhutta and Hizmo (2021). Panels B1 and B2 in Figure 1 show that Hispanic and Black borrowers pay only 0.3 and 0.5 basis points (b.p.) more than otherwise identical White borrowers with the same officer and bank. The Asian–White *residualized* cost disparity is slightly negative. Panel B3 indicates that Asian borrowers pay 3.1 b.p. less than otherwise identical White applicants with the same officer and bank.

Interestingly, in our second set of results, we uncover that the use of AUS is associated with smaller disparities in access, and that individual factors do not seem to matter much. Panel A in Table 1 shows that the *baseline* disparities in access are -5.4, -5.2, and -4.4 p.p., whereas AUS disparities are smaller at -0.2, 0.1, and -1.1 p.p. for Hispanic, Black and Asian applicants and not statistically different from zero for Hispanic and Black applicants. In contrast, the *minority officer* and *observed race* disparities are similar to the *baseline* for all minority categories.

Concerning cost disparities as measured by interest rate spreads, we find that the use of AUS is associated with slightly larger cost disparities for all minority categories, while individual factors make little difference. Panel B in Table 1 shows that the *baseline* disparities in mortgage cost are -8.9, -6.3, and -8.6 b.p. The *AUS* disparities are 1.2, 1.4, and -2.8 b.p. for Hispanic, Black, and Asian borrowers. In contrast, the *minority officer* and *observed race* disparities are similar or slightly smaller.

IV. Conclusion

This study employs unique data assembled by Hurtado and Sakong (2024) to investigate the extent and potential drivers of racial disparities in the U.S. mortgage market. These data allow us to compare mortgage outcomes for minority and otherwise identical White borrowers, with loans with the same characteristics, and with the same bank, loan officer, and underwriting method. We document racial disparities in mortgage access, but none in costs. Further, we show that the use of AUS is associated with substantially smaller access disparities but somewhat larger cost disparities for Hispanic, Black, and Asian borrowers.

Our approach and findings represent another step toward understanding the factors driving disparities and discriminatory forces in the mortgage market. Recent research suggests structural or organizational factors may also play a role and have been overlooked by previous studies (Hurtado and Sakong, 2024).

REFERENCES

Bernstein, Asaf, and Peter Koudijs. 2023. "The mortgage piggy bank: Building wealth through amortization." *The Quarterly Journal of Economics*.

Bhutta, Neil, and Aurel Hizmo. 2021. "Do minorities pay more for mortgages?" *The Review of Financial Studies*, 34(2): 763–789.

Cook, Lisa D., Matt Marx, and Emmanuel Yimford. 2022. "Funding Black High-Growth Startups." *Working Paper*.

D'Acunto, Francesco, Pulak Ghosh, Rajiv Jain, and Alberto G Rossi. 2021. "How costly are cultural biases? evidence from fintech." *Evidence from FinTech (October 25, 2021)*.

Fisman, Raymond, Daniel Paravisini, and Vikrant Vig. 2017. "Cultural proximity and loan outcomes." *American Economic Review*, 107(2): 457–92.

Frame, Scott, Ruidi Huang, Erica Jiang, Will Liu, Erik Mayer, and Adi Sunderam. 2024. "The Impact of Minority Representation at Mortgage Lenders." *The Journal of Finance*.

Howell, Sabrina, Theresa Kuchler, David Snitkof, Johannes Stroebel, and Jun Wong. 2023. "Lender automation and racial disparities in credit access." *Journal of Finance*.

Hurtado, Agustin, and Jung Sakong. 2024. "The effect of minority bank ownership on minority credit." Stigler Center New Working Paper Series No. 325.

Jordà, Òscar, Katharina Knoll, Dmitry Kuvshinov, Moritz Schularick, and Alan M Taylor. 2019. "The rate of return on everything, 1870–2015." *The Quarterly Journal of Economics*, 134(3): 1225–1298.

Munnell, Alicia H, Geoffrey MB Tootell, Lynn E Browne, and James McEneaney. 1996. "Mortgage lending in Boston: Interpreting HMDA data." *The American Economic Review*, 25–53.

The Effect of Minority Bank Ownership on Minority Credit*

Agustin Hurtado† Jung Sakong‡

January 2, 2024

Abstract

We construct the first matched data on bank ownership, employees, and mortgage borrowers to study the effect of racial minority bank ownership on minority credit. We address previous missing data and measurement error issues by introducing numerous novel sources and tools. Using our newly constructed data, we present four findings. First, minority-owned banks specialize in same-race mortgage lending. Almost 70 percent of their mortgages go to borrowers of the same race as their owners. Second, the effect of minority bank ownership on minority credit is large and exceeds that of minority loan officers. We find that minority borrowers applying for mortgages at banks whose owners are of the same minority group are nine percentage points more likely to be approved than otherwise identical minority borrowers at nonminority banks. This effect is over six times that of a minority loan officer. Third, evidence from plausibly exogenous bank failures suggests that the effect of minority bank ownership might reflect an expansion rather than a reallocation of credit to minorities. Fourth, the within-bank default rate of same-race borrowers is much lower than that of otherwise-identical borrowers of other races at minority banks. These findings are consistent with minority bank ownership reducing information asymmetry and inconsistent with owners' preferences driving the observed effects on minority credit. The evidence is also consistent with an organizational phenomenon, suggesting that the effect of banks' organizational culture and design on minority credit might outweigh that of banks' individual employees.

*This paper is based on Agustin Hurtado's dissertation at the University of Chicago. We are grateful to his dissertation committee members Pascal Noel, Raghuram Rajan (co-chair), Amir Sufi, Luigi Zingales (co-chair), and Eric Zwick for their guidance and support. We thank Diag Davenport (discussant), Pablo Slutzky, Liu Yang, and Rebecca Zarutskie (discussant), as well as participants at the BFI-Rustandy Discrimination, FDIC Bank Research, and NBER Innovative Data in Household Finance Conferences and numerous academic seminars for their comments and suggestions. We would also like to acknowledge Jairo Duarte, Tori Healey, Max Jaffe, and Brianna Smith for superb research assistance and help dealing with confidential data. This research was funded by the John and Serena Liew Fellowship Fund at the Fama-Miller Center for Research in Finance, the Stigler Center for the Study of the Economy and the State, and the Stevens Doctoral Office at the University of Chicago Booth School of Business. We acknowledge the Bright Initiative, the Community Development Bankers Association, CUCollaborate, the Federal Deposit Insurance Corporation, the Federal Reserve Bank of Chicago, Mighty Deposits, the National Credit Union Administration, the Rustandy Center for Social Sector Innovation, and the U.S. Treasury Department for research support and data access. The views here are ours and do not reflect those of the Federal Reserve System.

†University of Maryland Smith School of Business.

‡Federal Reserve Bank of Chicago.

I. Introduction

There is great interest in promoting bank ownership by racial minorities in the United States. The federal and local governments, corporations, and even large banks have invested billions in minority-owned banks (White House, 2022). Likely as a result, the share of minority-owned banks has grown thirtyfold since 1940 and tripled since 1990. However, we know little about the effect of minority bank ownership. In this paper, we ask *whether* and *why* minority bank ownership matters for minority credit. To answer these questions, we assemble the first comprehensive matched data on minority bank ownership, employees, and mortgage borrowers.

Our data address three significant challenges that have constrained other work on these questions due to missing data and measurement error issues. First, all federal bank regulators maintain separate minority bank registries with inconsistent coverage, public availability, definitions, and regulatory identification numbers. We address these inconsistencies by constructing a comprehensive list of minority-owned banks from data collected through Freedom of Information Act (FOIA) requests and public sources, using a consistent minority bank definition based on an ownership threshold and collecting unique bank identification numbers. Second, data on bank employee characteristics such as race and language have been sparse and inaccessible until now. We create these data using balanced face attribute recognition, Bayesian methods, and newly collected employee names, locations, professional headshots, languages, and job titles from LinkedIn and other novel sources. Notably, the subset of our data covering loan officers contains more precise race predictions than recent efforts in the literature, which is crucial for addressing measurement error issues in our analyses. Third, publicly available data on mortgage borrowers lack information on their credit risk, the identity of their loan officers, and defaults. Excluding borrower risk and the race of loan officers from our analyses might induce omitted-variable bias, and a lack of data on defaults would affect our ability to study mechanisms. To solve these issues, we access three confidential datasets that contain records of borrowers' credit risk, loan officers, and defaults. We match all these data using bank and loan officer identification numbers. Using this newly constructed dataset, we examine the effect of minority bank ownership on credit access by employing three distinct but complementary approaches: an initial exploration of the data, a fixed-effects design, and a generalized difference-in-differences design.

In the first part of the paper, we describe our data and shed light on minority-owned banks' business model. We start by exploring what kinds of activities minority-owned banks engage in. Minority banks specialize in mortgage lending, with close to 60 percent of their assets in real estate, twice the share of nonminority banks similar in size and clientele, which we call "peer banks". Minority-owned banks keep 70 percent of their residential mortgages on-balance sheet, despite only five percent being balance-sheet-intensive (jumbo) loans. By contrast, peer banks keep only half their mortgages on-balance sheet while having the same share of balance-sheet-intensive loans.

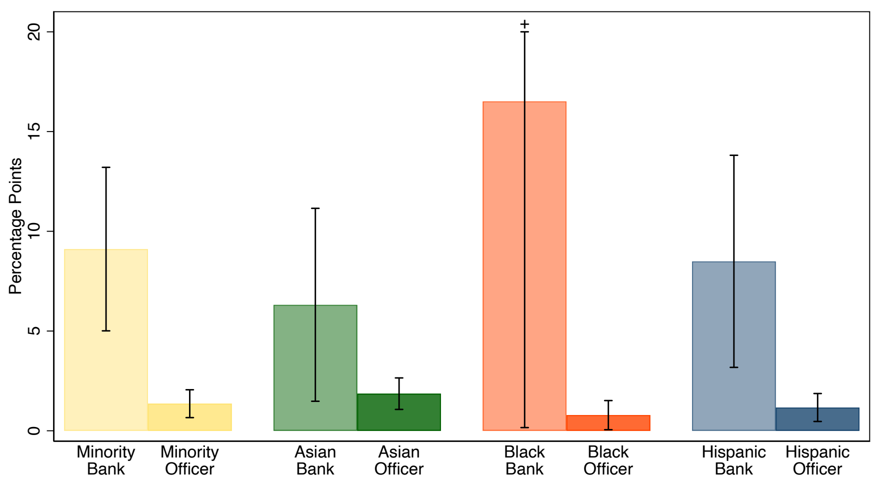
We next shed light on minority banks' employees and borrowers. Over 50 percent of minority-owned banks' employees are of the same race as the bank owners, and 48 percent natively speak languages other than English. By stark contrast, less than 10 percent of peer banks' employees belong to a racial minority group or natively speak languages other than English. We observe similar patterns among mortgage borrowers. Over 70 percent of minority-owned banks' borrowers are of the same race as the bank owners, whereas less than eight percent of peer banks' borrowers belong to any minority group. Finally, we find that the default rate of minority banks' same-race borrowers is only three percent, whereas that of other-race borrowers is almost five percent.

The second part of the paper empirically studies whether minority ownership matters for minority credit access. Ideally, to answer these questions, we would undertake an experiment in which minority mortgage borrowers who are identical in every (observable and unobservable) dimension are randomly assigned to banks. In this experiment, we could estimate the ownership effect as the difference in approval rates between minority borrowers assigned to same-race minority banks and those assigned to other-race banks. We mimic this ideal experiment by using a fixed-effects design that compares minority mortgage borrowers in the same location and period, with the same demographics, applying for mortgages with the same characteristics at minority and nonminority banks of similar size. We find that minority ownership has a large impact on minority credit access. The effect of having a minority-owned bank is equivalent to an increase in minority approvals of 10 percentage points, which fully closes the unconditional mortgage approval gap between minority and White borrowers. When we split minority banks and borrowers by racial group, we find that the effect of having an Asian, Black, and Hispanic-owned bank is equivalent to an increase in Asian, Black, and Hispanic approvals of 10, 13, and 9 percentage points, respectively.

The primary concern about this design is selection arising from the nonrandom matching between mortgage borrowers and banks. Despite including fixed effects for each location, period, demographic, mortgage, and bank characteristic, we worry about selection that produces an overestimated ownership effect. For example, minority borrowers with low credit risk or a preference for same-race loan officers might be more likely to apply to minority-owned banks. The benefit of the confidential part of our data is that we observe credit risk and construct a proxy for loan officers' race for the near-universe of mortgage borrowers for recent years, so controlling for some of these factors is possible. We show that the estimated ownership effects are robust to the inclusion of credit scores, debt-to-income and loan-to-value ratios, and loan officers' race. The fact that the estimated effects do not change much when we include these variables while R-squared values increase suggests that unobservable selection might not be a significant threat. Using the δ statistic of Oster (2019), we formally show that this is the case: the influence of unobservables would need to be between 1.4 and 5.1 times the influence of observables for the ownership effects that we estimate to be zero.

Using the confidential and newly constructed data, we also find that the large minority ownership effect that we estimate exceeds the effect of minority loan officers. We do not observe loan officers' race directly and rely on race predictions instead. Because we worry about measurement error that would underestimate the loan-officer effect, we construct predictions using professional headshots and a balanced face attribute recognition algorithm with accuracy rates of over 90 percent (Karkkainen and Joo, 2021).[1] Figure I shows that the effect of minority ownership is equivalent to an increase in same-race minority approvals of 9.1 percentage points; in contrast, the minority loan officer effect is only 1.4 percentage points. In other words, the effect of minority bank ownership is 6.7 times that of having a minority loan officer. When we split minority banks and borrowers by racial group, we find that the effect of Asian, Black, and Hispanic ownership is equivalent to 3.4, 21.2, and 7.3 times the effect of having an Asian, Black, and Hispanic loan officer, respectively.

Figure I: The Effect of Minority Bank Ownership and Loan Officers on Minority Credit



Notes: This figure plots $\hat{\beta}$s and their 95% confidence intervals from (1). See Appendix Table II for details.

Next, we follow a generalized difference-in-differences approach that improves on our fixed-effects design in two dimensions. First, it directly addresses selection concerns using fraud-induced bank failures that disrupt the nonrandom matching between mortgage borrowers and banks. Second, it sheds light on whether the effect of minority bank ownership reflects an expansion or a reallocation of minority credit. Even if minority banks are more likely to approve minority mortgage applications, the overall effect of minority ownership on minority credit is ambiguous. If minority banks are simply good at cream skimming, for example, the most creditworthy minority borrowers would still

[1] We use Bayesian Improved First and Surname Geocoding (BIFSG) for officers without professional headshots.

obtain credit after minority bank failures. In such a case, the overall effect of minority ownership would be zero and reflect a reallocation rather than an expansion of minority credit.

We implement two separate difference-in-differences designs around the near-collapse of Abacus Federal Savings Bank and the failure of Colonial Bank. Abacus, an Asian-owned bank on the East Coast, faced a wrongful fraud case and nearly collapsed in 2009 but was acquitted in 2015. Colonial, a nonminority bank in the South, was closed in 2009 by its regulator due to demonstrable fraud. Both designs exploit geographical variation in Asian borrowers' reliance on the banks in 2008. Asian borrowers in locations with Asian banks, excluding the banks, form the control group. If the identifying assumption holds—if the evolution of Asian approvals in exposed and nonexposed locations would have been similar absent the failures—then this research design is valid. Several sources suggest that the cases against Abacus and Colonial were unexpected, and graphical inspection of parallel trends indicates smooth pretrends.[2]

We find a sharp and persistent decrease in Asian approvals after the Abacus near-collapse, but no change after the Colonial failure. Mortgage approval rates for Asian borrowers declined by 30 percentage points per year over four years in fully exposed locations after the Abacus near-collapse. This effect likely underestimates the true effect of the collapse, because some Asian borrowers, particularly those without strong observable characteristics, might have been discouraged from applying to other nonminority banks. We show that this scenario is likely because per-capita applications from Asian borrowers declined after Abacus nearly collapsed. We also implement placebo tests showing no changes in Black, Hispanic, and White mortgage approvals around both the Abacus near-collapse and the Colonial failure. These findings—speficially, the stark difference between the effects of the Abacus near-collapse and the Colonial failure on Asian approvals—is consistent with the destruction of valuable relationships and specialized information about Asian borrowers when Abacus collapsed. After information and relationships are destroyed, Asian borrowers without strong observables might have had difficulty establishing a new bank relationship due to information asymmetry, consistent with Bernanke (1983). This interpretation suggests that the effect of Asian ownership might reflect an expansion rather than a simple reallocation of credit to Asian borrowers.

The third and last part of the paper studies why minority ownership matters for minority credit access. From a theoretical standpoint, minority bank ownership might matter because superior information (or more accurate prior beliefs) reduce information asymmetry between minority banks and minority borrowers of the same race as the owners. Considering the results in the second part of the paper, this superior information is likely orthogonal to the soft information collected by loan officers and might be embedded in the banks' organizational culture and design, for

[2]We perform these analyses using data constructed from public and commercial sources. Due to legal and time coverage restrictions, we cannot employ confidential data from the Federal Reserve System in these analyses.

example, through banks' loan policies.[3] Superior information might lead to improved screening and monitoring, mitigating adverse selection and moral hazard. Consequently, minority banks would originate more loans to same-race borrowers, who should exhibit lower default rates. By contrast, if the additional lending to minorities is due to the preferences of minority owners, possibly embedded in the organizational culture and design of those banks, we should see higher default rates among same-race borrowers.

Our initial exploration of the data shows that the default rate of minority banks' same-race borrowers is three percent, whereas that of those banks' other-race borrowers is almost five percent. However, this crude comparison is based on borrower default averages and might reflect differences in observed and unobserved characteristics. We address this issue by comparing minority and nonminority borrowers with the same credit risk and demographic characteristics, with mortgages with the same interest rate and other characteristics, from the same bank, underwritten by a loan officer of the same race. Due to data limitations, we can only perform this more refined comparison for borrowers at Asian banks. Within these banks, we still find that the default rate of the average same-race borrower is much lower than that of the average other-race borrower with the same characteristics. Asian banks' average Asian borrower is 1.29 percentage points less likely to default than their average non-Asian borrower with the same credit risk and other characteristics. This large difference is equivalent to half the average default rate at Asian banks. More important, this finding is consistent with reduced information asymmetry, which might be explained by superior information embedded in Asian banks' organizational culture and design, and inconsistent with owners' preferences.

Literature. This work is at the intersection of several strands of literature. Most directly, this paper relates to studies on minority banks. A paucity of data has limited the scope and validity of findings in this literature, which in the past has had to rely on ad hoc assumptions. Most of this research focuses on minority banks' financial performance and assumes that minority banks serve mostly minority groups. For example, studies showing that minority banks underperform, such as Elyasiani and Mehdian (1992), rationalize their results by assuming that these banks serve mostly minority borrowers.[4] The few papers documenting minority banks' positive impact on credit, homeownership, and employment across geographies are also grounded in this assumption and either pool all minorities in one category (Berger et al., 2022; Vatsa, 2022) or study only one bank (Stein and Yannelis, 2020).[5] This paper's core contribution is to assemble new microeconomic

[3]Loan policies are developed by banks and set the terms on how and to whom banks will lend, defining their market areas, lending specialization, and documentation standards.

[4]Starting with the work of Brimmer (1971), the first Black governor of the Federal Reserve, the literature on minority bank performance has focused primarily on Black banks. See Bates and Bradford (1980), Kwast and Black (1983), Hasan et al. (1996), and Henderson (1999). Two exceptions that examine minority banks other than Black banks are Meinster and Elyasiani (1988) and Elyasiani and Mehdian (1992).

[5]Stein and Yannelis (2020) study the failure of the first Black bank in the United States: the Freedman's Bank.

data to go beyond these assumptions and questions. Our work improves on prior efforts by using 30 years of data on over 90 million minority borrowers and four million minority bank borrowers, which we can split up by minority group. To our knowledge, this is the first paper to directly show that minority-owned banks serve mainly same-race mortgage borrowers and rely on minority employees to do so.

We also contribute to the literature on racial disparities in the mortgage market. Since the seminal study of Munnell et al. (1996), this research has consistently shown that minorities exhibit lower mortgage approval rates and higher interest rates. This literature has identified several plausible sources of racial disparities in this market, including information noise (Blattner and Nelson, 2021), discrimination (Bartlett et al., 2022; Bhutta and Hizmo, 2021; Zhang and Willen, 2021), and exposure to risky lenders (Bayer et al., 2018). However, other than Bostic (2003), these studies have rarely focused on minority-owned banks. Unlike that paper and the rest of this literature, our work here documents that minorities exhibit much higher approval rates at minority banks. Our study improves on Bostic (2003) in three dimensions. First, we use data on the near-universe of minority bank borrowers. Second, we address omitted-variable issues related to credit risk and loan officers' race. Third, we go beyond approvals and study loan-level performance to shed light on the likely mechanism driving higher mortgage approvals.

The paper also relates to research examining the effects of cultural proximity. The economics literature has explored the impact of cultural proximity on various outcomes, including education and health.[6] In financial economics, an emerging literature has studied the role of same-race bankruptcy trustees (Argyle et al., 2022), home appraisers (Ambrose et al., 2022), mortgage brokers (Ambrose et al., 2021), peer-to-peer lenders (D'Acunto et al., 2021), and loan officers (Fisman et al., 2017; Frame et al., 2024).[7] Although this research has largely ignored the role of same-race ownership, we show that bank ownership matters a great deal. To our knowledge, we are the first paper in this literature showing that ownership plays a much larger role than individual agents.

Finally, we contribute to work on information frictions in credit markets. Our study is consistent with minority bank ownership lowering information frictions and improving credit allocations. We

[6]See Bartanen and Grissom (2021); Dee (2004); Gershenson et al. (2022); Kofoed et al. (2019) on education, and Greenwood et al. (2020) on health. For other outcomes, see Ayres and Siegelman (1995) on car prices Ba et al. (2021); Shayo and Zussman (2011) on policing; Bekes et al. (2022) on soccer players' collaboration, Easterly and Levine (1997) on pro-growth policies, Helpman et al. (2008); Kogut and Singh (1988) on trade, Hjort (2014) on productivity, Perez-Saiz and Xiao (2022) on competition, and Price and Wolfers (2010) on basketball penalties.

[7]Much of this literature documents positive effects. Argyle et al. (2022) document that the outcomes for Black filers of Chapter 13 bankruptcy are more favorable when their cases are assigned to Black trustees; Ambrose et al. (2021) demonstrate that mortgage brokers charge same-race customers lower fees. D'Acunto et al. (2021) find that peer-to-peer lenders in India are more likely to provide credit to same-religion and same-caste borrowers and that this effect disappears when lenders use a robo-advising tool. Fisman et al. (2017) show that having a same-religion or same-caste loan officer increases credit access. Fisman et al. (2020) document that Hindu loan officers exposed to fatal Muslim riots lend less to Muslim borrowers. Frame et al. (2024) show that having a minority loan officer increases minority mortgage access. One exception to the trend of finding positive effects in finance settings is Ambrose et al. (2022), who shows no effect in home appraisals.

provide direct evidence of improved credit allocations in Asian banks: their Asian borrowers are much less likely to default than their non-Asian borrowers. Through the lens of theory work on information frictions in credit markets, Asian ownership might reduce credit rationing, due to superior information (Calomiris et al., 1994) or more accurate prior beliefs about Asian borrowers (Cornell and Welch, 1996; Coval and Thakor, 2005). We also contribute to the literature on relationship lending and bank failures by showing that Asian access to mortgage credit was highly disrupted after Abacus nearly collapsed but was unaffected after Colonial failed. These patterns are consistent with the Abacus near-collapse exacerbating information frictions among Asian borrowers à la Bernanke (1983) and with single-relationship Asian borrowers having a more challenging time building a relationship with a new bank (Degryse et al., 2011).

II. Institutional Setting and Data

This paper constructs the most complete data yet applied to study minority bank ownership. Federal financial regulations form the foundation of these data's three pillars: bank ownership, employees, and borrowers. This section presents a regulatory overview of each pillar, lays out its core definitions, and describes challenges and solutions in data collection and construction.

A. Bank Ownership

A.1. Regulatory Background

In 1989, Congress enacted the Financial Institutions Reform, Recovery, and Enforcement Act (FIRREA). Section 308 of FIRREA defines minority banks and establishes three policy goals: preservation of banks' minority character, promotion of new minority banks, and technical assistance. Federal bank regulators submit annual reports to Congress describing their efforts to achieve the policy goals. These reports are based on minority registries for the banks each regulator supervises. The registries are the bedrock of our data, but they present three issues. First, their coverage and public availability are inconsistent across regulators. For example, the Office of the Comptroller of the Currency (OCC) maintains a minority registry of certain national banks and all federally-chartered savings and loans and, until recently, did not make this registry public. Second, registries might have different definitions depending on each regulatory agency's interpretation of Section 308. For example, the OCC is the only regulator with women-owned banks in its registry. Third, some registries do not have or have non-unique bank identification numbers. For example, the OCC's registry contains OCC charters numbers, which are non-unique.

A.2. Definitions and Data

Banks. We use the standard definition of banks: insured financial institutions performing deposit-taking and loan-making activities. This definition applies to commercial banks and credit unions. Commercial banks include national and state-chartered banks and federally and state-chartered savings and loans. Credit unions encompass state and federal credit unions. Our data include all these bank types but come from different regulatory sources.

Minority Groups. We focus on racial minority groups and use three FIRREA categories: Asian American, Black American, and Hispanic American. The Hispanic category is defined as an ethnicity, but for simplicity, we refer to all categories as "racial." FIRREA categories are based on the Office of Management and Budget (OMB) Race and Ethnic Standards for Federal Statistics and Administrative Reporting, also known as OMB Directive No. 15. Appendix 1.1.1 includes details on the definitions and composition of each category under the Directive.

While broad, these categories provide a well-defined standard we consistently use to construct our data on bank ownership. We exclude the Native American category from our data because of its size and unique characteristics. Its small size prevents reliable statistical inference, and its unique laws, regulations, and geographies threaten external validity.

Minority Banks. Under the U.S. dual banking system, several federal and state agencies regulate banks. Among these agencies, four federal regulators maintain minority bank registries: the Federal Deposit Insurance Corporation (some state-chartered banks and all state-chartered savings and loans), the Federal Reserve (some national and state-chartered banks), the OCC (certain national banks and all federally-chartered savings and loans), and the National Credit Union Administration (some state-chartered and all federal credit unions).

In addition to covering different banks, these registries have inconsistent definitions depending on each regulatory agency's interpretation of FIRREA's Section 308. The Federal Deposit Insurance Corporation (FDIC) and OCC definitions include banks in which minority individuals represent at least 51 percent of the institution's ownership (minority-owned banks) or a majority of its board of directors (minority-board banks) or in which the community that the institution serves is a predominantly minority population (minority-market banks). The Federal Reserve definition includes only banks in which minority individuals represent at least 51 percent of the ownership (minority-owned banks). The National Credit Union Administration (NCUA) definition includes credit unions in which minority individuals form at least 50 percent of current members (minority-member credit unions) or a majority of the board of directors (minority-board credit unions). The FDIC, Federal Reserve, and NCUA define a minority as any non-Hispanic Asian, non-Hispanic Black, Hispanic, non-Hispanic Native, or multiracial (of two or more minority races or Hispanic ethnicity) individual. The OCC's definition of minority individuals also includes women.

We use a consistent definition based on an ownership threshold: banks in which Asian, Black, or Hispanic American individuals represent at least 51 percent of the institution's ownership (commercial banks) or membership (credit unions). Thus, we exclude definitions based on minority boards and markets. We also exclude multiracial and women categories.

Data on minority bank ownership come from five government agencies: The FDIC, Federal Reserve, OCC/Treasury, NCUA, and Government Accountability Office (GAO).

A.3. Data Construction

Three principles guide the creation of our bank ownership data. First, we use consistent definitions for minority owners and minority-owned banks (described above). Second, we construct comprehensive data in terms of banks and periods covered. We do so by creating a census of minority-owned banks through 10 Freedom of Information Act (FOIA) requests and public data from federal bank regulators supervising the universe of banks. The relevant period studied in this paper is 1990-2019, but the bank census goes back to 1940. Third, we collect Federal Reserve Board Entity numbers (RSSD9001) for every minority-owned bank in the census. Unlike other identification numbers, such as FDIC certificates, RSSD9001s are unique to each bank and cannot be transferred after a merger or acquisition. Using these unique numbers is essential to account for changes in minority ownership and to avoid matching the wrong banks in other datasets.

We create the ownership data in three steps. First, we clean each data source by dropping banks outside our definition. Second, we collect banks' unique identification numbers. Finally, we match the resulting datasets. Appendix 1.1.2 details the construction process and the five data sources we use (FDIC, Federal Reserve, OCC/Treasury, NCUA, and GAO). Panel A of Appendix Figure 1.1 shows the number of minority-owned banks in our census since 1940. Their absolute number exhibits a negative trend. However, Panel B indicates that their importance—the number of minority-owned banks relative to the total number of banks—has grown threefold since 1990 and thirtyfold since 1940.

B. Bank Employees

B.1. Regulatory Background

Congress passed the Secure and Fair Enforcement for Mortgage Licensing (SAFE) Act in 2008. Its main goal is to provide increased accountability and tracking of mortgage loan officers. The Act mandates a nationwide licensing and registration system for loan officers to achieve this goal. It creates the Nationwide Mortgage Licensing System, a comprehensive licensing and supervisory database housed at the Conference of State Bank Supervisors (CSBS). In recent years, regulatory agencies and data companies have improved and expanded data on loan officers from the CSBS.

B.2. Definitions and Data

Loan Officers. We focus on residential mortgage loan officers, who analyze mortgage borrowers' financial information and make approval decisions (or refer applications to management for a decision). Data on loan officers come from the CSBS and The Warren Group (TWG), a data company. CSBS data contain loan officer names, license numbers, office addresses, and lender names. TWG improves CSBS data by adding loan officers' contact information, social media accounts (LinkedIn, Twitter, and Facebook), Zillow profiles, and corporate websites. We also collect social media accounts, Zillow profiles, and corporate websites for loan officers not covered by TWG.

Board Members and CEOs. Board members and chief executive officers (CEOs) form banks' upper management. Board members guide, advise and operate banks. They set goals for CEOs who implement these goals and manage banks. We obtain data on credit union board members and CEOs from three FOIA requests submitted to the NCUA. [8] The data include names and office addresses of board members and CEOs for all credit unions regulated by the NCUA.

Other Employees. Other bank employees include bank tellers, branch managers, commercial loan officers, internal auditors, and loan processors. Data on employees come from LinkedIn profiles collected by BrightData, a data startup. LinkedIn data contain employees' names, job locations, professional headshots, languages, education, and past roles.

Minority Groups. We construct the employee data using all FIRREA categories: non-Hispanic Asian, non-Hispanic Black, Hispanic, non-Hispanic Native, and multiracial (of two or more minority races or Hispanic ethnicity). However, as in section A.2, we focus on the non-Hispanic Asian, non-Hispanic Black, and Hispanic categories.

B.3. Data Construction

We assemble our data on bank employees' language and race from eight data sources: The Census Bureau, CSBS, TWG, social media accounts, Zillow, corporate websites, NCUA, and BrightData. The language data is constructed from scraped profiles. We create Asian and Hispanic language categories for loan officers and other employees. Appendix 1.2.1 lists the languages in each category.

The employee race data contain race predictions constructed using Face Attribute Recognition

[8] We were unable to obtain data on bank board members and CEOs.

(FAR) and Bayesian Improved First and Surname Geocoding (BIFSG).[9] FAR predicts employees' race using their professional headshots from social media accounts, Zillow profiles, and corporate websites. BIFSG uses employees' full names and locations, and its predictions are much less precise than FAR's. Our goal in constructing these race data is to maximize prediction precision to minimize measurement error that would underestimate the effect of loan officers on credit access. Thus, we use FAR whenever professional headshots are available in our data sources. Consequently, our race predictions for loan officers are more precise than those of Frame et al. (2022) and Jiang et al. (2022), which use BIFSG. Appendices 1.2.1 and 1.2.2 present an overview and prediction accuracy measures for FAR and BIFSG, respectively. Appendix 1.2.1 also reports additional details on data sources and construction.

C. Mortgage Borrowers

C.1. Regulatory Background

In 1975, Congress enacted the Home Mortgage Disclosure Act (HMDA). Its original goal was to provide adequate mortgage financing to qualified borrowers on reasonable terms. Amendments in the FIRREA required public disclosure of data about borrower characteristics to supervise and enforce fair lending laws in 1989. Since then, the near universe of mortgage lenders has reported detailed mortgage application-level data—including borrowers' self-reported race—to the Federal Reserve, which has disclosed these data to the public. Since 2018, lenders have also had to report credit risk variables and loan officers' identification numbers for every mortgage application. However, this information is not disclosed to the public.

C.2. Definitions and Data

Borrowers. We define borrowers as individuals applying for mortgages regardless of their lenders' approval decisions.

Mortgage Applications. HMDA lenders report mortgage applications and purchase mortgage loans. Our definition excludes purchased loans.

Minority Groups. We construct all FIRREA's categories using self-reported race and ethnicity fields in HMDA data and a consistent definition that accounts for changes in its reporting over time. Most of our work focuses on the non-Hispanic Asian, non-Hispanic Black, and Hispanic categories. In the case of joint mortgage applications, we construct minority categories using the self-reported race and ethnicity of primary borrowers.

[9] Recent papers using these methods include Cook et al. (2022), Frame et al. (2022), Jiang et al. (2022), and Blattner and Nelson (2021).

Confidential Information. Credit scores, loan-to-value and debt-to-income ratios, and loan officers' identification numbers are considered confidential by HMDA. We access these data from a confidential version of HMDA under strict security protocols.

Mortgage Defaults. We define default as failing to make a scheduled mortgage payment for at least 60 consecutive days. We measure defaults within 12 months of origination for loans granted between January 2018 and March 2019 in the confidential HMDA and McDash datasets.

Geographic Units. Since minority-owned banks tend to be small and local, we use the census tracts of borrowers' properties—the smallest geographic unit in HMDA—as our primary geographic unit. Tracts have superior statistical properties relative to other small geographies, such as 5-digit ZIP codes.[10] One challenge in using tracts is that they can experience boundary changes every Decennial Census. HMDA incorporated these changes in 1992, 2003, and 2012. To account for these changes, we construct crosswalks from the Census Bureau's Relationship Files and Longitudinal Tract Data Base (LTDB).

Identification numbers. Lenders in HMDA have identification numbers different from the unique regulatory numbers (RSSD9001) we collected for minority banks. The "Avery file"—a dataset constructed by Robert Avery of the Federal Finance Housing Agency—provides a crosswalk between the two. Loan officers in confidential HMDA have NMLS identification numbers provided by the CSBS. Borrowers do not have identification numbers.

C.3. Data Construction

We employ four rules to construct our data on mortgage borrowers. The first rule is to match borrowers with as many datasets as possible. We match mortgage borrowers to our census minority bank using the newly collected regulatory numbers (RSSD9001) and the "Avery file" and to our loan officers' race data using NMLS numbers. Second, we go as micro as possible by using the smaller units among all datasets: mortgage borrowers and census tracts. Third, we use as much data as possible. The data construction and matching start with 1990, the first year HMDA disclosed borrower-level information. We construct and use data until 2019 to avoid selection concerns induced by the effect of the COVID-19 pandemic on minorities, the mortgage market, or both. The last rule is to go beyond public data to address econometric issues in our analyses and explore mechanisms. We do so by accessing and matching three non-public datasets: confidential HMDA, CSBS-TWG, and McDash.

As discussed above, the confidential HMDA data contain three credit risk variables for borrowers applying for mortgages in 2018 and 2019. This confidential data also has loan officer numbers that

[10] They are contiguous subdivisions of counties. Tracts' purpose is to provide stable geographic units for statistical purposes. They have a population size between 1,200 and 8,000 people, with an optimum size of 4,000.

we use to match officers to their predicted races constructed from the CSBS-TWG data. Including this information in our analyses is vital to address omitted-variable bias and assess the degree of unobserved selection.

McDash is a dataset on mortgage defaults. We adapt a matching algorithm from the Federal Reserve to obtain default data on minority banks' borrowers (without identifying banks or borrowers). The adapted algorithm fuzzy matches McDash, confidential HMDA, and our minority bank census on location, loan amounts, credit scores, and other variables. Despite providing a starting point to study mechanisms, the resulting data have a small sample size. In particular, we match less than 200 borrowers with Hispanic banks and none with Black banks. We have more encouraging numbers for Asian banks' borrowers, fortunately. Appendix 1.3 provides details on data sources and the construction process.

D. Other data

We employ several existing and newly constructed datasets, including the Summary of Deposits, a census of peer banks, and call reports. The Summary of Deposits provides geographic information on bank branches (and their deposits), which we re-geocode to obtain their census tracts. We use these and additional data to construct a census of peer (and non-peer) banks.

We define minority banks' peer institutions as those similar in size and primary local market areas (Toussaint-Comeau and Newberger, 2017). Peer banks are community development financial institutions (CDFI banks and credit unions) and low-income credit unions (LICUs). CDFIs and LICUs are certified by the Treasury and NCUA as specialized institutions that provide financial services to low-income communities and people who lack access to financing. They have sizes and clienteles similar to those of minority-owned banks. The peer group we construct excludes minority-owned banks with CDFI and LICU certifications. The peer census is constructed with data from partnerships with the Community Development Bankers Association (CDFI data, 1996-2019) and CUCollaborate (LICU data) and a FOIA request to the Treasury Department (CDFI data, 2013-2019). For each bank in the peer census, we collect unique identification numbers (RSSD9001) to perform the same data matches we did with minority-owned banks.

Call reports contain data on balance sheet, income statement, and other structural items for commercial banks and credit unions. We use these data to study minority banks' asset composition in section III. Appendix 1.3 presents an overview of the sources and data construction.

E. Analyses Samples and Summary Statistics

Our three major analyses use four different data samples. Table I reports summary statistics for all relevant variables in each analysis and sample. Its notes and Appendix 1.4 provide definitions.

The first analysis is performed on the (near) universe of minority borrowers. Panel A presents statistics. The sample contains almost 90 million minority borrowers who applied for mortgages between 1990 and 2019. We start by reporting the analysis's key variables. Panel A indicates that the mean approval rate is 60 percent. It also shows that minority-owned banks account for 2 percent of all mortgage applications, equivalent to 1,734,777 applications. The rest of the panel depicts statistics for covariates: borrower, loan, and confidential characteristics. The latter variables are available for minority borrowers who applied for mortgages between 2018 and 2019. Sections II and IV present details on the data and analysis.[11]

Panel B of Table I reports summary statistics for our second analysis. We construct a sample of borrowers with mortgages granted by minority-owned banks in 2018 and 2019. Statistics for key variables indicate that the average default rate among minority banks' borrowers is 3 percent, and 21 percent belong to a minority group. Sections II and V.A report further details.

In our last analysis, we use data on the (near) universe of Asian borrowers applying for mortgages between 2003 and 2019 in markets impacted by the collapse of Abacus and Colonial Banks. We present statistics in Panels C and D of Table I. Mean approval rates are similar in both datasets; 67 and 68 percent in the Abacus and Colonial samples, respectively. Section V.C presents further details on sample construction and the analyses.

[11]Appendix 1.5 depicts distributions of credit risk, demographic, and loan characteristics for this sample and shows that minority borrowers with same-race minority banks exhibit lower credit risk, but also lower incomes and loan amounts.

III. Minority-Owned Banks' Business Model

We begin with a brief exploration of the data that sheds light on minority-owned banks' business model. This exploration is guided by the notion that banks' specialness and ability to lend is tied to their collection of assets and relationships (Granja et al., 2017).

Data. We use data for minority-owned banks and their peer non-minority banks in 2019. As described in section II, peer banks are community development financial institutions (CDFI banks and credit unions) and low-income credit unions. These institutions are similar to minority banks in size, geographic scope, borrowers, and government support. We focus on 2019 because it is the last year in our data before the pandemic.

Assets. We start by measuring banks' asset composition with call report data. Minority banks' largest asset category is real estate loans. Panel A of Figure I shows that the (weighted) average ratio of real estate loans to assets in all minority banks is 59.37 percent; this ratio is 59.78, 54.61, and 62.34 percent in Asian, Black, and Hispanic banks, respectively. By contrast, the ratio of mortgages to assets is 33.42 percent in peer non-minority banks.[12]

Next, we show that balance-sheet retention partly drives the substantial difference in mortgage-to-asset ratios between minority and peer non-minority banks. Panel B of Figure I shows the (weighted) average share of mortgages kept on balance sheet computed from HMDA. Whereas minority-owned banks keep about 69.49 percent of their mortgages on-balance sheet, peer non-minority banks keep only 51.27 percent. A more refined comparison should exclude jumbo mortgages, which Buchak et al. (2022) label balance-sheet intensive because they are more difficult to securitize. Figure X in Appendix 2 shows that the share of jumbo mortgages is 4.59 percent in minority-owned banks and 5.12 percent in peer non-minority banks. Thus, minority-owned banks keep approximately 68.02 percent of their easy-to-sell mortgages on balance sheet. This share is only 48.64 percent in peer non-minority banks.[13]

Employees and Borrowers. We use our LinkedIn data to analyze race and language data on minority and peer non-minority banks' employees in all roles. Panel A of Figure II indicates that the share of same-race employees in minority banks is 52.97 percent on average; this share is 51.42, 39.13, and 54.41 percent in Asian, Black, and Hispanic banks, respectively. By stark contrast, Panel B shows that only 2.25, 0.78, and 8.29 percent of peer non-minority banks' employees belong to Asian, Black, or Hispanic groups, respectively. In terms of languages, Panel C of Figure II indicates that 48.38 percent of Asian banks' employees speak Asian languages, whereas less than 3 percent do so in other minority banks and peer non-minority banks. Similarly, Panel D shows that 53.39

[12] Appendix 2 shows that this ratio is 35 percent in small non-minority banks and 22 percent in large non-minority banks.

[13] That is, $\frac{69.49-4.59}{100-4.59} \approx 68.02$ and $\frac{51.27-5.12}{100-5.12} \approx 48.64$.

percent of Hispanic banks' employees speak Hispanic languages, and less than 8 percent do so in the other banks.[14]

We find similar patterns when examining the racial composition of mortgage borrowers. Panel D of Figure II indicates that 68.59 percent of minority banks' borrowers have the same race as the bank owners; this share is 62.95, 51.70, and 78.55 percent in Asian, Black, and Hispanic banks, respectively. At the other end of the spectrum, Panel F shows that only 6.69, 4.62, and 7.58 percent of peer non-minority banks' borrowers are Asian, Black, and Hispanic, respectively.

Finally, we zoom in on minority banks' mortgage borrowers and study their mortgage default rates. As detailed in section II, our default data only cover Asian and Hispanic banks. Panel A of Figure III indicates that the average default rate of same-race borrowers in minority banks is 3.24 percent, 70 percent that of their other-race borrowers. Panel B shows that the average default rate of Asian and non-Asian borrowers in Asian-owned banks is 2.11 and 2.82 percent, respectively. Panel C reports that Hispanic and non-Hispanic borrowers' defaults in Hispanic banks are 8.25 and 8.93 percent, respectively. We come back to these findings in section V.

Summary. We summarize the findings of this exploration in two points. First, minority-owned banks exhibit less off-balance-sheet activity than other banks, and off-balance-sheet mortgages are more transactional in nature.[15] Second, minority banks have more same-race employees than other banks and originate mortgages primarily to same-race borrowers, who have lower default rates than their other-race borrowers. Taken together, these findings are consistent with minority-owned banks relying less on transactional lending and having valuable information about same-race borrowers. We come back to this interpretation in section V.

[14] Appendix 2 shows similar patterns for the racial composition of CEOs, board members, and loan officers.

[15] Off-balance-sheet mortgages would be categorized as transactional loans by Boot and Thakor (2000), which they define as "a pure funding transaction, a commodity product... where the borrower's expected project payoff is unaffected by the bank's participation."

IV. Does Minority Bank Ownership Matter?

A. Fixed-Effects Design: Setup

Ideal Experiment. Does minority bank ownership matter for minority credit access? Ideally, we would answer this question with an experiment in which minority borrowers identical on every (observable and unobservable) dimension are randomly assigned to apply for mortgages at different banks. In this experiment, we could estimate the effect of minority bank ownership as

$$\beta = \overline{Approval}_m - \overline{Approval}_o,$$

where $\overline{Approval}_m$ and $\overline{Approval}_o$ are average approval rates of minority borrowers randomly assigned to same-race minority banks and other banks, respectively.

Empirical Setup. We approximate this experimental setting by using a fixed-effects research design that compares minority borrowers in the same location and period, with the same demographic characteristics, applying for mortgages with the same characteristics at minority and other banks of similar size. The baseline regression specification is

$$Approval_{ijkt} = \alpha_k + \alpha_t + \beta MinorityOwnedBank_{jkt} + \gamma X_{ijkt} + \xi_{ijkt}, \tag{1}$$

for borrower i, bank j, property's census tract k, and year t. $Approval_{ijkt}$ and $MinorityOwnedBank_{jkt}$ are approval and minority bank dummies. X_{ijkt} are covariates that we discuss more in the next paragraph. We cluster standard errors at the bank and census tract levels. The coefficient of interest β reflects the approval rate of minority borrowers applying for mortgages at same-race minority-owned banks relative to that of otherwise identical minority borrowers at non-minority banks. We call β the minority-ownership effect.

X_{ijkt} are borrower, loan, and bank characteristics. Borrower demographic characteristics include income-percentile fixed effects, gender, and co-borrower presence dummies. Loan characteristics include loan amount-percentile fixed effects and dummies for loan purpose (purchase, improvement, refinancing), loan type (conventional, FHA, VA, FSA/RHS), and occupancy (principal, second, investment property). Bank characteristics include percentile bank-size fixed effects.

Identification. The primary identification issue in this design is selection arising from the non-random matching between mortgage borrowers and banks. We worry about two cases in which observable selection might induce an overestimated ownership effect. First, matching with minority-owned banks might be positively correlated with the (observable) credit risk of same-race minority borrowers. We address this potential source of endogeneity by controlling for borrower credit scores and loan-to-value and debt-to-income ratios from confidential data. Second, matching with minority banks might be positively associated with borrowers' preference for same-race loan officers. Because our data on loan officers can be merged with borrower data, we address this issue by explicitly controlling for loan officers' race.

We also worry about unobservable selection. For example, after controlling for observable credit scores, unobservable credit risk might still correlate with matching and approval rates. We follow Altonji et al. (2005) and Oster (2019) and characterize the relative degree of unobservable selection needed for the minority ownership to be zero by constructing Oster's δ statistic.

B. Fixed-Effects Design: Findings

Main Findings. We estimate specification (1) for 1990-2019 to test whether minority bank ownership matters for minority credit. Results are presented in Figure IV and Appendix Table 3.1.

The first bar of Figure IV reports the effect of minority ownership when minority borrowers are pooled in a single category. In this case, $MinorityOwnedBank_{jkt}$ in (1) is equal to one for same-race minority banks, and zero otherwise. Minority borrowers applying for mortgages at same-race minority-owned banks are 9.8 percentage points more likely to get approved than minority borrowers at other banks. The second, third, and fourth bars present results by minority group. Asian, Black, and Hispanic borrowers applying for mortgages in Asian, Black, and Hispanic banks are respectively 9.9, 13.1, and 8.8 percentage points more likely to get approved than otherwise identical borrowers in other-race banks.

We address selection on observables by controlling for credit risk and loan officers' race in (1). We use credit scores, loan-to-value and debt-to-income ratios, and loan-officer identification numbers (linked to newly constructed loan officer race predictions) from confidential HMDA. Because the collection of confidential information started in 2018, we can estimate this augmented specification only for 2018-2019. Odd-numbered columns in Table II report baseline results similar to Appendix Table 3.1. Even-numbered columns show that controlling for risk and loan officers' race does not meaningfully change these results; estimated effects slightly decline and R-squared values increase. Column 2 indicates that minority borrowers applying for mortgages at same-race minority-owned banks are 9.11 percentage points more likely to get approved than minority borrowers with the same credit risk and loan officers' race at other banks. Columns 4, 6, and 8 indicate that this effect is 6.32, 16.52, and 8.49 percentage points for Asian, Black, and Hispanic borrowers at same-race banks, respectively.

The fact that the estimated effects do not meaningfully change, whereas R-squared values increase, suggest that the degree of selection on unobservables relative to observables might be modest. To formally characterize the degree of relative selection, we construct Oster's δ statistic and compare it with a bound of 1. Our δ statistic measures the degree of selection on unobservables relative to observables needed for the minority ownership effect to be zero; equation (12) in Appendix 4 details its calculation. We report δ statistics in the last row of Table II. Column 2 shows that the influence of unobservables would need to be 1.42 times that of observables for the minority-ownership effect to be zero; columns 4, 6, and 8 indicate that it would need to be 2.29, 5.11, and 1.25 times the influence of observables for the Asian, Black, and Hispanic ownership effects to be zero.

Economic Magnitudes. We employ three benchmarks to shed light on economic magnitudes: mortgage approvals, credit scores, and loan officers. Back-of-the envelope magnitudes are constructed using the most conservative specifications and benchmarks. For brevity, we discuss magnitudes for Asian, Black, and Hispanic borrowers pooled in the category "Minority," but magnitudes by group are summarized in Appendix Table 3.2.

First, we scale coefficients in the even-numbered columns in Table II by the mortgage approval mean and the gap between White and minority approvals. Column 1 of Appendix Table 3.2 shows that the effect of minority bank ownership is equivalent to 12 percent of the minority approval mean. Column 2 indicates that the minority-ownership effect is equivalent to closing the mortgage approval gap between minorities and Whites.

Second, we estimate specification (1) with credit scores in levels and calculate the ratio of minority bank to credit score coefficients.[16] Column 3 of Appendix Table 3.2 indicates that the effect of minority ownership on approvals is equivalent to a 76.08-point increase in credit score. We then use this number to compare the effect of minority ownership with that of bankruptcy flag removal. We use Gross et al. (2020)'s estimate, the largest we could find in this literature. The authors show that the effect of bankruptcy flag removals from credit reports is equivalent to a 19.20-point increase in credit score within 12 months.[17] Column 4 of Appendix Table 3.2 shows that the minority-ownership effect is equivalent to 3.96 times the effect of a bankruptcy flag removal.

Third, we compare the effect of minority bank ownership with that of minority loan officers. This benchmark is an important one because recent research by Frame et al. (2022) and Jiang et al. (2022) shows that minority borrowers having a minority loan officer are more likely get their mortgage applications approved than non-minority borrowers having a minority loan officer. Like these papers, we construct race predictions because we do not observe loan officers' race directly. These predictions might induce race misclassification, which is a form of measurement error that might produce underestimated loan-officer effects.[18] As detailed in section II and Appendix 1.2.1, we address this concern by using loan officers' professional headshots and a face-attribute recognition algorithm with accuracy rates of over 90 percent (Karkkainen and Joo, 2021). Even-numbered

[16] Table 3.3 in Appendix 3 reports the results for this specification. The credit-score coefficient is 0.12.

[17] For details, see column 9 of Table 1 in Gross et al. (2020).

[18] Appendix Table 3.4 shows that race predictions constructed using Frame et al. (2022)'s and Jiang et al. (2022)'s method induce attenuation in loan-officer coefficients in all specifications. Furthermore, the Black-loan-officer effect is not statistically significant.

columns in Table II report results using these predictions. Column 2 shows that having a minority loan officer is equivalent to a 1.36-percentage-point increase in same-race minority approvals. Thus, the minority-ownership effect is 6.70 times the effect of a minority loan officer.

C. Difference-in-Differences Design: Setup

Theoretical Motivation. Our findings so far do not provide direct evidence that Asian-owned banks expand credit for Asian borrowers. In section III, we show that the default rate of Asian banks' Asian borrowers is lower than that of their non-Asian borrowers, which might be consistent with Asian banks having superior information. However, if this superior information leads to Asian banks being better at cream-skimming the most creditworthy Asian borrowers, other Asian borrowers may find obtaining credit even more challenging. In a counterfactual world without Asian banks, the most creditworthy Asian borrowers would still obtain mortgage credit.

We can approach this counterfactual world using bank failures, which can also provide a valuable setting to study information and relationship lending theories, because failures exacerbate information frictions (Bernanke, 1983). A bank's ability to lend is tied to the breadth and depth of the relationships between its loan officers and borrowers. When a bank fails, lending relationships and the specialized information embodied in loan officers are destroyed. Ex-ante information frictions increase intermediation costs and hamper the formation of new lending relationships. If the Asian-ownership effect is driven by superior information and relationships, the impact of an Asian bank failure on Asian borrowers should be large and persistent because they might have a more challenging time switching to a new lender post-failure (Degryse et al., 2011). By contrast, the impact of a non-minority bank failure might have a more limited and short-lived effect on Asian mortgage borrowers, given the transactional nature of the mortgage market.

Ideal Experiment. The theoretical discussion above motivates an experiment in which Asian borrowers i are located in submarkets k within M, a larger mortgage market served by Asian-owned banks (and other banks). Borrowers and submarkets are identical in every possible dimension, except a group of submarkets, $k = f$, experiences a (randomly assigned) bank failure in year $\tilde{y}$. In this experiment, we could estimate the effect of the bank failure on Asian credit as the difference-in-differences

$$\beta = \{\mathbb{E}[A_{ikt}|k = f, t \geq \tilde{y}] - \mathbb{E}[A_{ikt}|k = f, t < \tilde{y}]\} - \{\mathbb{E}[A_{ikt}|k \neq f, t \geq \tilde{y}] - \mathbb{E}[A_{ikt}|k \neq f, t < \tilde{y}]\},$$

where A_{ikt} is a mortgage approval dummy. In the case of an Asian bank failure, $\beta < 0$ would be consistent with the bank expanding credit access thanks to information and lending relationships. By contrast, $\beta > 0$ would be consistent with the Asian bank acting as a transactional lender and simply reallocating credit.

The main challenge in approximating this ideal experiment is that bank failures are not randomly assigned; they are endogenous to local economic conditions. Changes in credit access and exposure to bank failures may be jointly determined by an omitted variable such as shocks household income. Shocked households can weaken their banks' balance sheets through non-performing loans or deposit withdrawals, and cause failures.

We use plausibly exogenous bank collapses induced by two fraud cases to address this challenge. In the first case, the owners of Abacus Federal Savings Bank, a Chinese bank in New York, discovered that employee Ken Yu was requesting bribes from customers. The bank's owners–the Sung family–fired Yu and launched an internal investigation in January 2010. The Sung family also reported the bribery scheme to regulators and the Manhattan District Attorney's (DA) office, which investigated the bank for over two years. In May 2012, the Manhattan DA office brought 184 charges against Abacus owners, who fought in court for three years. The bank and its owners were acquitted of all charges in June 2015.[19]

Abacus unexpectedly collapsed in 2010. Figure V shows that the investigations and the legal case disrupted Abacus's mortgage lending, its main line of business.[20] From 2003 to 2009, Abacus closely followed other Asian banks' lending patterns. Abacus's originations declined by 50 percent in 2010, completely dried up in 2011, and barely recovered after the bank's owners were acquitted. Furthermore, Abacus's little mortgage lending activity after the collapse concentrated on non-Asian borrowers. Appendix Figure 7.1 indicates that almost 100 percent of Abacus's mortgage originations went to Asian borrowers before 2009. This share sharply declined in 2011 and reached a trough of 14 percent in 2015, the year of the trial acquittal verdict. By contrast, the share of Asian mortgages in other Asian-owned banks was stable and moved around 50 and 75 percent before and after the case.

The second case is one of the largest bank fraud schemes in US history and caused the failure of Colonial Bank, a non-minority bank headquartered in Alabama.[21] The fraud started in 2002 and involved employees in Colonial's warehouse lending division and the firm Taylor, Bean, and Whitaker (TBW) colluding to submit reports of fictitious, valueless assets that served as collateral for TBW loans amounting to $2.9 billion. In September 2009, bank regulators discovered the scheme and promptly closed the bank.

[19] The New Yorker's article "The Accused" and the documentary "Abacus: Small Enough to Jail" provide detailed accounts of the wrongful nature of the case.

[20] Figures V and 7.1 use data constructed from public and commercial sources. Due to legal and time coverage restrictions, we are unable to employ Federal Reserve's confidential data on borrowers and loan officers.

[21] In 2011, Department of Justice Criminal Division's Attorney General Lanny A. Breuer stated "Lee Farkas, the former chairman of TBW, masterminded one of the largest bank fraud schemes in history." For details, see the Department of Justice's press release "Former Chairman of Taylor, Bean & Whitaker Convicted for $2.9 Billion Fraud Scheme That Contributed to the Failure of Colonial Bank."

Empirical Setup. We attempt to replicate the ideal experiment using a generalized difference-in-differences design around the collapse of Abacus Bank. In our setting, the experiment's markets M are counties served by Abacus, and submarkets $k \in M$ are census tracts served by Asian-owned banks. The design exploits variation in Asian borrowers' reliance on Abacus across census tracts before the collapse, which we measure as

$$AbacusExposure_{k,2008} = \frac{AbacusAsianMortgages_{k,2008}}{AsianMortgages_{k,2008}}, \tag{2}$$

where $AbacusAsianMortgages_{k,2008}$ and $AsianMortgages_{k,2008}$ are the number of Asian mortgages originated by Abacus and all banks in census tract k in 2008, respectively. Asian borrowers in tracts with other (non-Abacus, non-failing) Asian banks form the "pure control group," which have $AbacusExposure_{k,2008} = 0$. Figure VI show the geographical distribution of this exposure measure in New York City—Abacus's primary market—and indicates that census tracts in NYC Chinatown and surrounding tracts in Brooklyn, NY, were the most exposed to the Abacus Collapse.[22]

Our design compares Asian borrowers with the same demographics, applying for mortgages with the same characteristics, before and after the case, whose only observable difference is their exposure to Abacus before its collapse. We estimate

$$Approval_{ikt} = \alpha_k + \alpha_t + \sum_{y \neq 2009} \mathbb{1}_{t=y} \beta_y AbacusExposure_{k,2008} + \gamma X_{ikt} + \xi_{ikt}, \tag{3}$$

for borrower i, property's census tract k, and year t. X_{ikt} includes borrower demographics (income-percentile fixed effects; gender and co-borrower dummies) and loan characteristics (loan amount-percentile fixed effects; purpose, type, and occupancy dummies). We cluster standard errors at the census-tract level. The coefficients of interest $\{\beta_y\}_{y \neq 2009}$ reflect the difference in mortgage approvals of Asian borrowers fully exposed to Abacus pre-collapse relative to approvals of otherwise (observably) identical unexposed borrowers in year y, relative to the same difference in 2009.

We employ the same generalized difference-in-differences design around Colonial Bank's failure as a benchmark for the effect of the Abacus collapse on Asian credit.[23]

Identification. The validity of this design hinges on three identification assumptions. First, no anticipation must hold. The nature of the cases described above is consistent with this assumption. In the Abacus case, three facts support no anticipation. First, Abacus's owners were purportedly unaware that one of their employees requested bribes to process loan applications. Second, it is

[22] Figures 7.2 and 7.3 in Appendix 7 shows numerical values of Abacus exposure across census tracts in New York state and the East Coast.

[23] We perform these analyses using data constructed from public and commercial sources. Due to legal and time coverage restrictions, we are unable to employ Federal Reserve's confidential data on borrowers and loan officers.

unlikely that Abacus's owners, employees, or customers could have anticipated the disproportionate legal response to the "fraud" case–the Manhattan DA office brought 184 charges against Abacus and its owners. Furthermore, Abacus and its owners were all acquitted. Third, Figure V shows a sharp and persistent decline in Abacus's lending to Asian borrowers after the Manhattan DA office launched its investigation.[24]

The second assumption needed for validity is parallel trends. Under this assumption, the evolution of Asian approvals in exposed and nonexposed locations would have been similar absent the Abacus collapse. Graphical inspection of parallel trends in Figure VIII indicates smooth pretrends and a sharp and persistent decline in Asian approvals after the Abacus collapse.[25]

Third, our difference-in-differences design features continuous treatment intensity, and Callaway et al. (2021) show that identification in these designs requires homogeneity in gains from treatment. This assumption would be violated if selection of census tracts into treatment is related to potential outcomes. The risk of violating this assumption is limited because the Abacus collapse was induced by a likely unexpected and wrongful fraud case and caused a sudden and persistent decline in Asian approvals in census tracts exposed to Abacus. We do not observe such a decline in census tracts unexposed to Abacus in markets served by other Asian banks. We discuss these results next.

D. Difference-in-Differences Design: Findings

Main Findings. We start by investigating the short-term impact of the Abacus collapse on Asian credit. Figure VII shows the relationship between the 2009-2012 change in Asian mortgage approvals and Abacus exposure. We residualize both variables using the controls and fixed effects in specification (3), and present the data in a binscatter plot. Figure VII documents a strong negative relationship between changes in Asian approvals and exposure to Abacus. Asian borrowers in the most exposed census tracts experienced declines in mortgage approvals in the range of 20 to 40 percent between 2009 and 2012. By contrast, Asian borrowers in the average nonexposed census tract experienced no changes in mortgage approvals in the same period.

Next, we investigate the dynamic effects of the Abacus collapse. Figure VIII presents the results from specification (3). Asian approvals sharply declined in fully exposed census tracts in 2010 and did not recover until 2014-2015. Relative to Asian borrowers in nonexposed census tracts, those in fully exposed census tracts experienced a decline in mortgage approvals of 30 percentage points per year in 2010-2012 and 20 percentage points in 2013 (using 2009 as the base year). This difference in mortgage approvals disappeared in 2014-2015.

[24]Similar arguments support the no-anticipation assumption in the Colonial design. In particular, the prompt closure of the bank by its regulators after discovering the scheme is consistent with no anticipation.

[25]Similarly, the left panel of Figure X shows smooth pretrends around the failure of Colonial Bank.

The key identifying assumption of this design is that Asian approvals trends would be the same in exposed and nonexposed census tracts in the absence of the Abacus collapse. Figure VIII provides strong visual evidence of exposed and nonexposed census tracts with a common underlying trend before the collapse, and a treatment effect that induces a sudden and persistent deviation from this trend after the collapse. Although Asian borrowers in exposed and nonexposed census tracts can differ, this difference is meant to be captured by census tracts and year fixed effects, and borrower controls in specification (3).

Economic Magnitudes. We employ two benchmarks to shed light on economic magnitudes: Asian mortgage approvals and the effect of the Colonial Failure on Asian credit. We start with the mortgage approval mean as a benchmark. Table X shows that the mean Asian approval rate in the Abacus design is approximately 67 percent. Thus, the effect of the Abacus collapse in Figure VIII is equivalent to 45 and 30 percent of the Asian approval mean in 2010-2012 and 2013, respectively.

Next, we use the effect of Colonial's failure on Asian credit as a benchmark. Figure IX shows that the short-term effect of the Abacus collapse is strikingly strong relative to that of Colonial's failure. In fact, Panel B shows a weakly positive relationship between changes in (residualized) Asian approvals and exposure to the Colonial failure. Furthermore, Figure X features smooth pretrends around both bank collapses, but Asian mortgage approvals declined in exposed tracts only after the Abacus collapse. Consistent with Figure IX, Panel B of Figure X depicts a slight but non-significant increase in Asian approvals in 2011 and 2012 in tracts fully exposed to Colonial.

While large relative to both benchmarks above, the estimated effect of the Abacus collapse on Asian credit likely underestimates the true effect, because some Asian borrowers might have been discouraged from applying to other banks. To explore this possibility, we study the effect of the Abacus collapse on Asian mortgage applications per capita. We estimate

$$Applications_{kt} = \alpha_k + \alpha_t + \sum_{y \neq 2010} \mathbb{1}_{t=y} \beta_y AbacusExposure_{k,2008} + \gamma X_{kt} + \xi_{kt}, \tag{4}$$

where $Applications_{kt}$ is the number of Asian mortgage applications in tract k and year t as a percentage of the Asian population in tract k in the 2010 Decennial Census. $AbacusExposure_{k,2008}$ is defined in equation (2). We focus on the five-year period after the 2010 Decennial Census to minimize measurement error. X_{kt} includes borrower demographics (log income; gender and co-borrower shares) and loan characteristics (log loan amount; purpose, type, and occupancy shares). We estimate regression (4) using weighted-least squares, where tract-level Asian population is used as weights. Standard errors are clustered at the census tract level.

Figure XI reports the results and shows that Asian mortgage applications per capita declined in fully exposed census tracts until 2012. Relative nonexposed census tracts, fully exposed census tracts experienced a decline in Asian applications per capita of two and three percentage points per year in 2011 and 2012, respectively (using 2010 as the base year). This effect is equivalent to 48 and 72 percent of the Asian application per capita mean in 2011 and 2012, respectively.

Placebo Tests. We address two threats to this design using placebo tests. First, our design uses data from a period that includes the housing boom, bust, and recovery. Because we worry that shocks to local housing and mortgage markets unrelated to Abacus confound our estimates, we implement group placebo tests by estimating specification (3) for Black, Hispanic, and White borrowers. If local shocks drive the results in Figure VIII, mortgage approvals for other race groups should exhibit smooth pretrends and a sharp decline after Abacus collapsed. Figure XII reports placebo results and suggests local shocks might not be a major threat to our design. Black, Hispanic, and White approvals feature smooth pretends, but do not decline after the collapse of Abacus.

Second, we worry that 2008, the year used to construct Abacus exposure in equation (2), drives our results. To address this concern, we implement year placebo tests that use Abacus exposure measures constructed as

$$AbacusExposure_{k,\widetilde{t}} = \frac{AbacusAsianMortgages_{k,\widetilde{t}}}{AsianMortgages_{k,\widetilde{t}}}, \tag{5}$$

for $\widetilde{t} = \{2003, ..., 2007\}$. We estimate specification (3) and report results in Figure 7.4. We find that 2008 does not drive our results, because the effect of Abacus's collapse on Asian credit is the same regardless of the year used to construct our exposure measure.

V. Why Does Minority Bank Ownership Matter?

A. Fixed-Effects Design: Setup

Theoretical Motivation. Minority bank ownership might matter for minority credit access, because more accurate prior beliefs or superior information reduce information asymmetry between minority banks and minority borrowers via improved screening or monitoring, which mitigates adverse selection and moral hazard (Calomiris et al., 1994; Cornell and Welch, 1996; Coval and Thakor, 2005). In such a case, additional lending to minorities should exhibit lower default rates. By contrast, if the additional lending to minorities is due to the preferences of minority owners, we should see higher default rates among same-race borrowers (Becker, 1957).

We use mortgage default data to investigate whether the minority-ownership effect documented in section IV is consistent with reduced information asymmetry or preferences. In section III, we find that the default rate of minority banks' same-race borrowers is 3.24 percent, which is 70 percent that of their other-race borrowers. However, this crude comparison might reflect differences in observed and unobserved characteristics and suffer from omitted-variable and infra-marginality biases. We address these issues next.

Ideal Experiment. Minority bank j originates mortgage loans with characteristics W_i to borrowers i with race r_i and demographic characteristics X_i.

Bank j's loan-level profit function is given by

$$\Pi_j(r_i, W_i, X_i) = PV[I_j(r_i, W_i, X_i) - C_j(r_i, W_i, X_i)],$$

where $PV(\bullet)$ is present value, I_j is interest (and other) income, and C_j is costs that include default.

Assume we can perfectly identify marginal borrowers and they are identical in every dimension (W_i^*, X_i^*) except their race, which was randomly given to them. In this ideal experiment, the minority-ownership effect would be consistent with reduced information asymmetry if

$$\overline{\Pi}_j(r_s^*, W_s^*, X_s^*) > \overline{\Pi}_j(r_o^*, W_o^*, X_o^*) \implies \beta = \overline{C}_j(r_s^*, W_s^*, X_s^*) - \overline{C}_j(r_o^*, W_o^*, X_o^*) < 0,$$

where $\overline{\Pi}_j$ and $\overline{C}_j$ are bank j's average profits and defaults, and s and o denote same-race and other-race borrowers. This condition suggests that the ownership effect would be consistent with reduced information asymmetry if the default rate of same-race marginal borrowers is lower than that of other-race marginal borrowers within a minority bank.

This ideal experiment abstracts away from off-balance-sheet lending. Appendix 5 shows that under some assumptions, an experiment with off-balance-sheet activity yields a similar test. We explicitly address off-balance sheet lending in the empirical setup below.

Empirical Setup. We mimic this ideal experiment by comparing minority and non-minority borrowers with the same credit risk and demographic characteristics, with mortgages with the same interest rate and other characteristics, from the same minority bank, underwritten by a loan officer with the same race:

$$Default_{ijt} = \alpha_j + \alpha_t + \beta MinorityBorrower_{it} + \gamma InterestRate_{it} + \delta X_{it} + \xi_{ijt}, \tag{6}$$

for borrower i, minority bank j, and year t. $MinorityBorrower_{it}$ is a dummy variable equal to one for same-race minority borrowers and zero for other-race borrowers. $InterestRate_{it}$ is the rate on borrower i's mortgage. In the baseline specification, X_{it} includes borrower demographics (log income; gender and co-borrower dummies) and loan characteristics (log loan amount; purpose, type, and occupancy dummies). We augment this specification by adding four confidential controls to X_i: credit scores, loan-to-value and debt-income ratios, and loan officers' race. Both specifications include sold mortgage dummies as a way to deal with the off-balance-sheet lending issue described above. We cluster standard errors at the bank level. The coefficient of interest β reflects the default rate of minority borrowers with mortgages from a same-race minority-owned bank relative to that of otherwise (observably) identical other-race borrowers with mortgages from the same minority bank.

B. Fixed-Effects Design: Findings

Main Findings. We estimate specification (6) using a subsample of Asian and Hispanic banks matched in both confidential HMDA and McDash datasets in 2018 and 2019. As detailed in section II, we could not match Black-owned banks in both datasets. Mortgage defaults are measured within 12 months of origination for loans granted between January 2018 and March 2019 so that we exclude pandemic-induced defaults. Results from the baseline specifications are presented in columns 1, 3, and 7 of Table III. Column 1 reports results for all Asian and Hispanic banks pooled in a single category. It shows that the average same-race minority borrower is 1.08 percentage points less likely to default than the average other-race borrower with the same minority bank. Column 3 shows that the average Asian borrower is 1.20 percentage points less likely to default than the average non-Asian borrower with the same Asian bank. Column 7 reports that the difference in default rates between Hispanic and non-Hispanic borrowers with the same Hispanic bank is positive. However, its standard error is large due to a sample size smaller than the minimum size needed to detect a statistically significant effect. For details, see the discussion below.

Results in columns 1 and 3 might reflect differences in observed and unobserved characteristics. We address these concerns in columns 2, 4, and 8 of Table III, which report results from the augmented specifications. Columns 2 and 4 show that controlling for credit risk and loan officers' race makes the difference in average default rates slightly larger. Column 2 reports that the average same-race minority borrower is 1.12 percentage points less likely to default than the average other-race borrower with the same minority bank. Column 4 shows that the average Asian borrower is 1.29 percentage points less likely to default than the average non-Asian borrower with the same Asian bank. The Oster statistic suggests that the influence of unobservables would need to be between 12 and 29 times the influence of observable factors for the effects to be zero.[26]

Column 8 shows adding controls makes the difference in default rates between Hispanic and non-Hispanic borrowers negative. However, as in column 7, its standard error is large. Both columns are estimated on a sample of 150 mortgage borrowers with Hispanic banks. In Appendix 6, we show that under conservative assumptions, the minimum number of borrowers needed to detect a statistically significant effect in these specifications is 886. Thus, the results reported in columns 7 and 8 might be driven by a small sample size.

Like the ideal experiment, columns 2, 4, and 8 compare "identical" borrowers by including a rich set of fixed effects and controls. But unlike the ideal experiment, they do not compare borrowers at the margin of approval. To address this potential issue, we estimate specification (6) on a sample of mortgage borrowers who were rejected by an automated underwriting software but were ultimately approved by the minority bank. The sample contains 241 borrowers, all with Asian banks. Columns 5 and 6 show that the difference in default rates between Asian and non-Asian marginal borrowers with the same Asian bank is negative but not statistically significant. Unfortunately, this sample is also smaller than the minimum sample size needed to detect a statistically significant effect.

Economic Magnitudes. To shed light on magnitudes, we scale the coefficients in columns 2 and 4 of Table III by the default mean. The negative difference in default rates between same and other-race borrowers is equivalent to 37.33 and 48.90 percent of the default mean in minority and Asian banks, respectively. The negative difference in default rates between Hispanic and non-Hispanic borrowers in Hispanic banks is also large relative to the Hispanic default mean. However, as discussed above, it is not statistically significant due to a small sample.

Limitations. The paucity of default data from minority-owned banks, particularly Black and Hispanic banks, limits our analysis in two ways. First, most of the minority banks that we match in both confidential HMDA and McDash datasets are Asian owned. Consequently, Asian banks drive the results presented in Table III. We do not have enough observations to perform reliable inference for Hispanic banks, and no observations at all for Black banks. Second, although the ideal experiment compares borrowers at the margin of approval and we are able to identify such borrowers in Asian banks, a small sample size limits our inference. Reliable results, reported in columns 2 and 4, are valid for the average borrower. Addressing these limitations is work in progress.

[26] Because the Oster statistic is negative, unobservables would need to be negatively correlated with the borrower's race for the effects to be zero.

VI. Conclusion

This paper assembles unique data to answer three first-order questions in corporate and household finance: *whether*, *how*, and *why* minority bank ownership matters. In the mortgage market, we find that minority bank ownership does indeed matter–more, in fact, than minority loan officers–and that the reason it matters is information and not owners' preference, at least in the case of Asian banks. By reducing information asymmetry, Asian bank ownership expands credit access to Asian borrowers.

Our findings imply that if minority ownership matters in the mortgage market–where lending relationships typically are less important–and its effect is due to information, we should expect minority ownership to be much more important in relationship-based markets such as the market for small business credit or venture capital financing. We leave this question for future research.

A second implication from this work is that bank regulators' long-held views on the clientele and positive impact of minority-owned banks might be correct. If policymakers aim to provide more and better financial services for minority groups, encouraging minority bank ownership and investing in minority banks might be warranted.

The key open questions for future research concern organizational aspects of minority ownership. Why is the role of ownership so much larger than that of individual agents? How do minority owners shape their organizations so that information frictions are reduced? Understanding the link between minority ownership and information frictions is critical because minority borrowers, especially underrepresented minority borrowers, might be more informationally opaque and credit rationed than non-minority borrowers.

References

Altonji, J. G., T. E. Elder, and C. R. Taber (2005). Selection on observed and unobserved variables: Assessing the effectiveness of catholic schools. *Journal of political economy 113*(1), 151–184.

Ambrose, B. W., J. N. Conklin, N. E. Coulson, M. Diop, and L. A. Lopez (2022). Do appraiser and borrower race affect valuation?

Ambrose, B. W., J. N. Conklin, and L. A. Lopez (2021). Does borrower and broker race affect the cost of mortgage credit? *The Review of Financial Studies 34*(2), 790–826.

Argyle, B., S. Indarte, B. Iverson, and C. Palmer (2022). Explaining racial disparities in personal bankruptcy outcomes.

Ayres, I. and P. Siegelman (1995). Race and gender discrimination in bargaining for a new car. *The American Economic Review*, 304–321.

Ba, B. A., D. Knox, J. Mummolo, and R. Rivera (2021). The role of officer race and gender in police-civilian interactions in chicago. *Science 371*(6530), 696–702.

Bartanen, B. and J. A. Grissom (2021). School principal race, teacher racial diversity, and student achievement. *Journal of Human Resources*, 0218–9328R2.

Bartlett, R., A. Morse, R. Stanton, and N. Wallace (2022). Consumer-lending discrimination in the fintech era. *Journal of Financial Economics 143*(1), 30–56.

Bates, T. and W. Bradford (1980). An analysis of the portfolio behavior of black-owned commercial banks. *The Journal of Finance 35*(3), 753–768.

Bayer, P., F. Ferreira, and S. L. Ross (2018). What drives racial and ethnic differences in high-cost mortgages? the role of high-risk lenders. *The Review of Financial Studies 31*(1), 175–205.

Becker, G. S. (1957). *The economics of discrimination.* University of Chicago press.

Bekes, G., G. I. Ottaviano, et al. (2022). Cultural homophily and collaboration in superstar teams. Technical report, Centre for Economic Performance, LSE.

Berger, A. N., M. P. Feldman, W. S. Langford, and R. A. Roman (2022). "let us put our moneys together:" minority-owned banks and resilience to crises. *Working Paper*.

Bernanke, B. (1983). Nonmonetary effects of the financial crisis in the propagation of the great depression. *The American Economic Review 73*(3), 257–276.

Bernstein, D. E. (2022). *Classified: The Untold Story of Racial Classification in America.* Bombardier Books.

Bhutta, N. and A. Hizmo (2021). Do minorities pay more for mortgages? *The Review of Financial Studies 34*(2), 763–789.

Blattner, L. and S. Nelson (2021). How costly is noise? data and disparities in consumer credit. *arXiv preprint arXiv:2105.07554*.

Boot, A. W. and A. V. Thakor (2000). Can relationship banking survive competition? *The journal of Finance 55*(2), 679–713.

Bostic, R. W. (2003). A test of cultural affinity in home mortgage lending. *Journal of Financial Services Research 23*(2), 89–112.

Brimmer, A. F. (1971). The black banks: An assessment of performance and prospects. *the Journal of Finance 26*(2), 379–405.

Buchak, G., G. Matvos, T. Piskorski, and A. Seru (2022). Beyond the balance sheet model of banking: Implications for bank regulation and monetary policy. *Working Paper*.

Callaway, B., A. Goodman-Bacon, and P. H. Sant'Anna (2021). Difference-in-differences with a continuous treatment. *arXiv preprint arXiv:2107.02637*.

Calomiris, C. W., C. M. Kahn, and S. D. Longhofer (1994). Housing-finance intervention and private incentives: helping minorities and the poor. *Journal of Money, Credit and Banking 26*(3), 634–674.

Cook, L. D., M. Marx, and E. Yimford (2022). Funding black high-growth startups. *Working Paper*.

Cornell, B. and I. Welch (1996). Culture, information, and screening discrimination. *Journal of Political Economy 104*(3), 542–571.

Coval, J. D. and A. V. Thakor (2005). Financial intermediation as a beliefs-bridge between optimists and pessimists. *Journal of Financial Economics 75*(3), 535–569.

Czibor, E., D. Jimenez-Gomez, and J. A. List (2019). The dozen things experimental economists should do (more of). *Southern Economic Journal 86*(2), 371–432.

D'Acunto, F., P. Ghosh, R. Jain, and A. G. Rossi (2021). How costly are cultural biases? evidence from fintech. *Evidence from FinTech (October 25, 2021)*.

Dee, T. S. (2004). Teachers, race, and student achievement in a randomized experiment. *Review of economics and statistics 86*(1), 195–210.

Degryse, H., N. Masschelein, and J. Mitchell (2011). Staying, dropping, or switching: the impacts of bank mergers on small firms. *The Review of Financial Studies 24*(4), 1102–1140.

Diamond, R., T. McQuade, and F. Qian (2019). The effects of rent control expansion on tenants, landlords, and inequality: Evidence from san francisco. *American Economic Review 109*(9), 3365–94.

Easterly, W. and R. Levine (1997). Africa's growth tragedy: policies and ethnic divisions. *The quarterly journal of economics*, 1203–1250.

Elyasiani, E. and S. Mehdian (1992). Productive efficiency performance of minority and nonminority-owned banks: A nonparametric approach. *Journal of Banking & Finance 16*(5), 933–948.

Fisman, R., D. Paravisini, and V. Vig (2017). Cultural proximity and loan outcomes. *American Economic Review 107*(2), 457–92.

Fisman, R., A. Sarkar, J. Skrastins, and V. Vig (2020). Experience of communal conflicts and intergroup lending. *Journal of Political Economy 128*(9), 3346–3375.

Frame, W. S., R. Huang, E. Jiang, Y. Lee, W. Liu, E. J. Mayer, and A. Sunderam (2024). The impact of minority representation at mortgage lenders. *Journal of Finance, Forthcoming*.

Frame, W. S., R. Huang, E. J. Mayer, and A. Sunderam (2022). The impact of minority representation at mortgage lenders. Technical report, Working Paper.

Gerardi, K., P. Willen, and D. H. Zhang (2020). Mortgage prepayment, race, and monetary policy.

Gershenson, S., C. M. Hart, J. Hyman, C. Lindsay, and N. W. Papageorge (2022). The long-run impacts of same-race teachers. *AMERICAN ECONOMIC JOURNAL: ECONOMIC POLICY*.

Granja, J., G. Matvos, and A. Seru (2017). Selling failed banks. *The Journal of Finance 72*(4), 1723–1784.

Greenwood, B. N., R. R. Hardeman, L. Huang, and A. Sojourner (2020). Physician–patient racial concordance and disparities in birthing mortality for newborns. *Proceedings of the National Academy of Sciences 117*(35), 21194–21200.

Gross, T., M. J. Notowidigdo, and J. Wang (2020). The marginal propensity to consume over the business cycle. *American Economic Journal: Macroeconomics 12*(2), 351–84.

Hasan, I., W. C. Hunter, et al. (1996). Management efficiency in minority-and women-owned banks. *Economic Perspectives-Federal Reserve Bank of Chicago 20*, 20–28.

Helpman, E., M. Melitz, and Y. Rubinstein (2008). Estimating trade flows: Trading partners and trading volumes. *The quarterly journal of economics 123*(2), 441–487.

Henderson, C. C. (1999). The economic performance of african-american-owned banks: The role of loan loss provisions. *American Economic Review 89*(2), 372–376.

Hjort, J. (2014). Ethnic divisions and production in firms. *The Quarterly Journal of Economics 129*(4), 1899–1946.

Jiang, E. X., Y. Lee, and W. S. Liu (2022). Disparities in consumer credit: The role of loan officers in the fintech era. *Working Paper*.

Karkkainen, K. and J. Joo (2021). Fairface: Face attribute dataset for balanced race, gender, and age for bias measurement and mitigation. In *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision*, pp. 1548–1558.

Kempf, E. and M. Tsoutsoura (2021). Partisan professionals: Evidence from credit rating analysts. *The Journal of Finance 76*(6), 2805–2856.

Kofoed, M. S. et al. (2019). The effect of same-gender or same-race role models on occupation choice evidence from randomly assigned mentors at west point. *Journal of Human Resources 54*(2), 430–467.

Kogut, B. and H. Singh (1988). The effect of national culture on the choice of entry mode. *Journal of international business studies 19*(3), 411–432.

Kwast, M. L. and H. Black (1983). An analysis of the behavior of mature black-owned commercial banks. *Journal of Economics and Business 35*(1), 41–54.

List, J. A., S. Sadoff, and M. Wagner (2011). So you want to run an experiment, now what? some simple rules of thumb for optimal experimental design. *Experimental Economics 14*(4), 439–457.

Meinster, D. R. and E. Elyasiani (1988). The performance of foreign owned, minority owned, and holding company owned banks in the us. *Journal of Banking & Finance 12*(2), 293–313.

Munnell, A. H., G. M. Tootell, L. E. Browne, and J. McEneaney (1996). Mortgage lending in boston: Interpreting hmda data. *The American Economic Review*, 25–53.

Oster, E. (2019). Unobservable selection and coefficient stability: Theory and evidence. *Journal of Business & Economic Statistics 37*(2), 187–204.

Perez-Saiz, H. and H. Xiao (2022). Cultural affinity, regulation, and market structure: Evidence from the canadian retail banking industry. *American Economic Journal: Microeconomics 14*(1), 451–89.

Price, J. and J. Wolfers (2010). Racial discrimination among nba referees. *The Quarterly journal of economics 125*(4), 1859–1887.

Shayo, M. and A. Zussman (2011). Judicial ingroup bias in the shadow of terrorism. *The Quarterly journal of economics 126*(3), 1447–1484.

Stein, L. C. and C. Yannelis (2020). Financial inclusion, human capital, and wealth accumulation: Evidence from the freedman's savings bank. *The Review of Financial Studies 33*(11), 5333–5377.

Toussaint-Comeau, M. and R. Newberger (2017). Minority-owned banks and their primary local market areas. *Economic Perspectives 4*(4), 1–31.

Vatsa, P. (2022). Do minority banks matter? evidence from the community reinvestment act. *Working Paper*.

Voicu, I. (2018). Using first name information to improve race and ethnicity classification. *Statistics and Public Policy 5*(1), 1–13.

Vorsatz, M. B. (2022). *Costs of political polarization: Evidence from mutual fund managers during covid-19*. Ph. D. thesis, The University of Chicago.

Ye, J., S. Han, Y. Hu, B. Coskun, M. Liu, H. Qin, and S. Skiena (2017). Nationality classification using name embeddings. In *Proceedings of the 2017 ACM on Conference on Information and Knowledge Management*, pp. 1897–1906.

Zhang, D. H. and P. S. Willen (2021). Do lenders still discriminate? a robust approach for assessing differences in menus. Technical report, National Bureau of Economic Research.

Main Exhibits

Table I: Summary Statistics: All Analyses Samples

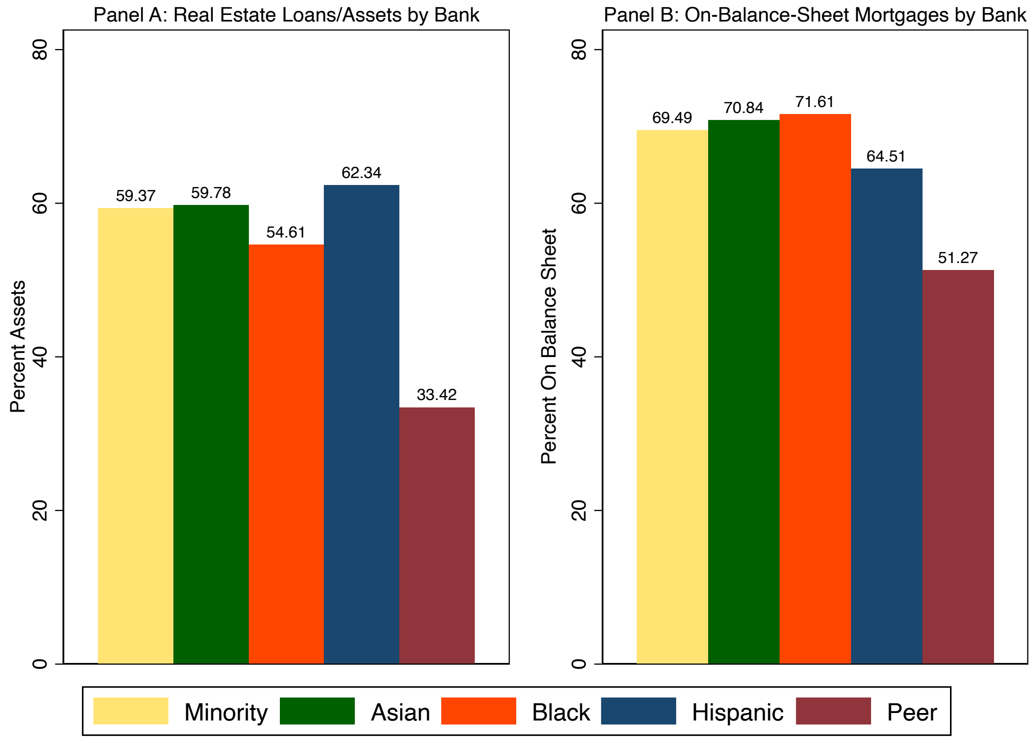
	Mean	P10	P50	P90	Observations
Panel A. Minority Borrowers' Universe					
Key Variables					
$\mathbb{1}$(Approval)	0.60				86,994,013
$\mathbb{1}$(Minority-Owned Bank)*	0.02				86,994,013
Borrower Variables					
Income ($1K)	74.06	17	55	137	86,994,013
$\mathbb{1}$(Female)	0.35				86,994,013
$\mathbb{1}$(Co-borrower)	0.41				86,994,013
Loan Variables					
Amount ($1K)	166.80	26	125	353	86,994,013
$\mathbb{1}$(Home Purchase)	0.44				86,994,013
$\mathbb{1}$(Conventional)	0.84				86,994,013
$\mathbb{1}$(Principal Residence)	0.91				86,994,013
Confidential Variables					
Credit Score	713.35	630	717	795	3,853,217
LTV Ratio (%)	79.52	50.00	80.46	100.00	3,853,217
DTI Ratio (%)	43.81	25.80	41.75	56.12	3,853,217
$\mathbb{1}$(Minority Loan Officer)*	0.22				3,853,217
Panel B. Mortgage Default Sample					
Key Variables					
$\mathbb{1}$(Default)	0.03				2,465
$\mathbb{1}$(Minority Borrower)*	0.21				2,465
Borrower Variables					
Income ($1K)	145.84	63	121	254	2,465
$\mathbb{1}$(Female)	0.34				2,465
$\mathbb{1}$(Co-borrower)	0.49				2,465
Loan Variables					
Amount ($1K)	360.96	175	345	549	2,465
$\mathbb{1}$(Home Purchase)	0.82				2,465
$\mathbb{1}$(Conventional)	0.93				2,465
$\mathbb{1}$(Principal Residence)	0.87				2,465
Interest Rate (%)	4.43	3.88	4.38	4.88	2,465
Confidential Variables					
Credit Score	751.89	689	761	800	2,465
LTV Ratio (%)	75.79	50.00	80.00	95.00	2,465
DTI Ratio (%)	36.11	23.72	36.86	47.58	2,465
$\mathbb{1}$(Asian Loan Officer)	0.05				2,465
$\mathbb{1}$(Hispanic Loan Officer)	0.05				2,465
$\mathbb{1}$(White Loan Officer)	0.90				2,465

Table I: Summary Statistics: All Analyses Samples (cont.)

	Mean	P10	P50	P90	Observations
Panel C. Abacus Collapse Sample					
Key Variables					
𝟙(Approval)	0.67				492,576
Abacus Exposure	0.02	0.00	0.00	0.08	492,576
Abacus Exposure, Exposed	0.12	0.03	0.07	0.25	105,124
Borrower Variables					
Income ($1K)	132.99	47	103	225	492,576
𝟙(Female)	0.31				492,576
𝟙(Co-borrower)	0.41				492,576
Loan Variables					
Amount ($1K)	312.53	86	280	540	492,576
𝟙(Home Purchase)	0.51				492,576
𝟙(Conventional)	0.95				492,576
𝟙(Principal Residence)	0.90				492,576
Panel D. Colonial Failure Sample					
Key Variables					
𝟙(Approval)	0.68				888,964
Colonial Exposure	0.00	0.00	0.00	0.00	888,964
Colonial Exposure, Exposed	0.15	0.03	0.06	0.33	12,384
Borrower Variables					
Income ($1K)	129.49	42	96	225	888,964
𝟙(Female)	0.34				888,964
𝟙(Co-borrower)	0.42				888,964
Loan Variables					
Amount ($1K)	294.93	80	250	528	888,964
𝟙(Home Purchase)	0.43				888,964
𝟙(Conventional)	0.95				888,964
𝟙(Principal Residence)	0.86				888,964

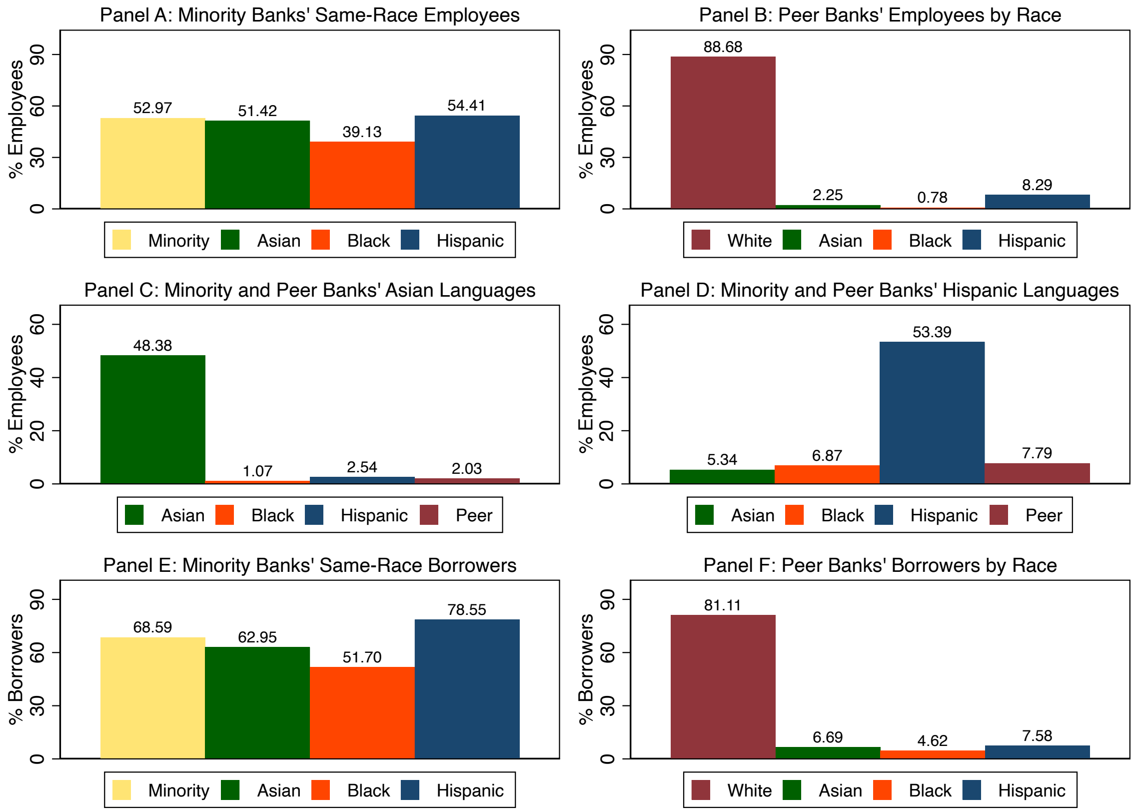
Notes: This table presents statistics for all analyses in this paper. The unit of observation in all panels is a mortgage borrower. Panel A reports summary statistics for the near universe of non-Hispanic Asian, non-Hispanic Black, and Hispanic categories borrowers applying for mortgages between 1990 and 2019 and between 2018 and 2019 for confidential variables. The data are derived from HMDA. 𝟙(Minority Bank)* and 𝟙(Minority Loan Officer)* indicate same-race minority bank and loan officer, respectively. Sections II and IV provide data construction details. Panel B presents statistics for a sample of borrowers of any race that obtained mortgages from minority banks between January 2018 and March 2019. The sample is derived from HMDA and McDash. 𝟙(Minority Borrower)* indicate same-race minority borrower. Sections II and A provide data construction details. Panel C reports summary statistics for Asian borrowers in the Abacus design applying for mortgages between 2003 and 2019. Panel D presents summary statistics for Asian borrowers in the Colonial design applying for mortgages between 2003 and 2019. Both samples are derived from HMDA. Sections II and C provide data construction details.

Figure I: Assets and Balance-Sheet Retention in Minority and Peer Banks



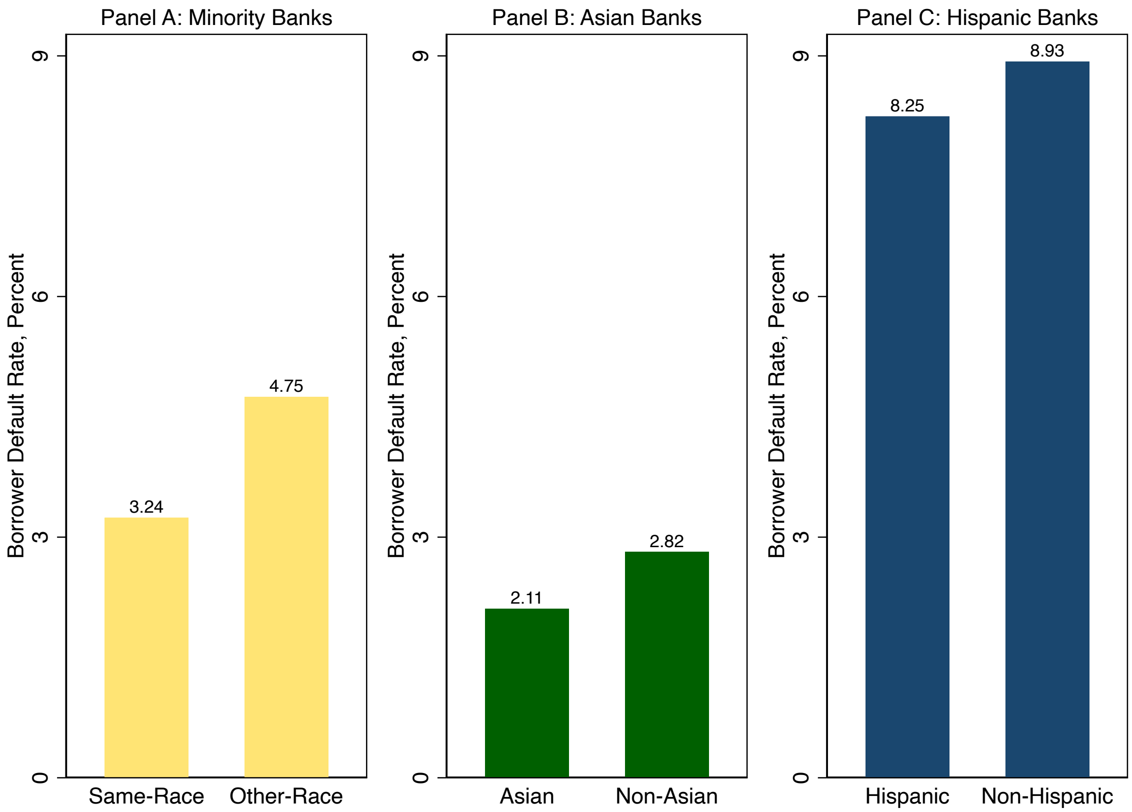
Notes: This figure shows the weighted average of mortgage-to-asset ratios (Panel A) and on-balance-sheet-mortgage shares (Panel B) for minority-owned banks in a single category (labeled as "Minority"), minority banks by race group (labeled as "Asian," "Black," and "Hispanic"), and peer non-minority banks (labeled as "Peer"). Peer banks are the sum community development financial institutions (CDFI) banks and credit unions, and low-income credit unions. Vertical axes are in percent. Panel A is constructed using call report data as of December 2019. Panel B is constructed using public HMDA data as of 2019.

Figure II: Employees, Languages, and Borrowers in Minority and Peer Banks



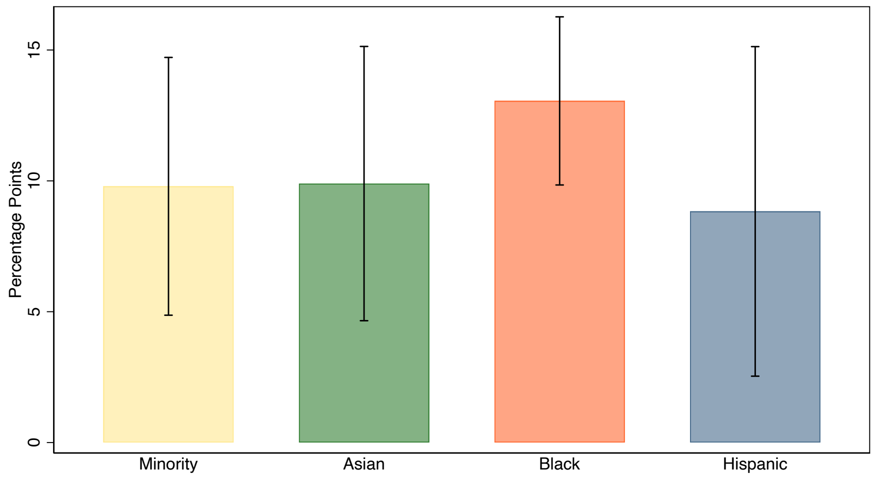
Notes: Panel A of this figure shows the weighted average of same-race employee shares for minority-owned banks in a single category (labeled as "Minority"), and minority banks by race group (labeled as "Asian," "Black," and "Hispanic"). Employees are considered same-race if they have the same race as the bank owner, e.g., Asian employees in Asian-owned banks. Panel B shows the weighted average of race employee shares for peer non-minority banks. Panels C and D show Asian, Black, Hispanic and peer banks' weighted average of Asian and Hispanic language shares, respectively. Asian language share is the percentage of employees speaking Bahasa Indonesia, Bangla, Bengali, Chinese, Filipino, Gujarati, Hindi, Hmong, Japanese, Korean, Lao, Malay, Marathi, Mon-Khmer, Nepali, Punjabi, Taishanese, Thai, and Vietnamese, in addition to English. Hispanic language share is the percentage of employees speaking Portuguese and Spanish, in addition to English. Panel E shows the weighted average of same-race borrower shares for minority-owned banks. Mortgage borrowers are considered same-race if they have the same race as the bank owner, e.g., Asian borrowers with Asian-owned banks. Panel F shows the weighted average of race borrower shares for peer non-minority banks. Peer banks are the sum community development financial institutions (CDFI) banks and credit unions, and low-income credit unions. Vertical axes are in percent. Panels A, B, C, and D are constructed using LinkedIn data as of December 2019. Panels E and F are constructed using public HMDA data as of 2019.

Figure III: Mortgage Default Rates in Minority-Owned Banks by Borrower Race



Notes: Panel A of this figure shows the weighted average of same-race and other-race mortgage defaults in minority-owned banks. Mortgage borrowers are considered same-race if they have the same race as the bank owner, e.g., Asian borrowers with Asian-owned banks, and other-race otherwise. Panel B shows the weighted average of Asian and non-Asian mortgage defaults in Asian-owned banks. Panel B shows the weighted average of Hispanic and non-Hispanic mortgage defaults in Hispanic-owned banks. Vertical axes are in percent. All panels are constructed using a confidential HMDA-McDash matched data with mortgages originated between January 2018 and March 2019. Mortgage defaults are measured within 12 months of origination for loans granted between January 2018 and March 2019 to exclude pandemic-induced defaults. Minority-owned banks do not include Black banks in this matched data.

Figure IV: The Effect of Minority Bank Ownership on Minority Credit



Notes: This figure plots coefficients $\hat{\beta}$ and their 95% confidence intervals from regressions of the form:

$$Approval_{ijkt} = \alpha_k + \alpha_t + \beta MinorityOwnedBank_{jkt} + \gamma X_{ijkt} + \xi_{ijkt},$$

for borrower i, bank j, property's census tract k, and year t. Because census tracts can experience boundary changes every decennial census due to population growth, each census tract k is constructed as the concatenation of its tract number and boundary period: 1990-1991, 1992-2002, 2003-2011, or 2012-2019. $Approval_{ijkt}$ and $MinorityOwnedBank_{jkt}$ are approval and minority bank dummies. X_{ijkt} contains borrower demographics (income-percentile fixed effects; gender and co-borrower dummies), loan characteristics (loan amount-percentile fixed effects; purpose, type, and occupancy dummies), and bank size percentile fixed effects. The first bar pools Asian, Black, and Hispanic borrowers in the category "Minority Borrowers," thus $MinorityOwnedBank_{jkt}$ is a dummy equal to one for same-race minority banks and zero otherwise. The second, third, and fourth bars report results for Asian, Black, and Hispanic mortgage borrowers, respectively. Standard errors are clustered at the bank and census tract levels. The data span 1990-2019. See Appendix Table 3.1 for more details.

Table II: The Effect of Minority Bank Ownership and Loan Officers on Minority Credit

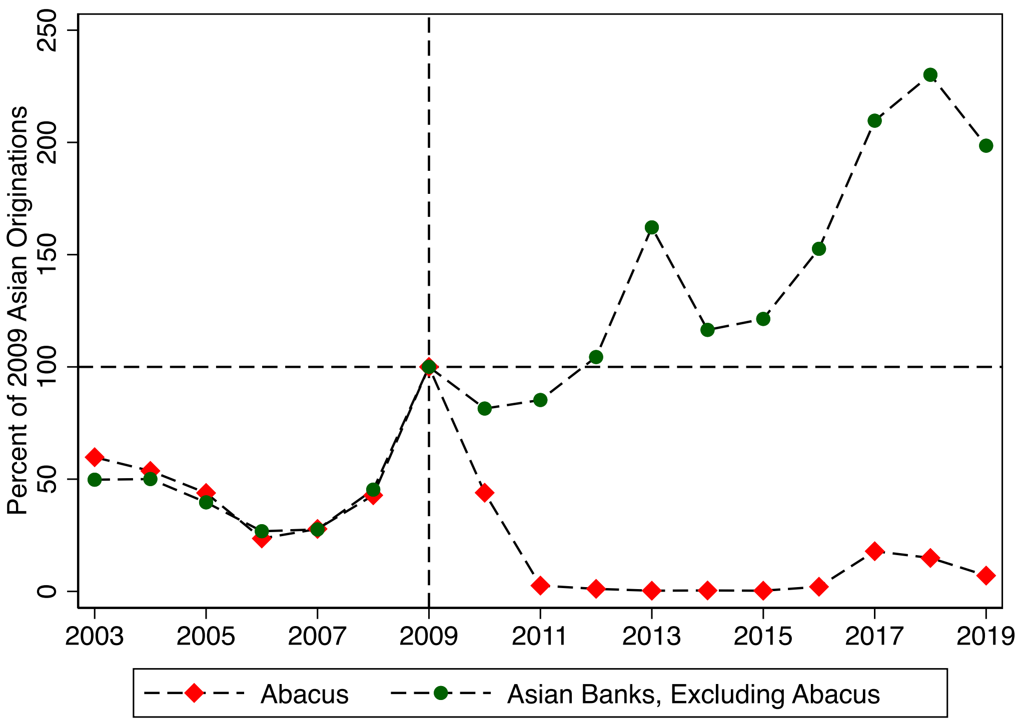
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Minority-Owned Bank	13.23***	9.11***						
	(2.51)	(2.09)						
Minority Loan Officer		1.36***						
		(0.36)						
Asian-Owned Bank			9.24***	6.32**				
			(3.30)	(2.47)				
Asian Loan Officer				1.86***				
				(0.40)				
Black-Owned Bank					18.03*	16.52**		
					(9.64)	(8.34)		
Black Loan Officer						0.78**		
						(0.37)		
Hispanic-Owned Bank							12.24***	8.49***
							(3.11)	(2.71)
Hispanic Loan Officer								1.17***
								(0.36)
Credit Risk Controls	No	Yes	No	Yes	No	Yes	No	Yes
Sample Borrowers	Minority	Minority	Asian	Asian	Black	Black	Hispanic	Hispanic
Approval Mean	76.19	76.19	82.23	82.23	71.92	71.92	77.49	77.49
Approval Gap	8.84	8.84	2.79	2.79	13.10	13.10	7.54	7.54
Observations	3,850,840	3,850,840	1,000,013	1,000,013	1,103,769	1,103,769	1,726,861	1,726,861
R-squared	0.47	0.56	0.39	0.53	0.53	0.60	0.50	0.58
Oster Statistic		1.42		2.29		5.11		1.25

Notes: This table estimates regressions of the form:

$$Approval_{ijkt} = \alpha_k + \alpha_t + \beta MinorityOwnedBank_{jkt} + \gamma X_{ijkt} + \xi_{ijkt},$$

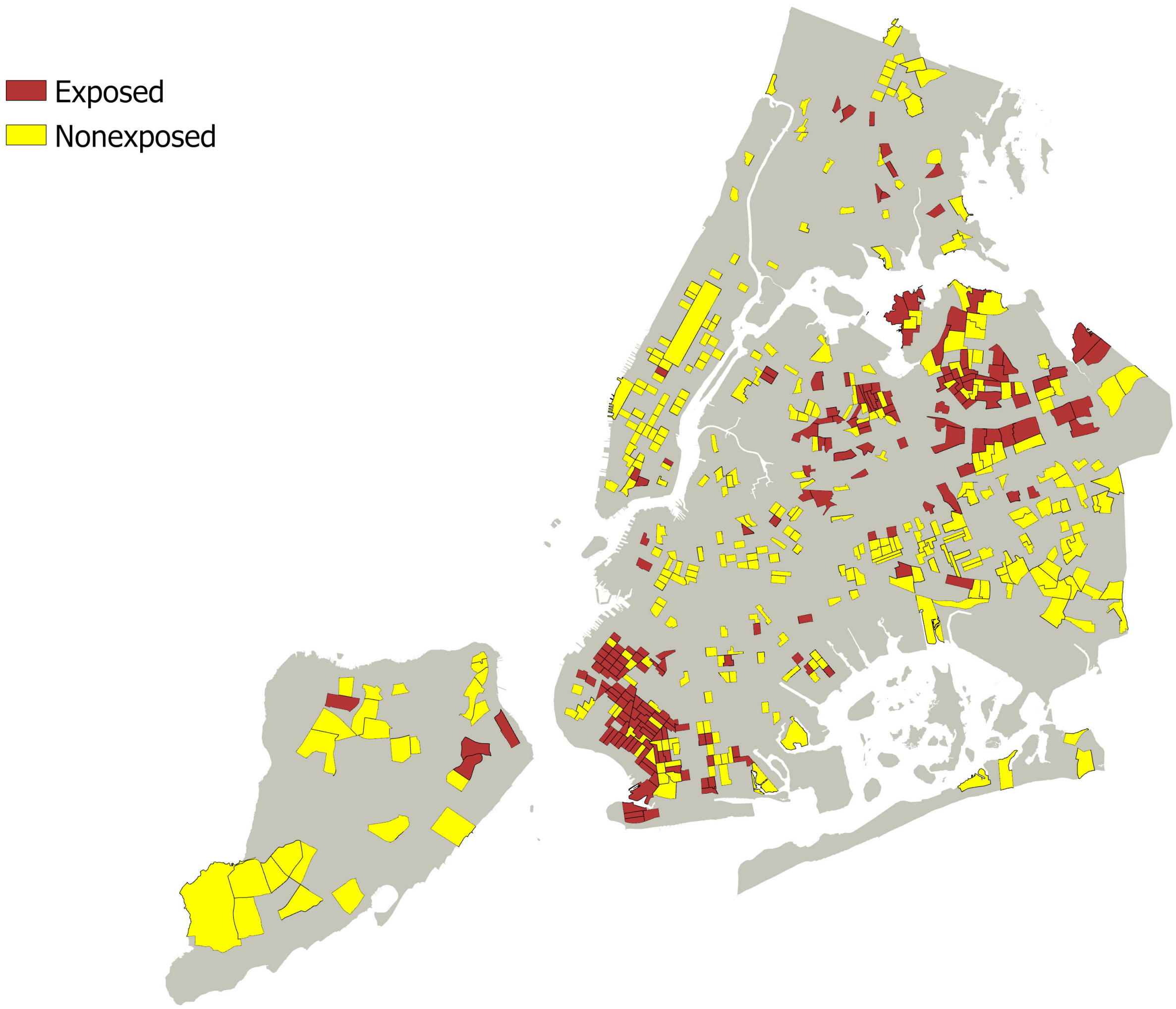
for borrower i, bank j, property's census tract k, and year t. $Approval_{ijkt}$ and $MinorityOwnedBank_{jkt}$ are approval and minority bank dummies. Odd-numbered columns report the baseline specification with borrower demographics (income-percentile fixed effects; gender and co-borrower dummies), loan characteristics (loan amount-percentile fixed effects; purpose, type, and occupancy dummies), and bank size percentile fixed effects. Even-numbered columns augment this specification with loan officers' race dummies, and borrower credit risk (credit score, loan-to-value and debt-to-income ratio percentile fixed effects). Columns 1-2 pool Asian, Black, and Hispanic borrowers in the category "Minority Borrowers," thus $MinorityOwnedBank_{jkt}$ is a dummy equal to one for same-race minority banks and zero otherwise. Columns 3-4, 5-6, and 7-8 report results for Asian, Black, and Hispanic mortgage borrowers. Approval gap is the difference between White and minority approval mean. Approval mean and gap, and coefficients are in percentage point units. Standard errors clustered at the bank and census tract levels are in parenthesis. ***, **, and * indicate coefficient estimates statistically distinct from 0 at the 1 percent, 5 percent, and 10 percent levels, respectively. Oster statistic is the degree of selection on unobservables relative to observables needed for the minority ownership to be zero and should be compared it to a bound of 1. Equation (12) in Appendix 4 details its calculation. The data span 2018-2019.

Figure V: Asian Mortgage Originations by Abacus and other Asian Banks



Notes: This figure shows the time series evolution of (normalized) Asian mortgage originations by Abacus Federal Savings Bank and other Asian-owned banks. Normalized originations are computed as the number of mortgages originated to Asian borrowers relative to 2009. The unit of the vertical axis percent 2009 Asian mortgages. Refinancing and home improvement loans are excluded to minimize seasonality. Data are constructed from public and commercial sources. Due to legal and time coverage restrictictions, we are unable to employ Federal Reserve's confidential data on borrowers and loan officers.

Figure VI: Asian Borrowers' Exposure to Abacus Federal Savings Bank in New York City, 2008

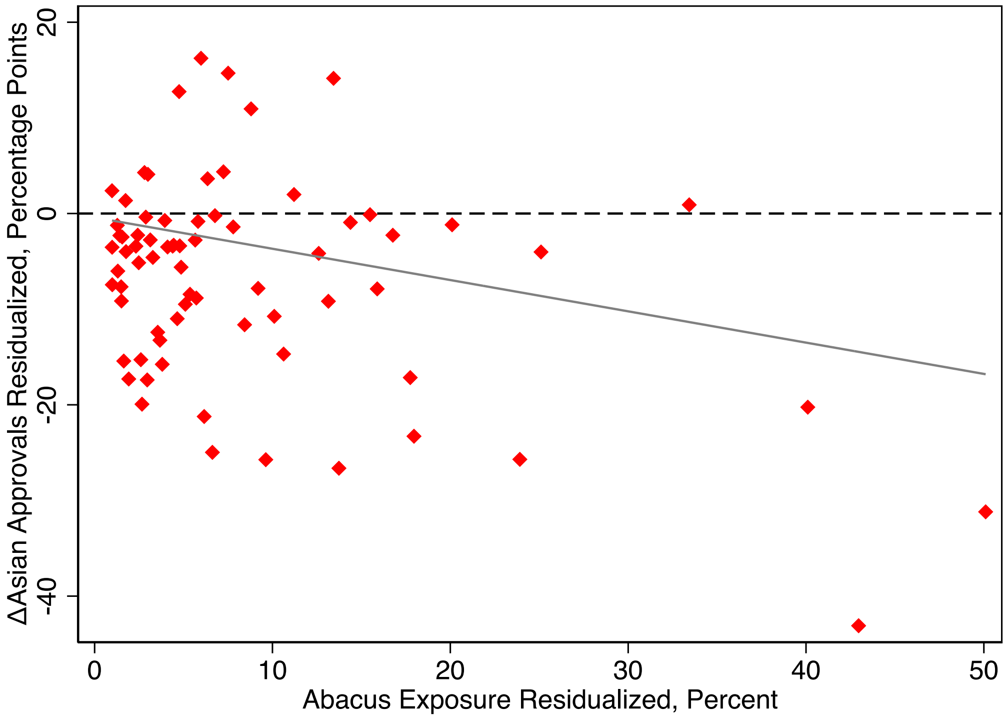


Notes: This figure shows the distribution of Asian borrowers' reliance on Abacus Bank across census tracts in New York City in 2008, one year before its collapse. "Exposed" tracts are those with $AbacusExposure_{k,2008} > 0$. Tracts with other non-Abacus, non-failing Asian banks are labeled as "Nonexposed." They have $AbacusExposure_{k,2008} = 0$, thus forming the pure control group in the research design described in section V.C. The Abacus exposure measure is constructed as:

$$AbacusExposure_{k,2008} = \frac{AbacusAsianMortgages_{k,2008}}{AsianMortgages_{k,2008}},$$

where $AbacusAsianMortgages_{k,2008}$ and $AsianMortgages_{k,2008}$ are the number of Asian mortgages originated by Abacus and all banks in census tract k in 2008, respectively. Data are constructed from public and commercial sources. Due to legal and time coverage restrictictions, we are unable to employ Federal Reserve's confidential data on borrowers and loan officers.

Figure VII: The Short-Term Effect of Abacus Bank's Collapse on Asian Credit

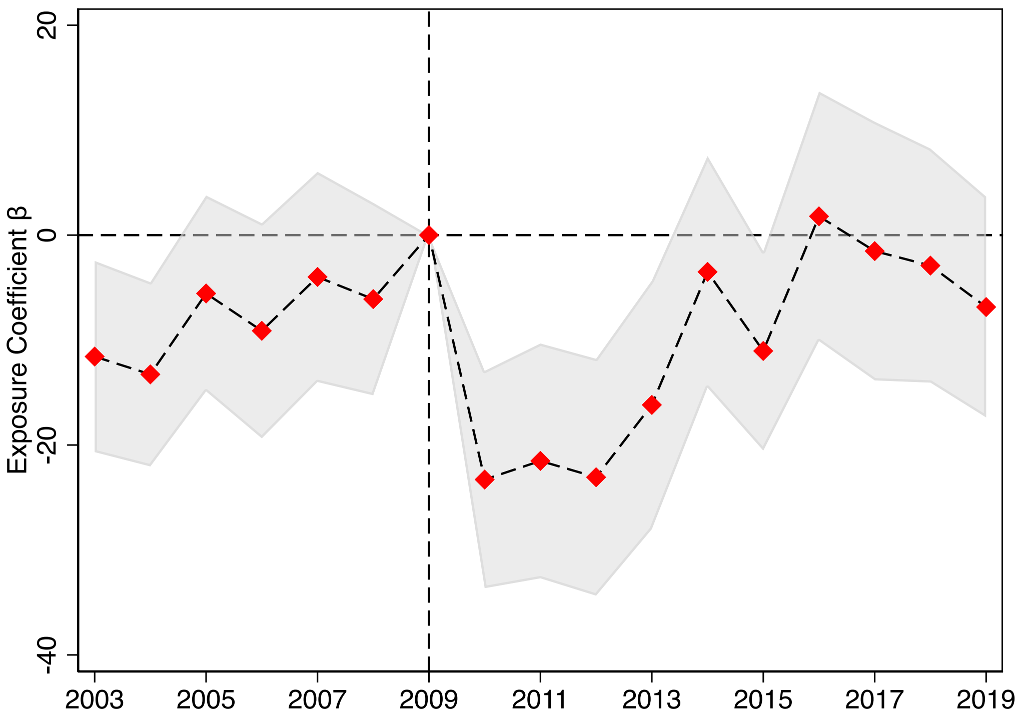


Notes: This figure plots the binscatter of the 2009-2012 change in Asian approvals against Abacus exposure in 2008. The Abacus exposure measures Asian borrowers' reliance on Abacus Bank across census tracts in 2008 and is constructed as:

$$AbacusExposure_{k,2008} = \frac{AbacusAsianMortgages_{k,2008}}{AsianMortgages_{k,2008}},$$

where $AbacusAsianMortgages_{k,2008}$ and $AsianMortgages_{k,2008}$ are the number of Asian mortgages originated by Abacus and all banks in census tract k in 2008, respectively. Asian borrowers in locations with other (non-Abacus) Asian banks form the "pure control group," and have $AbacusExposure_{k,2008} = 0$. Asian approvals and Abacus exposure are residualized using borrower demographics (income-percentile fixed effects; gender and co-borrower dummies), loan characteristics (loan amount-percentile fixed effects; purpose, type, and occupancy dummies), census-tract fixed effects, and year fixed effects. Data are constructed from public and commercial sources. Due to legal and time coverage restrictictions, we are unable to employ Federal Reserve's confidential data on borrowers and loan officers.

Figure VIII: The Effect of Abacus Bank's Collapse on Asian Credit



Notes: This figure plots estimated coefficients and confidence intervals for β_y from the regression:

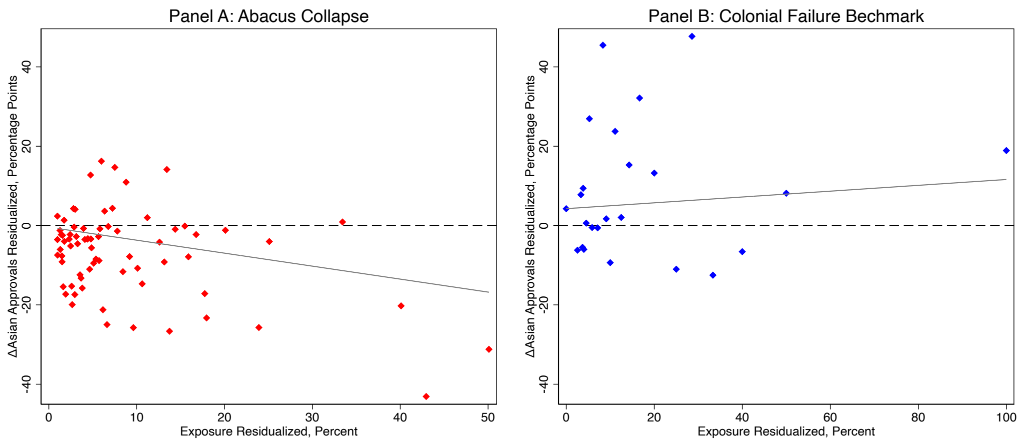
$$Approval_{ikt} = \alpha_k + \alpha_t + \sum_{y \neq 2009} \mathbb{1}_{t=y} \beta_y AbacusExposure_{k,2008} + \gamma X_{ikt} + \xi_{ikt},$$

for borrower i, property's census tract k, and year t. This regression is estimated on a sample of Asian borrowers. $Approval_{ijkt}$ is a mortgage approval dummy and $AbacusExposure_{k,2008}$ is computed as:

$$AbacusExposure_{k,2008} = \frac{AbacusAsianMortgages_{k,2008}}{AsianMortgages_{k,2008}},$$

where $AbacusAsianMortgages_{k,2008}$ and $AsianMortgages_{k,2008}$ are the number of Asian mortgages originated by Abacus and all banks in census tract k in 2008, respectively. X_{ikt} includes borrower demographics (income-percentile fixed effects; gender and co-borrower dummies) and loan characteristics (loan amount-percentile fixed effects; purpose, type, and occupancy dummies). Standard errors are clustered at the census tract level. The dependent variable mean in this design is 66.95 percent. Data are constructed from public and commercial sources. Due to legal and time coverage restrictictions, we are unable to employ Federal Reserve's confidential data on borrowers and loan officers.

Figure IX: The Short-Term Effect of Abacus Bank's Collapse, Colonial Benchmark

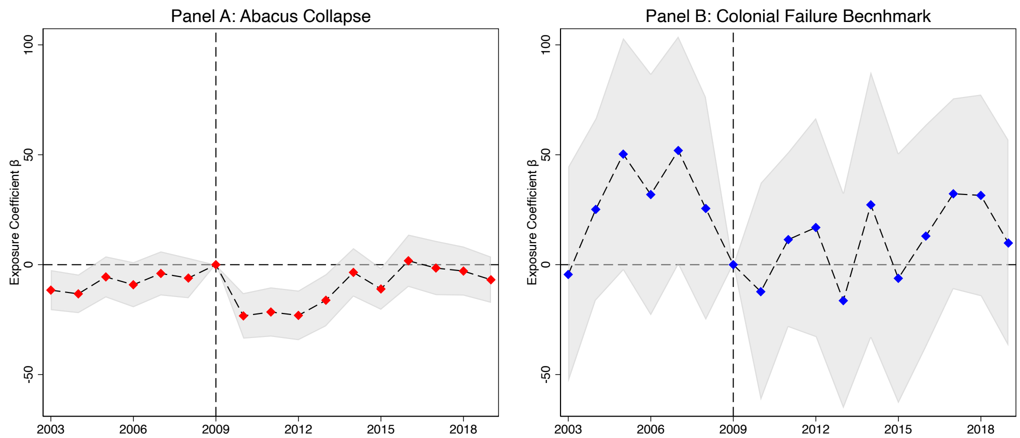


Notes: This figure plots the binscatter of the 2009-2012 change in Asian approvals against Abacus and Colonial exposure in 2008. Exposure variables measure Asian borrowers' reliance on Abacus or Colonial across census tracts in 2008 and is constructed as:

$$Exposure_{k,2008} = \frac{CollapsedBankAsianMortgages_{k,2008}}{AsianMortgages_{k,2008}},$$

where $CollapsedBankAsianMortgages_{k,2008}$ is the number of Asian mortgages originated by Abacus or Colonial, and $AsianMortgages_{k,2008}$ is the number of Asian mortgages originated by all banks in census tract k in 2008. X_{ikt} includes borrower demographics (income-percentile fixed effects; gender and co-borrower dummies) and loan characteristics (loan amount-percentile fixed effects; purpose, type, and occupancy dummies). Standard errors are clustered at the census tract level. Data are constructed from public and commercial sources. Due to legal and time coverage restrictictions, we are unable to employ Federal Reserve's confidential data on borrowers and loan officers.

Figure X: The Effect of Abacus Bank's Collapse, Colonial Benchmark



Notes: This figure plots estimated coefficients and confidence intervals for β_y from the regression:

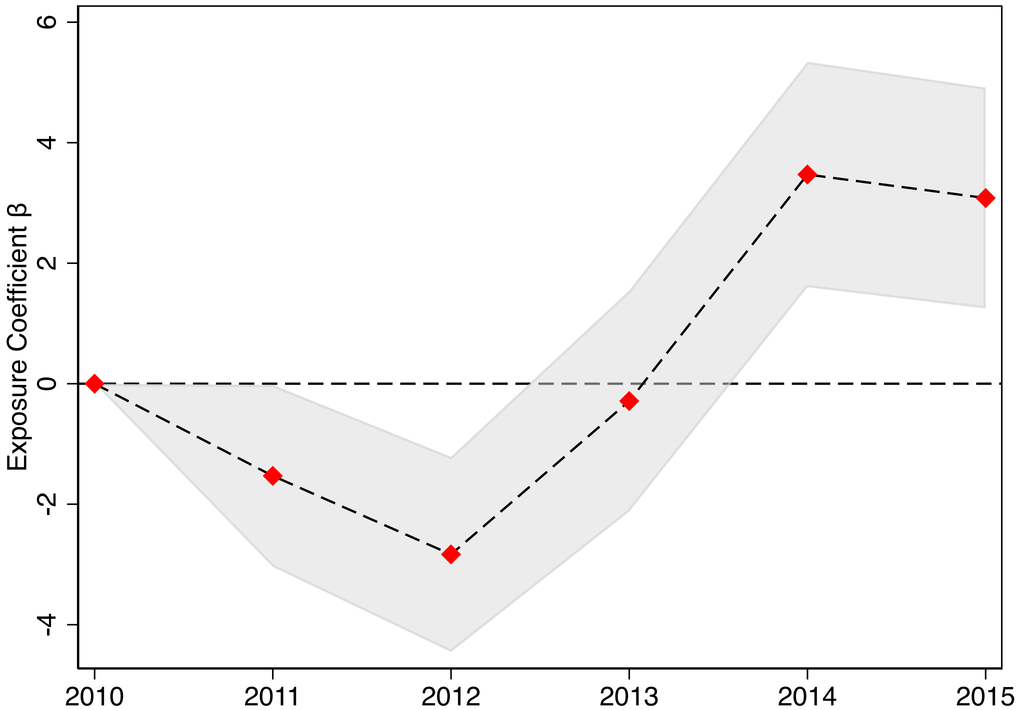
$$Approval_{ikt} = \alpha_k + \alpha_t + \sum_{y \neq 2009} \mathbb{1}_{t=y} \beta_y Exposure_{k,2008} + \gamma X_{ikt} + \xi_{ikt},$$

for borrower i, property's census tract k, and year t. This regression is estimated on a sample of Asian borrowers. $Approval_{ijkt}$ is a mortgage approval dummy and $Exposure_{k,2008}$ is computed as:

$$Exposure_{k,2008} = \frac{CollapsedBankAsianMortgages_{k,2008}}{AsianMortgages_{k,2008}},$$

where $CollapsedBankAsianMortgages_{k,2008}$ is the number of Asian mortgages originated by Abacus or Colonial, and $AsianMortgages_{k,2008}$ is the number of Asian mortgages originated by all banks in census tract k in 2008. X_{ikt} includes borrower demographics (income-percentile fixed effects; gender and co-borrower dummies) and loan characteristics (loan amount-percentile fixed effects; purpose, type, and occupancy dummies). Standard errors are clustered at the census tract level. The dependent variable mean is 66.95 and 71.02 percent in Panel A's and B's designs, respectively. Data are constructed from public and commercial sources. Due to legal and time coverage restrictictions, we are unable to employ Federal Reserve's confidential data on borrowers and loan officers.

Figure XI: The Effect of Abacus Bank's Collapse on Asian Applications, Dynamic 2010-2015



Notes: This figure plots estimated coefficients and confidence intervals for β_y from the regression:

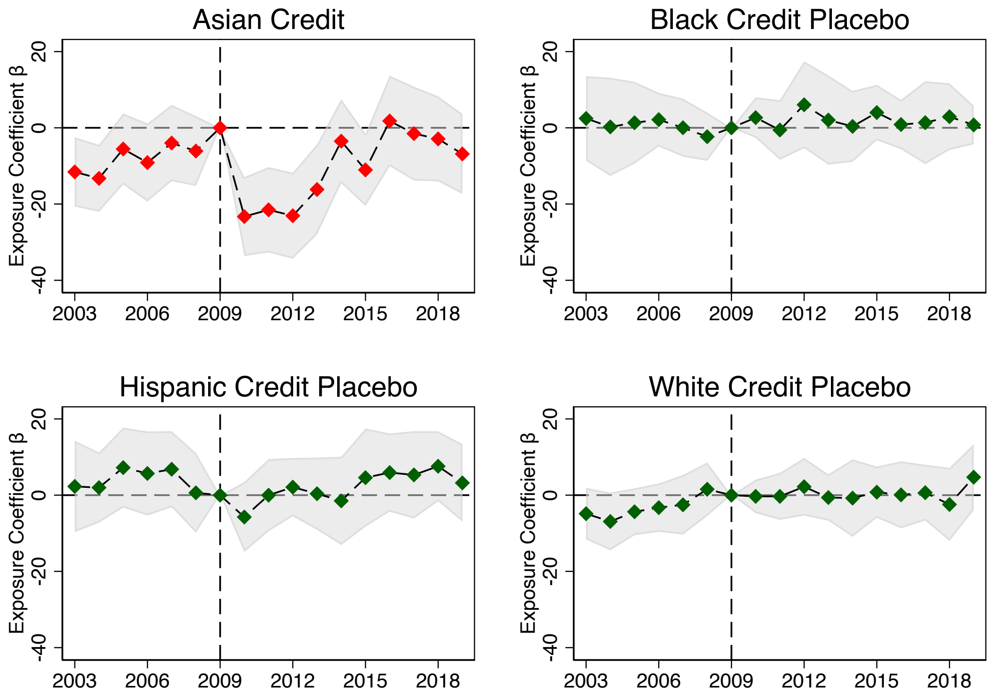
$$Applications_{kt} = \alpha_k + \alpha_t + \sum_{y \neq 2010} \mathbb{1}_{t=y} \beta_y AbacusExposure_{k,2008} + \gamma X_{kt} + \xi_{kt},$$

for property's census tract k and year t. $Applications_{kt}$ is Asian mortgage applications per capita and is constructed using tract-level Asian population from the 2010 Decennial Census. $AbacusExposure_{k,2008}$ is computed as:

$$AbacusExposure_{k,2008} = \frac{AbacusAsianMortgages_{k,2008}}{AsianMortgages_{k,2008}},$$

where $AbacusAsianMortgages_{k,2008}$ and $AsianMortgages_{k,2008}$ are the number of Asian mortgages originated by Abacus and all banks in census tract k in 2008, respectively. X_{kt} includes borrower demographics (log income; gender and co-borrower shares) and loan characteristics (log loan amount; purpose, type, and occupancy shares). The regression is estimated via weighted-least squares, where tract-level Asian population is used as weights. Standard errors are clustered at the census tract level. The dependent variable mean in this design is 4.18 percent. Data are constructed from public and commercial sources. Due to legal and time coverage restrictictions, we are unable to employ Federal Reserve's confidential data on borrowers and loan officers.

Figure XII: The Effect of Abacus Bank's Collapse on Credit, Group Placebos



Notes: This figure plots estimated coefficients and confidence intervals for β_y from the regression:

$$Approval_{ikt} = \alpha_k + \alpha_t + \sum_{y \neq 2009} \mathbb{1}_{t=y} \beta_y AbacusExposure_{k,2008} + \gamma X_{ikt} + \xi_{ikt},$$

for borrower i, property's census tract k, and year t. This regression is estimated on a sample of Asian, Black, Hispanic, and White borrowers, respectively. $Approval_{ijkt}$ is a mortgage approval dummy and $AbacusExposure_{k,2008}$ is computed as:

$$AbacusExposure_{k,2008} = \frac{AbacusAsianMortgages_{k,2008}}{AsianMortgages_{k,2008}},$$

where $AbacusAsianMortgages_{k,2008}$ and $AsianMortgages_{k,2008}$ are the number of Asian mortgages originated by Abacus and all banks in census tract k in 2008, respectively. X_{ikt} includes borrower demographics (income-percentile fixed effects; gender and co-borrower dummies) and loan characteristics (loan amount-percentile fixed effects; purpose, type, and occupancy dummies). Standard errors are clustered at the census tract level. Data are constructed from public and commercial sources. Due to legal and time coverage restrictictions, we are unable to employ Federal Reserve's confidential data on borrowers and loan officers.

Table III: Mortgage Default Rates in Minority-Owned Banks: Same- vs. Other-Race Borrowers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Minority Borrower	–1.080***	–1.121***						
	(0.265)	(0.275)						
Asian Borrower			–1.201**	–1.292**				
			(0.348)	(0.362)				
Asian Marginal Borrower					–0.239	–0.776		
					(1.791)	(2.205)		
Hispanic Borrower							0.259	–1.252
							(0.552)	(1.779)
Confidential Controls	No	Yes	No	Yes	No	Yes	No	Yes
Sample Banks	Minority	Minority	Asian	Asian	Asian	Asian	Hispanic	Hispanic
Default Mean	3.003	3.003	2.642	2.642	1.752	1.752	8.496	8.496
Observations	2,455	2,455	2,301	2,301	241	241	150	150
R-squared	0.039	0.053	0.042	0.053	0.355	0.360	0.203	0.250
Oster Statistic		–28.889		–11.786				

Notes: This table estimates regressions of the form:

$$Default_{ijt} = \alpha_j + \alpha_t + \beta MinorityBorrower_i + \gamma InterestRate_i + \delta X_i + \xi_{ijt},$$

for borrower i, minority bank j, and year t. $Default_{ijt}$ and $MinorityBorrower_i$ are default and same-race minority borrower dummies, and $InterestRate_i$ is the interest rate on borrower i's mortgage. Odd-numbered columns report the baseline specification with borrower demographics (log income; gender and co-borrower dummies), loan characteristics (log loan amount; purpose, type, and occupancy dummies). Even-numbered columns augment this specification with confidential controls (loan officers' race dummies, credit scores, and loan-to-value and debt-to-income ratios). We do not have default data for Black-owned banks' borrowers, thus Columns 1-2 pool Asian and Hispanic banks in the category "Minority Banks." In these columns, $MinorityBorrower_i$ is a dummy equal to one for same-race minority borrowers and zero otherwise. Columns 3-6 report results for Asian-owned banks. Columns 5-6 are estimated on a sample of borrowers at the margin of approval. This sample is constructed using mortgage borrowers that were rejected by an automated underwriting software, but approved by the minority bank. For construction details, see Appendix 1.4. Columns 6-7 show results for Hispanic banks. Default mean and coefficients are in percentage point units. Standard errors clustered at the bank level are in parenthesis. ***, **, and * indicate coefficient estimates statistically distinct from 0 at the 1 percent, 5 percent, and 10 percent levels, respectively. Oster statistic is the degree of selection on unobservables relative to observables needed for the minority ownership to be zero and should be compared it to a bound of 1. Equation (12) in Appendix 4 details its calculation. In all specifications, the minimum sample size needed to detect a statistically significant effect is 886 borrowers. For computation details, see Appendix 6. The data is a subsample of minority-owned banks in both confidential HMDA and McDash datasets. Defaults are measured within 12 months of origination for loans granted between January 2018 and March 2019.

Appendix

1. Appendix for "II. Institutional Setting and Data"

1.1. Bank Ownership

1.1.1. Minority Definitions

The definitions of minority groups in data from federal registries are based on the Office of Management and Budget (OMB) Race and Ethnic Standards for Federal Statistics and Administrative Reporting, also known as OMB Directive No. 15. The OMB has updated its original Directive No. 15 several times. FIRREA defines minority banks using the Directive's 1997 update, which includes five categories:

1. *Asian American.* A person having origins in any of the original peoples of the Far East, Southeast Asia, or the Indian subcontinent, including, for example, Cambodia, China, India, Japan, Korea, Malaysia, Pakistan, the Philippine Islands, Thailand, and Vietnam.

2. *Black or African American.* A person having origins in any of the black racial groups of Africa.

3. *Hispanic or Latino American.* A person of Cuban, Mexican, Puerto Rican, South or Central American, or other Spanish culture or origin, regardless of race.

4. *Native American or American Indian, or Alaska Native.* A person having origins in any of the original peoples of North and South America (including Central America) and who maintains tribal affiliation or community attachment.

5. *Native Hawaiian or Other Pacific Islander American.* A person having origins in any of the original peoples of Hawaii, Guam, Samoa, or other Pacific Islands.

The term "minority" in FIRREA refers to any Asian, Black, Hispanic, Multiracial, or Native American. The Asian American category includes two OMB groups: *Asian American* and *Native Hawaiian or Other Pacific Islander American.* Multiracial Americans are defined as individuals of two or more minority races or Hispanic ethnicity.

These categories are broad and diverse. In particular, the Asian and Hispanic American categories exhibit substantial within-group heterogeneity regarding race, ethnicity, and country of origin. Factors other than race and ethnicity might explain the inclusion and exclusion of some groups from these categories (Bernstein, 2022).[27]

[27] The White American category is defined as a residual, that is, a person not beloning to any OMB minority category. This category also exhibits substantial heterogeneity in terms of race, ethnicity, and country of origin. For example, Arab, Italian, and Polish Americans belong to this category.

Despite their drawbacks, these categories provide a well-defined standard that we can use to guide our data efforts. We construct our data using only the Asian American, Black American, and Hispanic American categories. We exclude the Native American category for two reasons. First, their small size in the critical dimensions of this paper (bank ownership, employees, and borrowers) prevents reliable statistical inference. Second, their unique laws, regulations, and geographies (e.g., on reservations) threaten the external validity of this study.[28]

1.1.2. Data Construction Details

We create the ownership data using five data sources: FDIC, Federal Reserve, OCC/Treasury, NCUA, and GAO. Our workflow for each data source is as follows:

1. Perform initial digitization and basic cleaning.
2. Drop minority banks outside our definition: multiracial, Native, and women banks; then minority-board and minority-market banks.
3. Collect banks' unique identification numbers (RSSD9001).
4. Match the resulting datasets.

Next, we describe each data source, its coverage, types of minority banks, key information, original sources, availability, and construction process.

FDIC Data

Description. List of minority banks regulated by the FDIC.

Coverage. Some state-chartered banks and all state-chartered savings and loans.

Types. Minority-owned, minority-board, and minority-market banks.

Key Information. Bank name, city, state, and FDIC certificate number.

Sources. FDIC Minority Depository Institutions List and two FOIA requests.

Availability. 2000-2022.

Data Construction. We drop multiracial and Native banks. We then drop minority-board and minority-market banks. Finally, we collect Federal Reserve Board Entity numbers (RSSD9001) through a fuzzy match with the FFIEC repository using name, city, and state.

[28]Furthermore, some argue that the Native American category is a "political classification" because they have different sovereignty (Bernstein, 2022).

Federal Reserve Data

Description. List of minority banks regulated by the Federal Reserve and other agencies.

Coverage. National and state-chartered banks.

Types. Minority-owned banks.

Key Information. Bank name, city, state, year opened, year closed, and Federal Reserve Board Entity number (RSSD9001).

Sources. FFIEC Repository and two FOIA requests.

Availability. 1940-2022.

Data Construction. We combine data on closed and active banks. We drop multiracial and Native banks.

OCC/Treasury Data

Description. List of minority banks regulated by the OCC/Treasury.

Coverage. Certain national banks and all federally-chartered savings and loans.

Types. Minority-owned, minority-board, and minority-market banks (minority definition includes racial/ethnic minorities and women).

Key Information. Bank name, city, state, and OCC charter number.

Sources. Annual Reports to Congress and three FOIA requests.

Availability. 2009-2021.

Data Construction. We digitize reports. We then drop multiracial, Native, and Women banks. Next, we drop minority-board and minority-market banks. Finally, we collect Federal Reserve Board Entity numbers (RSSD9001) through a fuzzy match with the FFIEC repository using name, city, and state.

NCUA Data

Description. List of minority credit unions regulated by the NCUA.

Coverage. Some state-chartered and all federal credit unions.

Types. Minority-member and minority-board credit unions.

Key Information. Credit union name, city, state, and NCUA number.

Sources. NCUA Minority Depository Institutions List, Call Reports, and two FOIA requests.

Availability. 2010-2021.

Data Construction. We clean the NCUA list and call report data. We then drop multiracial and Native credit unions. Next, we drop minority-board credit unions. Finally, we collect missing Federal Reserve Board Entity numbers (RSSD9001) through a fuzzy match with the FFIEC repository using name, city, and state.

GAO Data

Description. List of minority banks regulated by the FDIC, Federal Reserve, OCC, and OTS.

Coverage. All commercial banks.

Types. Minority-owned, minority-board, and minority-market banks.

Key Information. Bank name.

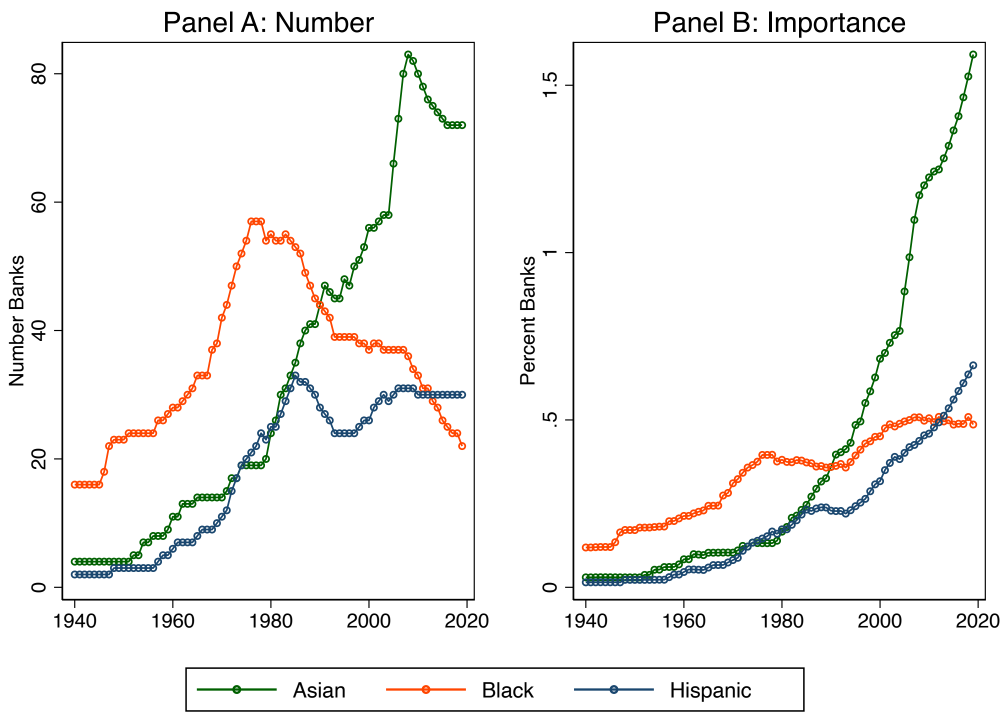
Sources. GAO reports and a FOIA request.

Availability. 1993-2011.

Data Construction. We digitize reports and confirm that minority banks regulated by the OTS are in our FDIC, Federal Reserve, and OCC data. The OTS ceased to exist on October 2011.

1.1.3. Minority-Owned Banks, 1940-2019

Figure 1.1: Number and Importance of Minority-Owned Banks



This figure shows the time series evolution of the number and importance of Asian, Black, and Hispanic-owned banks. Panel A shows the absolute number of minority-owned commercial banks. Panel B shows the number of minority-owned commercial banks relative to the total number of commercial banks. The units of the vertical axes are number and percent of banks in Panels A and B, respectively. The data span 1940-2019.

1.2. Bank Employees

1.2.1. Data Construction Details

We create data on bank employees' languages from LinkedIn. Our race data is constructed using six data sources: The Census Bureau, CSBS, TWG, LinkedIn, NCUA, and BrightData. Each source provides inputs to predict employees' race: census tracts' population by race, names, locations, or professional headshots of employees. We employ two prediction methods that use some of these inputs and have varying levels of accuracy: FAR and BIFSG. We present an overview of each prediction method below.

1. **Face Attribute Recognition (FAR).** We use a Residual Neural Network model trained on FairFace, a face dataset with an emphasis on balanced race composition.[29] We use racially balanced training data due to their superior prediction accuracy (Karkkainen and Joo, 2021).

   FairFace contains over 100 thousand images collected from the YFCC-100M Flickr dataset. To label these images with race, gender, and age groups, Karkkainen and Joo (2021) assigned three Amazon Mechanical Turk workers to each image and used rules standard in the literature.[30] FairFace's race categories include White, Black, Indian, East Asian, Southeast Asian, Middle Eastern, and Hispanic. We make two slight changes in these categories so that our race predictions are consistent with our minority-ownership and borrower data. First, we add Middle Eastern to the White category. Second, we create an Asian category that includes the Indian, East Asian, and Southeast Asian categories.

2. **Bayesian Improved First and Surname Geocoding (BIFSG).** This method requires race priors, which are then updated using geography-level population data by race. We first produce race priors using the name embedding classifier of Ye et al. (2017), which trains a model using name labels in 57 million contact lists from an email company and Census Bureau data on popular first and surnames for six groups: non-Hispanic Asian, non-Hispanic Black, Hispanic, non-Hispanic Native, and multiracial (two or more minority races or Hispanic ethnicity), and non-Hispanic White.[31] Let l be employee, Y_l race of employee l, r racial group, and n_l full name of employee l (first and surnames). Using n_l as an input, we obtain predictions $\Pr(Y_l = r|n_l)$. According to Ye et al. (2017), this is the most accurate non-commercial name-based race classifier. Other research using this method includes Diamond et al. (2019), Kempf and Tsoutsoura (2021), and Vorsatz (2022).

   We then update our race priors using geography-level population data by race in a Bayes classifier introduced by Voicu (2018). Let g be geography and $\Pr(Y_l = r|n) = \Pr(r|n)$ a prior probability. Define $\widetilde{r} \equiv r|n$ and rewrite the prior as $\Pr(\widetilde{r}) \equiv \Pr(r|n)$. We update $\Pr(\widetilde{r})$ using a naive Bayes rule:

$$\Pr(\widetilde{r}|g) = \frac{\Pr(\widetilde{r}) \times \Pr(g|\widetilde{r})}{\Pr(g)}, \tag{7}$$

   which can be rewritten as:

[29] A Residual Neural Network (ResNet) is a Convolutional Neural Network (CNN) with up to 152 layers.
[30] For details, see Karkkainen and Joo (2021), section 3.
[31] The method exploits the homophily principle in communication, which states that people tend to communicate more frequently with others of similar race/Hispanicity, language, age, and location.

$$\Pr(\widetilde{r}|g) = \frac{\Pr(\widetilde{r}) \times \Pr(g|\widetilde{r})}{\sum_{r'} \Pr(r'|n) \times \Pr(g|r')}, \tag{8}$$

$$= \frac{\Pr(r|n) \times \Pr(g|r)}{\sum_{r'} \Pr(r'|n) \times \Pr(g|r')}, \tag{9}$$

where (8) uses the law of total probability, $\sum_{\widetilde{r}'} \Pr(\widetilde{r}') \times \Pr(g|\widetilde{r}') = \sum_{r'} \Pr(r'|n) \times \Pr(g|r')$, and (9) uses $\Pr(g|\widetilde{r}) = \Pr(g|r, n) = \Pr(g|r)$ in (7). Since we already have prior probabilities $\Pr(\widetilde{r})$, we only need to calculate $\Pr(g|r)$:

$$\Pr(g|r) \equiv \frac{\Pr(g \cap r)}{\Pr(r)},$$

$$= \frac{r \textit{ population in } g}{r \textit{ population}}, \tag{10}$$

that is, the proportion of the population of race r in geography g. We use census tracts as geographic units g due to their superior statistical properties.[32]

Next, we describe each data source, its coverage, key information, original sources, availability, and construction process.

Census Bureau Population Data

Description. Population data.

Coverage. United States (mainland and territories).

Key Information. Census tract-level population by race and ethnicity.

Source. 2010 Decennial Census.

Availability. 2010.

Data Construction. We construct population numbers for six groups: non-Hispanic Asian, non-Hispanic Black, Hispanic, non-Hispanic Native, multiracial (two or more minority races or Hispanic ethnicity), and non-Hispanic White.

Census Bureau Geospatial Data

Description. Geospatial data for census tract-level.

Coverage. United States (mainland and territories).

[32]Census tracts are small contiguous and relatively permanent statistical subdivisions of a county or statistically equivalent entity. Their primary purpose is to provide a stable set of geographic units for the presentation of statistical data from the Census Bureau. Census tracts generally have a population size between 1,200 and 8,000 people, with an optimum size of 4,000 people.

Key Information. Shapefiles for 2010 census tracts.

Source. 2010 Decennial Census.

Availability. 2010.

Data Construction. We perform a spatial merge between these shapefiles and geocoded loan officers' work addresses from the **CSBS Loan Officer Data**.

CSBS Loan Officer Data

Description. Data on mortgage loan officers.

Coverage. Universe of federal and state licenses and registrations from mortgage loan officers employed by banks, credit unions, and shadow banks.

Key Information. NMLS license identification numbers, full legal names, work addresses, and work address types (main, branch, work) of mortgage loan officers.

Sources. NMLS B2B Access Data.

Availability. 2012-2022.

Data Construction. We obtain race predictions as follows.

1. We construct race priors using the name embedding classifier of Ye et al. (2017).
2. We obtain loan officers' census tracts by geocoding their work addresses and spatially merging them with shapefiles from the **Census Bureau Geospatial Data**.
3. We use BIFSG. For each loan officer's census tract, we calculate $\Pr(g|r)$ using equation (10) and census tract-level population data by race from the **Census Bureau Population Data**.

TWG Loan Officer Data

Description. Data on mortgage loan officers.

Coverage. Seventy percent of the federal and state licenses and registrations from mortgage loan officers employed by banks, credit unions, and shadow banks.

Key Information. NMLS license identification numbers, full names, and work addresses of mortgage loan officers. Social media accounts (LinkedIn, Twitter, and Facebook) for a subset of mortgage loan officers.

Sources. NMLS B2B Access and TWG LO Contact Data.

Availability. 2018-2022.

Data Construction. We scrape approximately 75,000 LinkedIn profiles using professional scrapers.

LinkedIn Loan Officer Data

Description. Scraped LinkedIn accounts of mortgage loan officers.

Coverage. Ten thousand officers from own data collection (plus 75,000 from scraped **TWG Data**).

Key Information. Professional headshots and languages for a subset of mortgage loan officers.

Sources. Own construction using lead generators and names from the **CSBS Loan Officer Data**.

Availability. 2012-2022.

Data Construction. We present construction details for our race and language data below.

1. **Race Data.** We obtain race predictions for each professional headshot using Karkkainen and Joo (2021)'s model (trained on FairFace's racially balanced data).
2. **Language Data.** We construct two language categories from loan officers' language information on LinkedIn: Asian and Hispanic. The Asian language category includes Bahasa Indonesia, Bangla, Bengali, Chinese, Filipino, Gujarati, Hindi, Hmong, Japanese, Korean, Lao, Malay, Marathi, Mon-Khmer, Nepali, Punjabi, Taishanese, Thai, and Vietnamese. The Hispanic language category includes Portuguese and Spanish.

NCUA Board Members and CEO Data

Description. Data on credit union board members and CEOs.

Coverage. Some state-chartered and all federal credit unions.

Key Information. Full names of board members and CEOs.

Sources. Three FOIA requests.

Availability. 2012-2021.

Data Construction. We construct race predictions using the name classifier of Ye et al. (2017).

LinkedIn Bank Employee Data

Description. Data on bank employees.

Coverage. Minority-owned banks, their peer banks, and top five banks (commercial banks and credit unions).

Key Information. Full names, professional headshots, and languages for employees.

Sources. Own construction using lead generators and bank names, cities, and states from the "Minority Bank Ownership Data" and "Other Data."

Availability. 2018-2022.

Data Construction. We present construction details for our race and language data below.

1. **Race Data.** We construct race predictions for professional headshots (when available) using Karkkainen and Joo (2021)'s model. We obtain race predictions for names using BIFSG.

2. **Language Data.** We construct two language categories from language information on LinkedIn: Asian and Hispanic. The Asian language category includes Bahasa Indonesia, Bangla, Bengali, Chinese, Filipino, Gujarati, Hindi, Hmong, Japanese, Korean, Lao, Malay, Marathi, Mon-Khmer, Nepali, Punjabi, Taishanese, Thai, and Vietnamese. The Hispanic language category includes Portuguese and Spanish.

1.2.2. Race Data Prediction Accuracy

Our goal in constructing the employee data is to maximize the accuracy of race predictions to minimize bias induced by measurement error in our analyses.

For each method $m \in \{FAR, BIFSG\}$ and racial group $i \in \{Asian, Black, Hispanic, White\}$, we measure race prediction accuracy as $A_{m,i} = \Pr(\hat{Y} = i|Y = i, m)$, where $\hat{Y}$ and Y are predicted and true race, respectively. We choose the method attaining the maximum accuracy rate $A_{m,i}$, which we compute as follows:

1. **FAR.** Table 6 in Karkkainen and Joo (2021) reports accuracy rates $\Pr(\hat{Y} = i|Y = i)$.

2. **BIFSG.** We calculate BIFSG accuracy as $\Pr(\hat{Y} = i|Y = i) = 1 - FP - FN$, where FP and FN are false positive and false negative rates from Table 6 in Voicu (2018).

Table 1.1 summarizes accuracy rates and shows that FAR's accuracy is substantially higher for all groups. Thus, we use FAR whenever professional headshots are available. Otherwise, we use BIFSG. In robustness exercises, we discard predictions with $\Pr(Y = i) < 0.9$ and $\Pr(Y = i) < 0.8$.

Table 1.1: Summary of Prediction Accuracy by Method

Category	FAR	BIFSG
Asian	97.7%	73.1%
Black	96.9%	42.5%
Hispanic	99.0%	76.4%
White	98.5%	90.8%

Notes: Column FAR is taken from Table 6 in Karkkainen and Joo (2021). Column BIFSG is constructed from Table 6 in Voicu (2018).

Since FAR's accuracy is substantially higher for all groups, our bank employee data contains race predictions more precise than recent efforts by Frame et al. (2022) and Jiang et al. (2022), which use BIFSG.

1.3. Mortgage Borrowers

Public HMDA Data

Description. Applicant-level mortgage data.

Coverage. Near universe of banks, credit unions, and shadow. Very small and rural mortgage lenders might be exempted from reporting some or all information.

Key Information. HMDA lender identification numbers, loan application status (denied, approved, or originated), loan purpose (home purchase, refinancing, or home improvement), applicant characteristics such as race, income, and gender.

Sources. HMDA Loan Application Register.

Availability. 1990-2021.

Confidential HMDA Data

Description. Applicant-level mortgage data with additional confidential information.

Coverage. Near universe of banks, credit unions, and shadow. Very small and rural mortgage lenders might be exempted from reporting some or all information.

Key Information. HMDA lender identification numbers, loan application status (denied, approved, or originated), loan purpose (home purchase, refinancing, or home improvement), applicant characteristics such as race, income, and gender. Credit scores, exact debt-to-income and combined loan-to-value ratios of applicants, the use of automated underwriting software in applications, the Nationwide Multi-State Licensing System (NMLS) license identification numbers of loan officers.

Sources. Confidential HMDA Loan Application Register.

Availability. 1990-2021. Confidential information is available since 2018.

HMDA "Avery File"

Description. HMDA and regulatory identification numbers for lenders in the HMDA Loan Application Register.

Coverage. Public HMDA coverage.

Key Information. HMDA respondent identification numbers (1990-2017), HMDA legal entity identification numbers (LEIs 2018-2021) numbers, and Federal Reserve Board Entity numbers (RSSD9001s, 1990-2021).

Sources. Robert Avery from the Federal Housing Finance Agency.

Availability. 1990-2021.

1.4. Data Dictionary: Selected Variables

$\mathbb{1}$**(Approval):** Dummy equal to one if a borrower applying for a mortgage gets approved by the lender, and zero otherwise.

$\mathbb{1}$**(Minority-Owned Bank):** Dummy equal to one if a bank is minority owned, and zero otherwise.

$\mathbb{1}$**(Minority Loan Officer):** Dummy equal to one if a loan officer belongs to a minority group, and zero otherwise.

$\mathbb{1}$**(Default):** Dummy equal to one if a borrower fails to make a scheduled mortgage payment for at least 60 consecutive days, and zero otherwise.

$\mathbb{1}$**(Minority Borrower):** Dummy equal to one if a borrower belongs to a minority group, and zero otherwise.

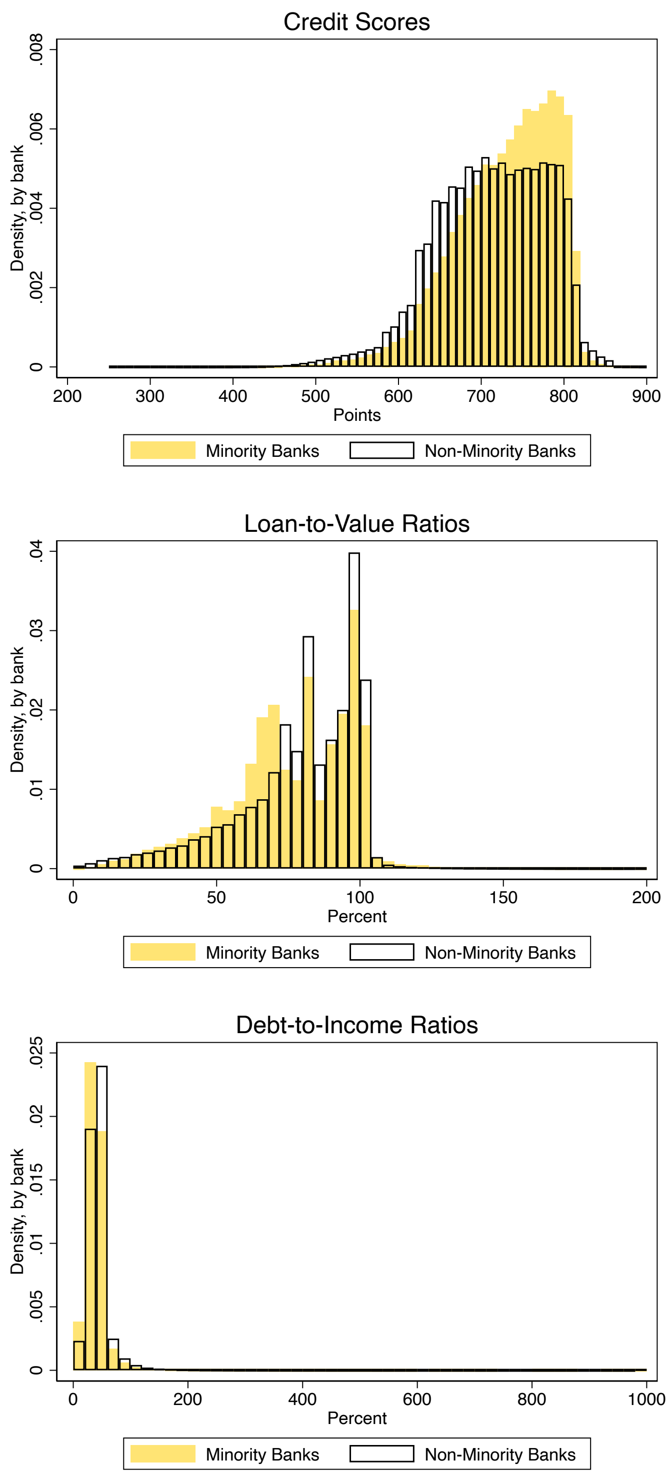
Marginal borrowers: Mortgage borrowers rejected by an automated underwriting software (AUS) but approved by the bank.[33]

1.5. Distributions of selected characteristics by bank

Below we present distributions of continuous credit risk, demographic, and loan characteristics for the universe of minority mortgage applicants in 2018-2019. Credit risk characteristics include credit score, loan-to-value, and debt-to-income ratios. Demographic and loan characteristics include income and loan amount.

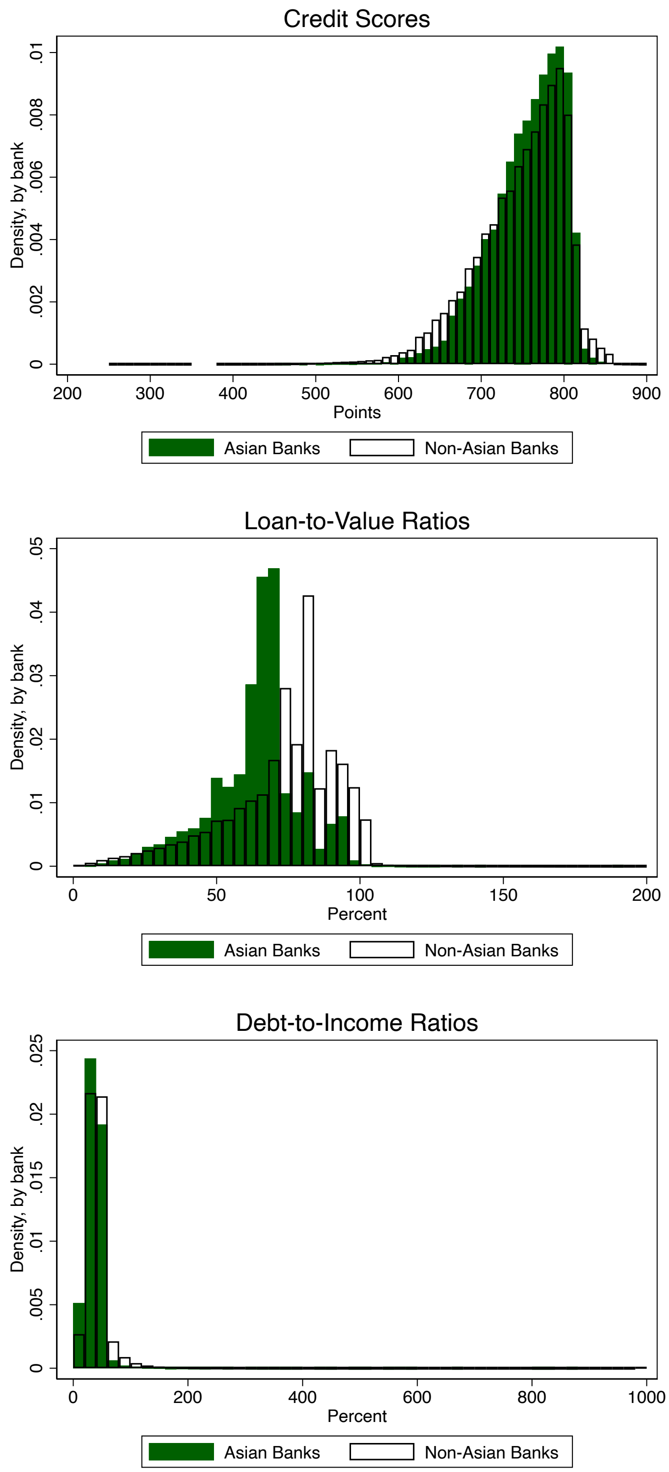
[33]The following AUS results imply a mortgage rejection: Refer/Eligible (3), Refer/Ineligible (4), Refer with Caution (5), Out of Scope (6), Error (7), Caution (9), Ineligible (10), Incomplete (11), Invalid (12), Refer (13), Unable to Determine or Unknown (15), Other (16), Not Applicable (17), Refer with Caution/Eligible (21), Refer with Caution/Ineligible (22), Refer/Unable to Determine (23), Refer with Caution/Unable to Determine (24). The following AUS results imply a mortgage approval: Approve/Eligible (1), Approve/Ineligible (2: borrower with acceptable risk but not eligible for a government loan), Accept (8), Eligible (14), Accept/Eligible (18), Accept/Ineligible (19), Accept/Unable to Determine (20).

Figure 1.2: Minority Mortgage Applicants' Credit Risk by Bank



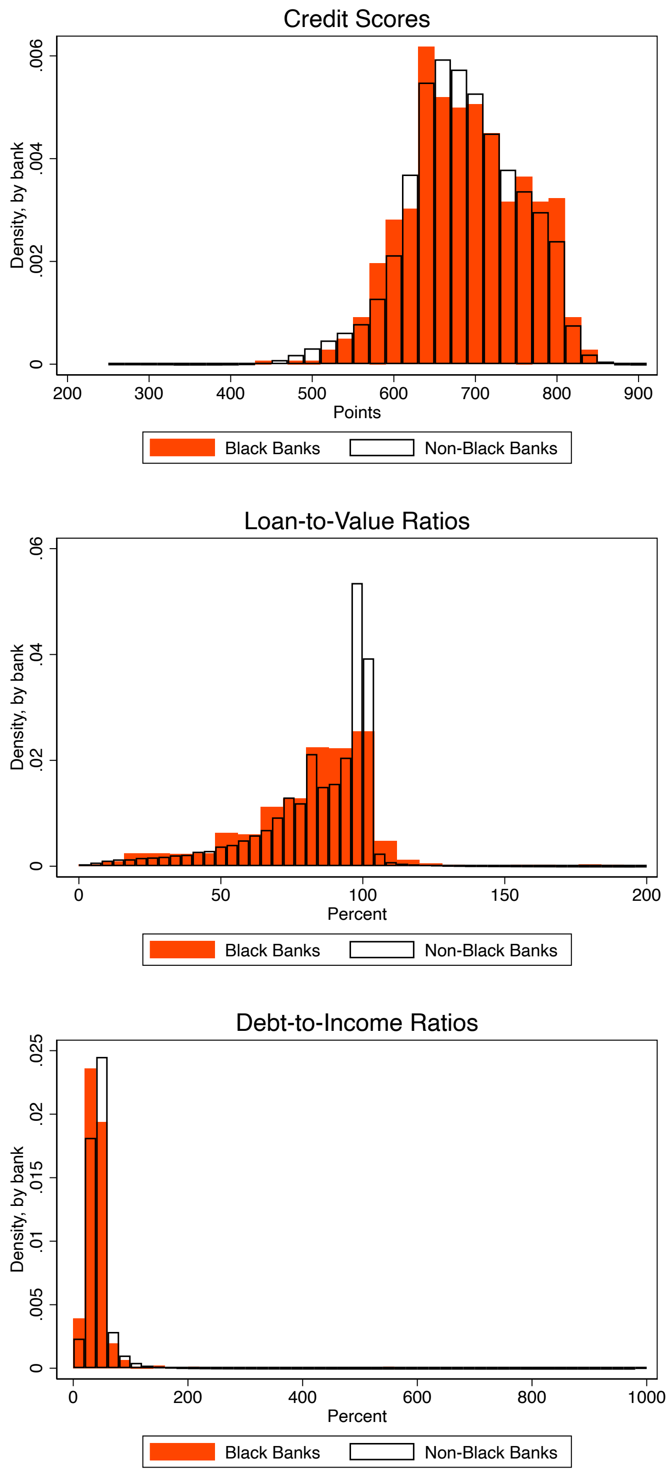
This figure shows credit risk distributions for minority mortgage applicants with same-race minority and non-minority banks. The unit of the vertical axis unit is density. The data span 2018-2019.

Figure 1.3: Asian Mortgage Applicants' Credit Risk by Bank



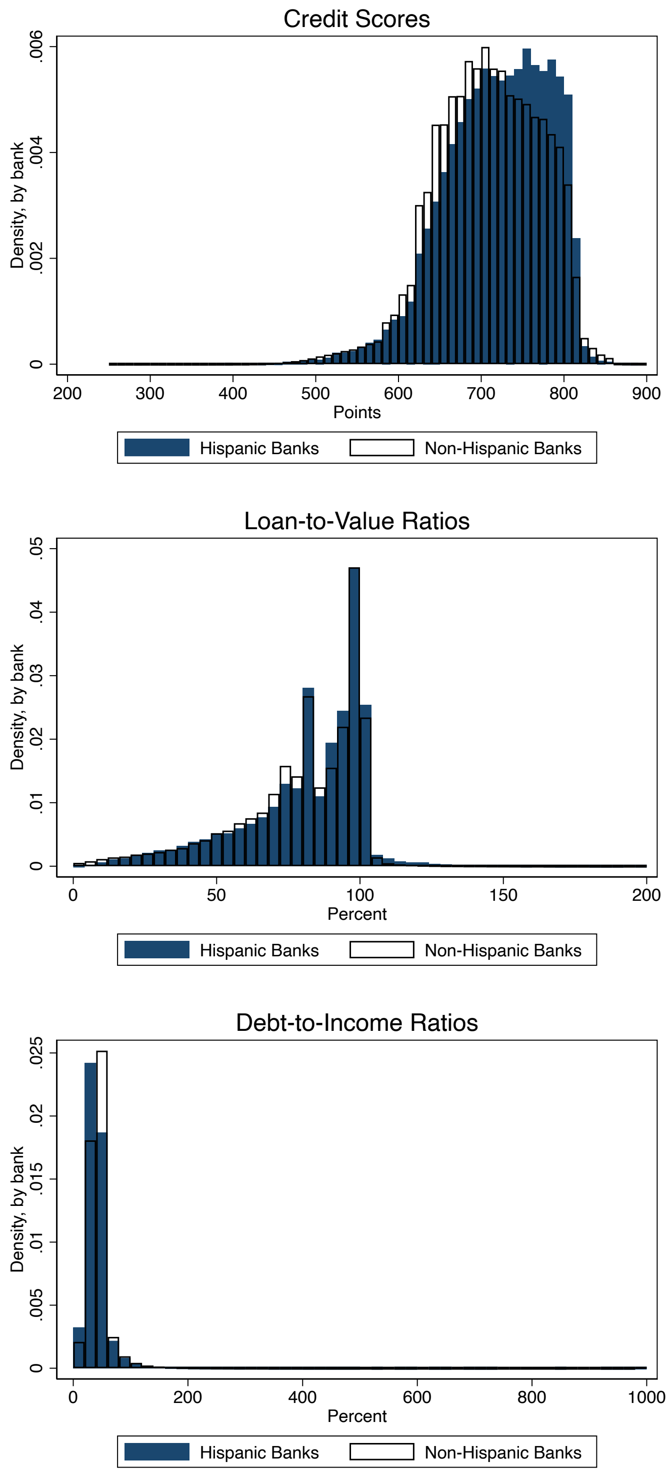
This figure shows credit risk distributions for Asian mortgage applicants with Asian and non-Asian banks. The unit of the vertical axis unit is density. The data span 2018-2019.

Figure 1.4: Black Mortgage Applicants' Credit Risk by Bank



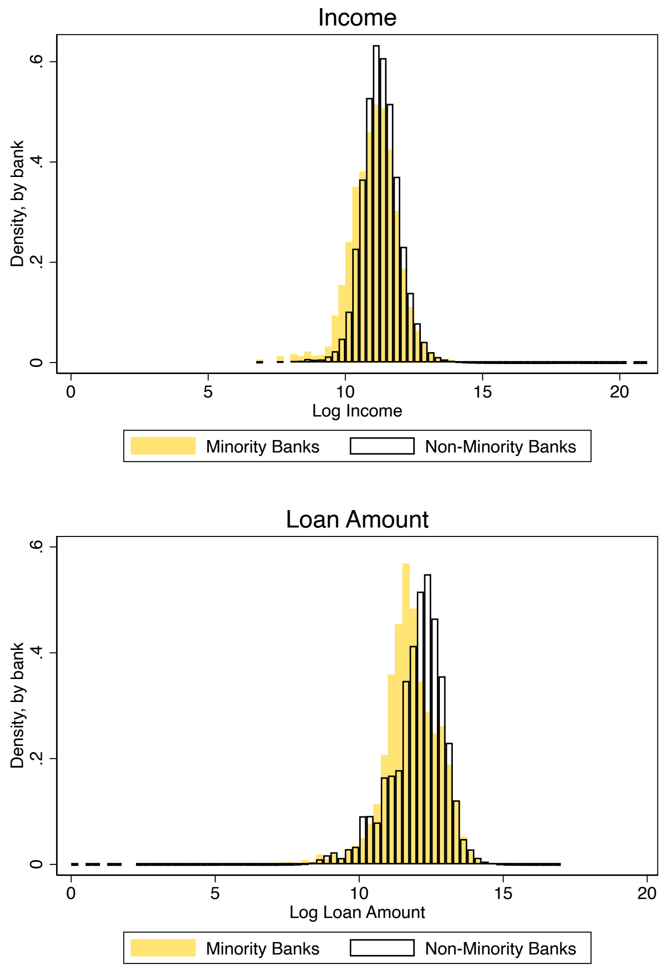
This figure shows credit risk distributions for Black mortgage applicants with Black and non-Black banks. The unit of the vertical axis unit is density. The data span 2018-2019.

Figure 1.5: Hispanic Mortgage Applicants' Credit Risk by Bank



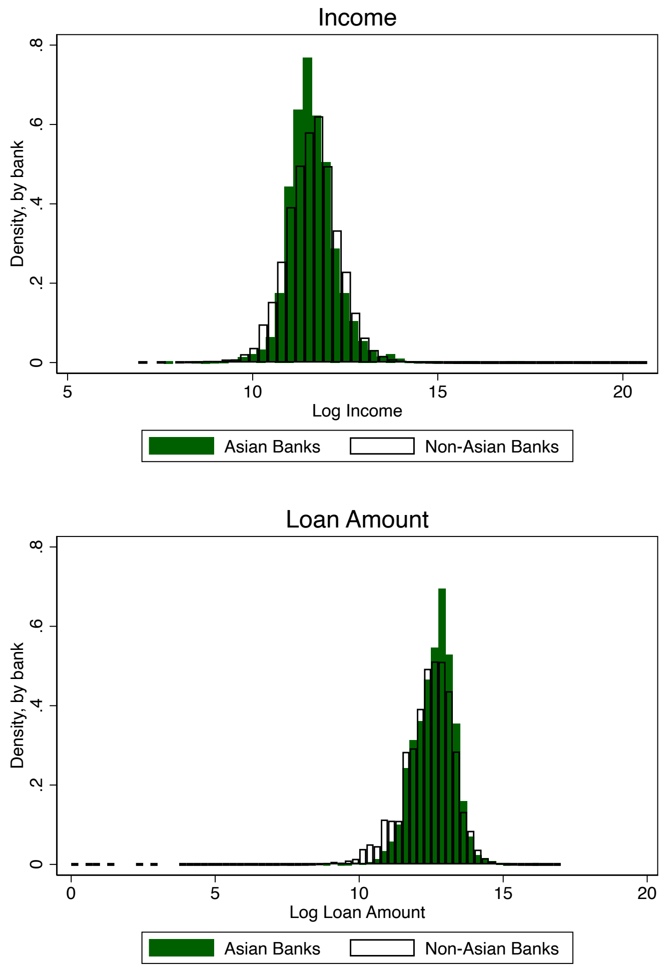
This figure shows credit risk distributions for Hispanic mortgage applicants with Hispanic and non-Hispanic banks. The unit of the vertical axis unit is density. The data span 2018-2019.

Figure 1.6: Minority Mortgage Applicants' Income and Loan Amount by Bank



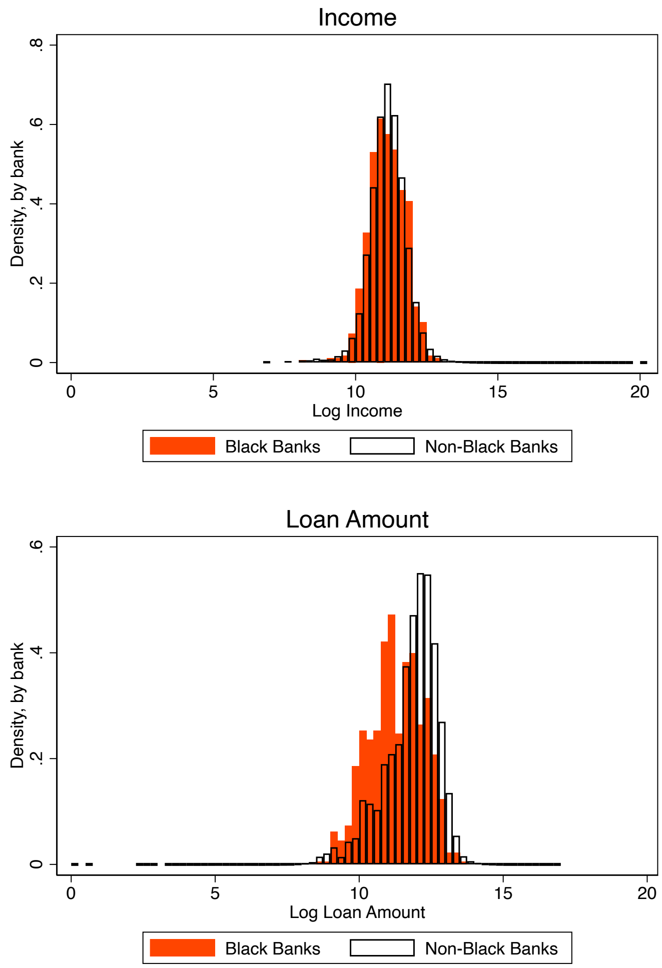
This figure shows income and loan amount distributions for minority mortgage applicants with same-race minority and non-minority banks. The unit of the vertical axis unit is density. The data span 2018-2019.

Figure 1.7: Asian Mortgage Applicants' Income and Loan Amount by Bank



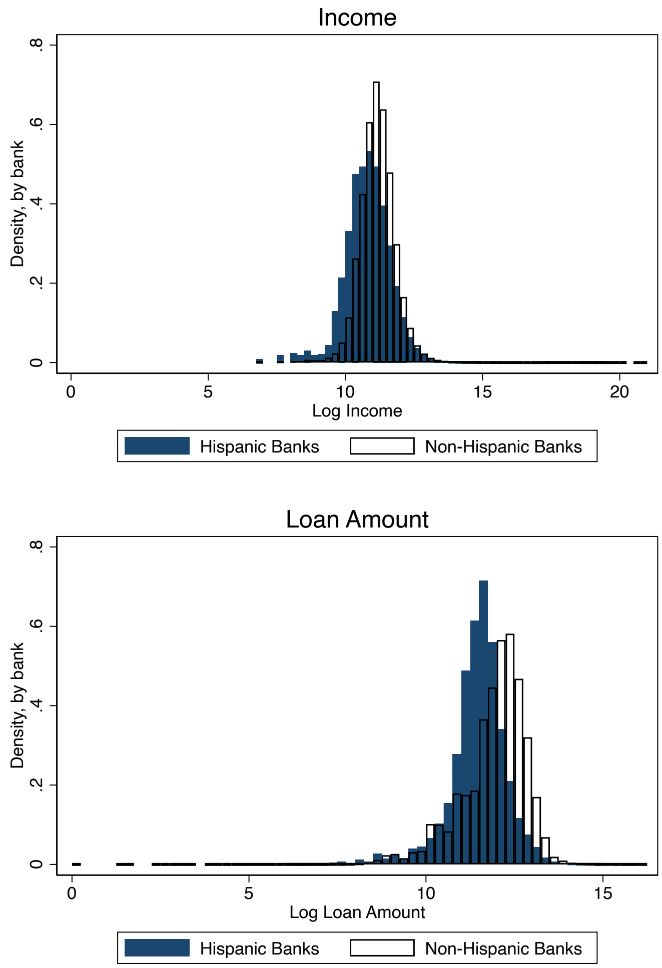
This figure shows income and loan amount distributions for Asian mortgage applicants with Asian and non-Asian banks. The unit of the vertical axis unit is density. The data span 2018-2019.

Figure 1.8: Black Mortgage Applicants' Income and Loan Amount by Bank



This figure shows income and loan amount distributions for Black mortgage applicants with Black and non-Black banks. The unit of the vertical axis unit is density. The data span 2018-2019.

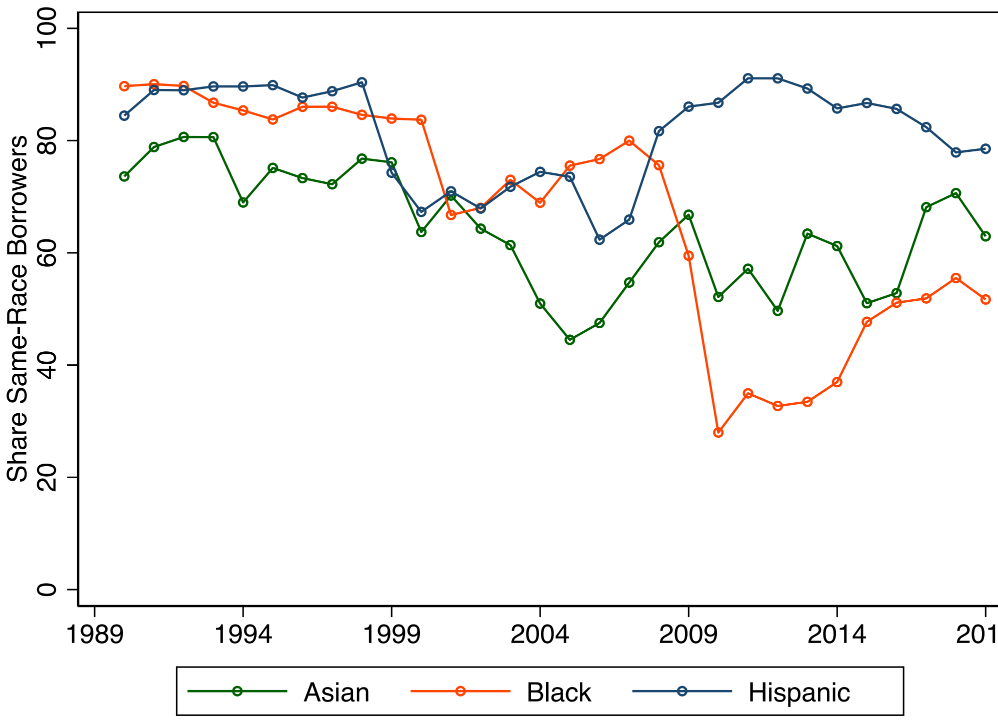
Figure 1.9: Hispanic Mortgage Applicants' Income and Loan Amount by Bank



This figure shows income and loan amount distributions for Hispanic mortgage applicants with Hispanic and non-Hispanic banks. The unit of the vertical axis unit is density. The data span 2018-2019.

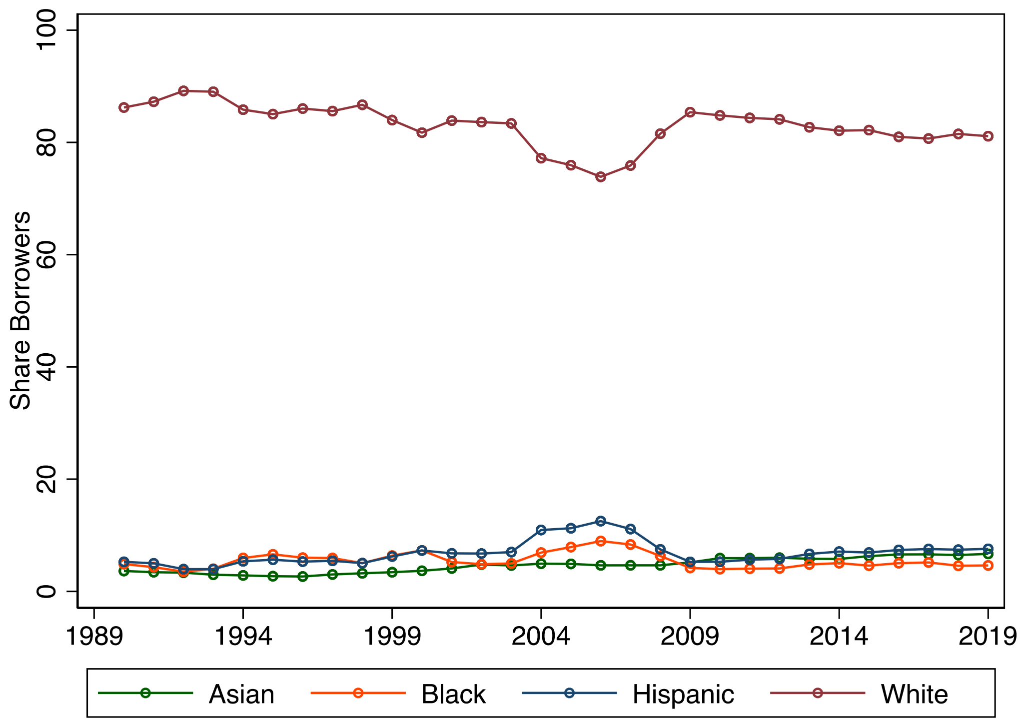
2. Appendix for "III. Minority-Owned Banks' Business Model"

Figure 2.1: Mortgage Borrowers in Minority-Owned Banks



This figure shows the time series evolution of the share of same-race mortgage loans in Asian, Black, and Hispanic-owned banks. The unit of the vertical axis unit is percent. The data span 1990-2019.

Figure 2.2: Mortgage Borrowers in Peer Banks



This figure shows the time series evolution of the share of mortgages granted to Asian, Black, Hispanic, and White borrowers in peer banks. The unit of the vertical axis unit is percent. The data span 1990-2019.

3. Appendix for "IV. Does Minority Bank Ownership Matter?"

Table 3.1: The Effect of Minority Bank Ownership on Minority Credit

	(1)	(2)	(3)	(4)
Minority-Owned Bank	9.79***			
	(2.51)			
Asian-Owned Bank		9.90***		
		(2.67)		
Black-Owned Bank			13.05***	
			(1.64)	
Hispanic-Owned Bank				8.83***
				(3.21)
Sample Borrowers	Minority	Asian	Black	Hispanic
Approval Mean	59.86	70.13	53.38	60.42
Observations	86,966,438	17,820,053	31,473,338	37,628,699
R-squared	0.38	0.36	0.39	0.38

Notes: This table estimates regressions of the form:

$$Approval_{ijkt} = \alpha_k + \alpha_t + \beta MinorityOwnedBank_{jkt} + \gamma X_{ijkt} + \xi_{ijkt},$$

for borrower i, bank j, property's census tract k, and year t. Because census tracts can experience boundary changes every decennial census due to population growth, each census tracts k is constructed as the concatenation of its tract number and boundary period: 1990-1991, 1992-2002, 2003-2011, or 2012-2019. $Approval_{ijkt}$ and $MinorityOwnedBank_{jkt}$ are approval and minority bank dummies. X_{ijkt} contains borrower demographics (income-percentile fixed effects; gender and co-borrower dummies), loan characteristics (loan amount-percentile fixed effects; purpose, type, and occupancy dummies), and bank size percentile fixed effects. Column 1 pools Asian, Black, and Hispanic borrowers in the category "Minority Borrowers," thus $MinorityOwnedBank_{jkt}$ is a dummy equal to one for same-race minority banks and zero otherwise. Columns 2, 3, and 4 report results for Asian, Black, and Hispanic mortgage borrowers, respectively. Approval gap is the difference between White and minority approval mean. Approval mean and gap, and coefficients are in percentage point units. Standard errors clustered at the bank and census tract levels are in parenthesis. ***, **, and * indicate coefficient estimates statistically distinct from 0 at the 1 percent, 5 percent, and 10 percent levels, respectively. The data span 1990-2019.

Table 3.2: The Effect of Minority Bank Ownership on Minority Credit, Summary of Magnitudes

	(1)	(2)	(3)	(4)	(5)
Minority-Owned Bank	0.12	1.03	76.08	3.96	6.70
Asian-Owned Bank	0.08	2.27	58.36	3.04	3.40
Black-Owned Bank	0.23	1.26	124.54	6.49	21.18
Hispanic-Owned Bank	0.11	1.13	77.73	4.05	7.26
Benchmark	App. Mean	App. Gap	Credit Score	Bankruptcy	Loan Officer

Notes: This table summarizes economics magnitudes of the minority bank-ownership effect reported in Table II. Columns 1-2 show effects as a percentage of the mortgage approval mean and gap. They are constructed by scaling coefficients in the even-numbered columns in Table II by the mortgage approval mean and the gap between White and minority approvals. Column 3 reports effects in credit score point units and it is constructed as the ratio of minority bank to credit score coefficients from Table 3.3, which estimates specification (1) with credit scores in levels. Column 4 compares ownership effects to the impact of bankruptcy flag removals from credit reports on credit scores. It is constructed by dividing column 3 by Gross et al. (2020)'s estimated impact. For details, see in Column 9 of Table 1 of their paper. Column 5 compares the effect of minority bank ownership to that of minority loan officers. It is constructed by dividing minority bank ownership coefficients by those of minority loan officers in the even-numbered columns in Table II.

Table 3.3: The Effect of Minority Ownership on Mortgage Approvals, Linear Credit Score Control

	(1)	(2)	(3)	(4)
Minority-Owned Bank	9.13***			
	(2.12)			
Minority Loan Officer	1.37***			
	(0.36)			
Asian-Owned Bank		6.42**		
		(2.51)		
Asian Loan Officer		1.88***		
		(0.40)		
Black-Owned Bank			16.19*	
			(8.34)	
Black Loan Officer			0.87**	
			(0.37)	
Hispanic-Owned Bank				8.55***
				(2.74)
Hispanic Loan Officer				1.26***
				(0.36)
Credit Score	0.12***	0.11***	0.13***	0.11***
	(0.01)	(0.01)	(0.01)	(0.01)
Sample Borrowers	Minority	Asian	Black	Hispanic
Approval Mean	76.19	82.23	71.92	77.49
Observations	3,850,840	1,000,013	1,103,769	1,726,861
R-squared	0.56	0.53	0.60	0.58

Notes: This table estimates regressions of the form:

$$Approval_{ijkt} = \alpha_k + \alpha_t + \beta MinorityOwnedBank_{jkt} + \gamma X_{ijkt} + \xi_{ijkt},$$

where $Approval_{ijkt}$ and $MinorityOwnedBank_{jkt}$ are approval and minority bank dummies. X_{ijkt} contains borrower demographics (income-percentile fixed effects; gender and co-borrower dummies), loan characteristics (loan amount-percentile fixed effects; purpose, type, and occupancy dummies), bank size percentile fixed effects, loan officers' race dummies, and borrower credit risk (credit score in levels; loan-to-value and debt-to-income ratio percentile fixed effects). Column 1 pools Asian, Black, and Hispanic borrowers in the category "Minority Borrowers," thus $MinorityOwnedBank_{jkt}$ is a dummy equal to one for same-race minority banks and zero otherwise. Columns 2, 3, and 4 report results for Asian, Black, and Hispanic mortgage borrowers. Approval mean and coefficients are in percentage point units. Standard errors clustered at the bank and census tract levels are in parenthesis. ***, **, and * indicate coefficient estimates statistically distinct from 0 at the 1 percent, 5 percent, and 10 percent levels, respectively. The data span 2018-2019.

Table 3.4: The Effect Loan Officers' Race predicted using BIFSG

	(1)	(2)	(3)	(4)
Minority Loan Officer	1.30***			
	(0.27)			
Asian Loan Officer		1.70***		
		(0.37)		
Black Loan Officer			0.70	
			(0.44)	
Hispanic Loan Officer				1.14***
				(0.25)
Sample Borrowers	Minority	Asian	Black	Hispanic
Approval Mean	76.19	82.23	71.92	77.49
Observations	3,780,227	987,909	1,079,117	1,692,857
R-squared	0.55	0.52	0.60	0.57

Notes: This table estimates regressions of the form:

$$Approval_{ijkt} = \alpha_k + \alpha_t + \beta MinorityLoanOfficer_{jkt} + \gamma MinorityOwnedBank_{jkt} + \gamma X_{ijkt} + \xi_{ijkt},$$

where $Approval_{ijkt}$,$MinorityLoanOfficer_{jkt}$, and $MinorityOwnedBank_{jkt}$ are approval, minority loan officer, and minority bank dummies. X_{ijkt} includes borrower demographics (income-percentile fixed effects; gender and co-borrower dummies) and credit risk (credit score, loan-to-value and debt-to-income ratio percentile fixed effects), loan characteristics (loan amount-percentile fixed effects; purpose, type, and occupancy dummies), bank size percentile fixed effects, and loan officers' race dummies. Race is predicted using Bayesian Improved First Surname Geocoding (BIFSG) developed by Voicu (2018). Columns 1 pool Asian, Black, and Hispanic borrowers in the category "Minority Borrowers." Columns 2, 3, and 4 report results for Asian, Black, and Hispanic mortgage borrowers. Approval mean and coefficients are in percentage point units. Standard errors clustered at the bank and census tract levels are in parenthesis. ***, **, and * indicate coefficient estimates statistically distinct from 0 at the 1 percent, 5 percent, and 10 percent levels, respectively.

4. Appendix for Oster Statistic

Using the proof of proposition 1 in Oster (2019), pp. 192 and 193, we can show that:

$$\beta^* \approx \widetilde{\beta} - \delta[\mathring{\beta} - \widetilde{\beta}] \times \frac{R_{max} - \widetilde{R}}{\widetilde{R} - \mathring{R}}, \tag{11}$$

where β^* is the true minority bank-ownership effect; $\mathring{\beta}, \widetilde{\beta}$ are ownership effects estimated from the baseline and augmented specifications (1), respectively; $\mathring{R}, \widetilde{R}$ are R-squared values from the baseline and augmented specifications, respectively; R_{max} is the R-squared from a hypothetical regression of mortgage approval dummy on a minority-owned bank dummy and all observed and unobserved controls; δ is the degree of selection on unobservables relative to observables.

Using $\beta^* = 0$ in (11), and solving for δ:

$$\delta \approx \frac{\widetilde{\beta}}{\mathring{\beta} - \widetilde{\beta}} \times \frac{\widetilde{R} - \mathring{R}}{R_{max} - \widetilde{R}}, \tag{12}$$

which is the degree of selection on unobservables relative to observables that would explain away the minority bank-ownership effect. We call this value the "Oster Statistic." For each specification, we compute it using $R_{max} = \Pi\widetilde{R}$, where Π is calculated by Oster (2019) so that at least 90% of the results from a large sample of experimental articles published in top journals would survive. This value is $\Pi = 1.3$.

5. Appendix for Ideal Experiment with Off-Balance Sheet Lending

Bank j's loan-level profit function is given by:

$$\Pi_j(r_i, W_i, X_i) = \begin{cases} PV[I_j(r_i, W_i, X_i) - C_j(r_i, W_i, X_i)] & p = \theta \\ \phi PV[I_j(r_i, W_i, X_i) - C_j(r_i, W_i, X_i)] + (1-\phi)G_j(r_i, W_i, X_i) & p = 1 - \theta \end{cases},$$

- $PV(\bullet)$: Present value operator.
- $I_j(r_i, W_i, X_i)$: Interest income of bank j from loan to borrower i with characteristics (r_i, X_i).
- $C_j(r_i, W_i, X_i)$: Cost of loan to borrower i, including default and fixed-costs.
- $G_j(r_i, W_i, X_i)$: Income from selling loan (known as gain-on-sale).
- $\phi > 0$: Probability of put-back.[34]
- θ: Probability of successfully selling loan.

We can perfectly identify marginal borrowers that are identical in every dimension (W_i^*, X_i^*), except their race which was randomly given to them. In this ideal experiment, the minority bank-ownership effect would be consistent with reduced information asymmetry if:

$$\begin{aligned} \Pi_j(r_s^*, W_s^*, X_s^*) &> \Pi_j(r_o^*, W_o^*, X_o^*), \\ \phi PV(r_s^*, W_s^*, X_s^*) + (1-\phi)G_j(r_s^*, W_s^*, X_s^*) &> \phi PV(r_o^*, W_o^*, X_o^*) + (1-\phi)G_j(r_o^*, W_o^*, X_o^*), \\ C_j(r_s^*, W_s^*, X_s^*) &< C_j(r_o^*, W_o^*, X_o^*), \end{aligned}$$

only if $G_j(r_s^*, W_s^*, X_s^*) \approx G_j(r_o^*, W_o^*, X_o^*)$. More work is needed to validate this assumption. Gerardi et al. (2020) document differences in prepayment rates across racial groups that can lead to differences in gain-on-sale. However, it is unclear if these differences exist for marginal borrowers.

[34] ϕ was 1-2 percent during the Great Recession and less than 1 percent post-Great Recession.

6. Appendix for Minimum Sample Size for Default Tests

Our goal is to derive the minimum sample size required to detect an effect in specification (6). We assume a significance level α of 0.05, implying $t_{\frac{\alpha}{2}} \approx 1.96$, and a statistical power β of 0.80, which implies $t_{\beta} \approx 0.84$. As for the minimum detectable effect (MDE), in order to detect a change of one standard deviation in the outcome variable, $\sigma_{Default}$, we would need at least:

$$N_{min} = 2\left(t_{\frac{\alpha}{2}} + t_{\beta}\right)^2 \times \left(\frac{\sigma_{Default}}{\sigma_{Default}}\right)^2 \approx 16$$

observations per treatment.[35] The MDE assumption is conservative.

However, we require a larger sample size to account for multiple hypotheses testing (MHT). Of the three main cases of MHT (multiple outcomes, multiple treatments, and multiple subgroups), we are specifically concerned with multiple treatments. We adjust our power calculations as failure to account and correct for MHT may increase the likelihood of false positives, as discussed in Czibor et al. (2019). To deal with this issue, we use the Bonferroni single-step procedure consisting of computing an individual p-value for each hypothesis tested, and rejecting the hypothesis only of its p-value does not exceed α/S, where S is the number of comparisons performed.

The rich set of fixed effects and controls in specification (6) implies $S = 28$. Hence, our adjusted significance level is $\alpha/28 \approx 0.0018$, implying $t_{\frac{\alpha}{2}} \approx 3.13$. As for the MDE, to detect a change of one standard deviation in defaults, we therefore would need at least:

$$N_{min} = 2\left(3.13 + 0.84\right)^2 \times 1^2 \approx 32$$

observations per comparison. The minimum sample size is then:

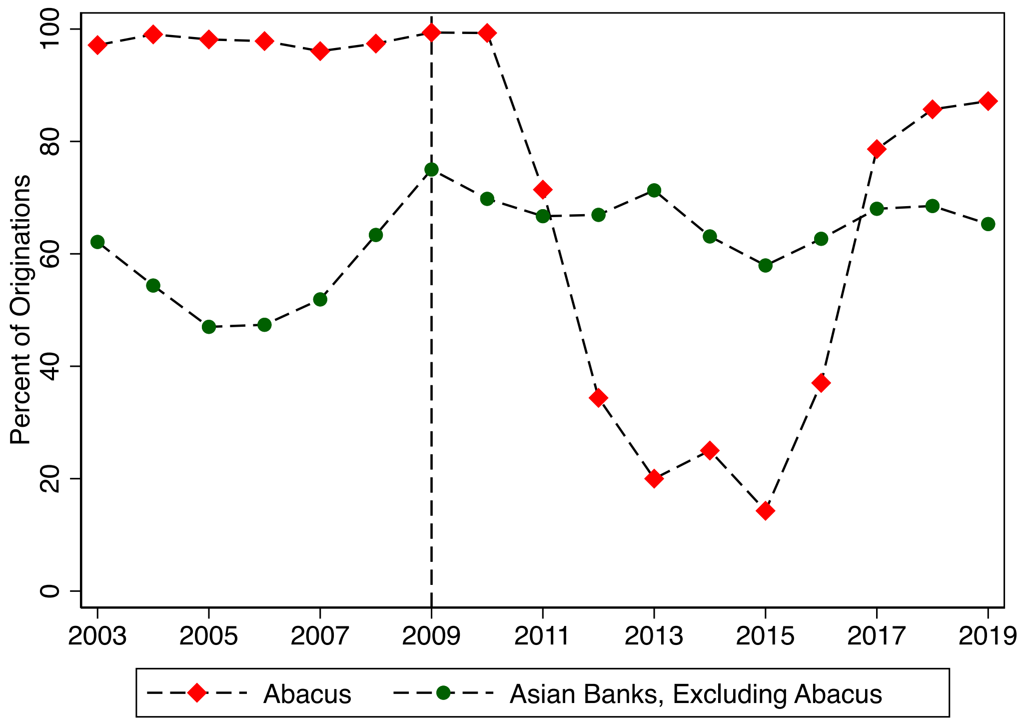
$$N_{sample} = S \times N_{min} \approx 886$$

borrowers.

[35] List et al. (2011) provides the derivation for this optimal size formula.

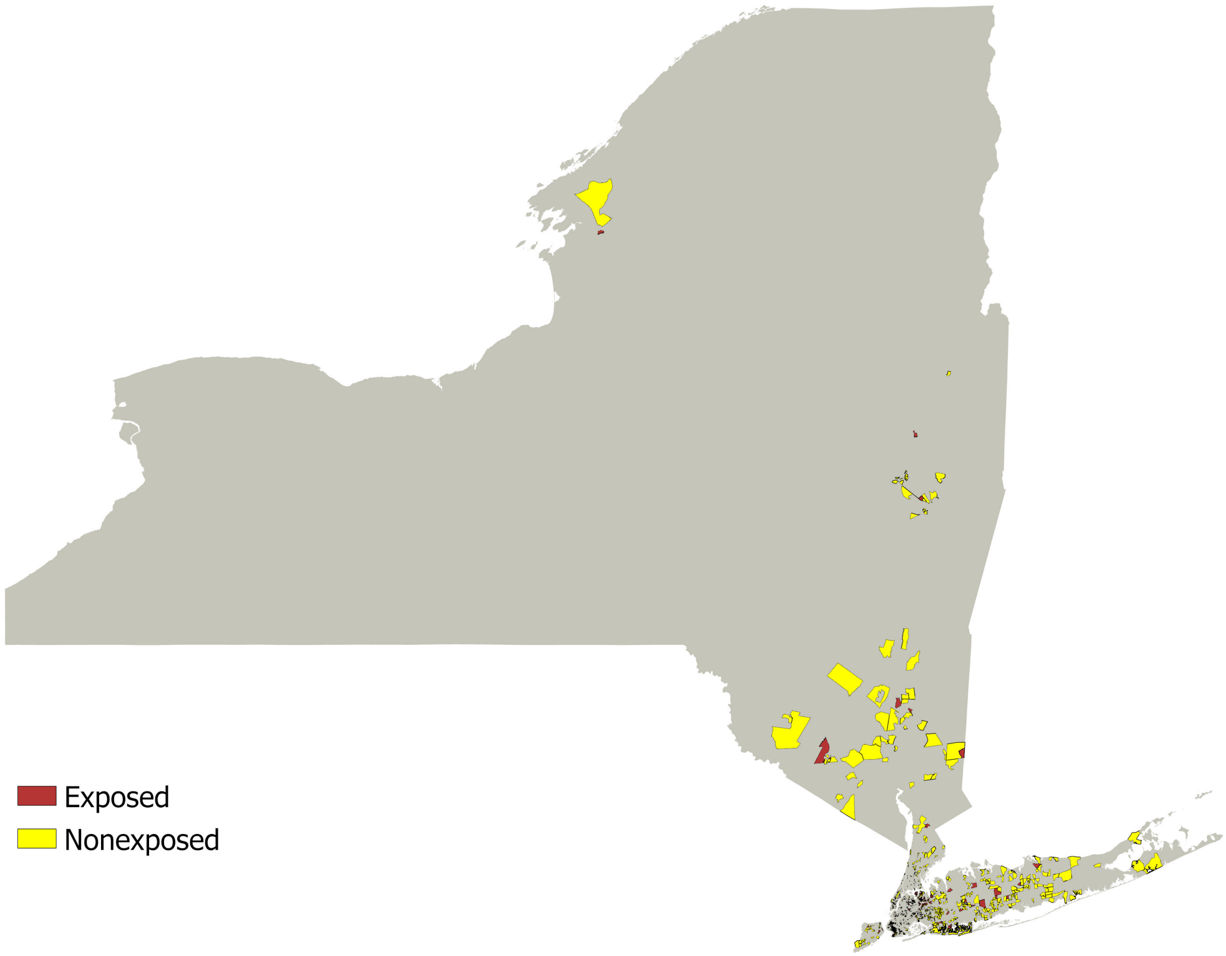
7. Appendix for Abacus Bank Collapse

Figure 7.1: Asian Mortgage Shares in Abacus and other Asian Banks



Notes: This figure shows the time series evolution of Asian mortgages shares in Abacus Federal Savings Bank and other Asian-owned banks. Asian mortgage shares are computed as the number of mortgages originated to Asian borrowers relative to all borrowers each year. The unit of the vertical axis is percent of all mortgages as of each year. Refinancing and home improvement loans are excluded to minimize seasonality. Data are constructed from public and commercial sources. Due to legal and time coverage restrictictions, we are unable to employ Federal Reserve's confidential data on borrowers and loan officers.

Figure 7.2: Asian Borrowers' Exposure to Abacus Federal Savings Bank in New York State, 2008

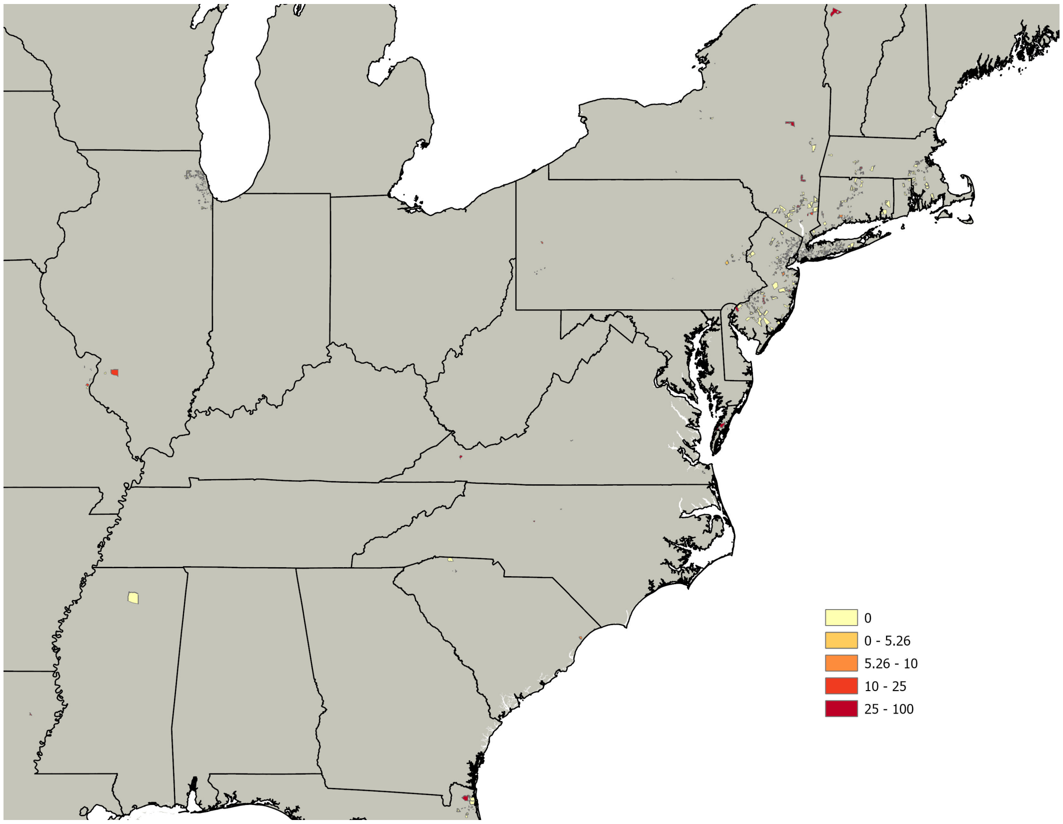


Notes: This figure shows the distribution of Asian borrowers' reliance on Abacus Bank across census tracts in New York state in 2008, one year before its collapse. "Exposed" tracts are those with $AbacusExposure_{k,2008} > 0$. Tracts with other non-Abacus, non-failing Asian banks are labeled as "Nonexposed." They have $AbacusExposure_{k,2008} = 0$, thus forming the pure control group in the research design described in section V.C. The Abacus exposure measure is constructed as:

$$AbacusExposure_{k,2008} = \frac{AbacusAsianMortgages_{k,2008}}{AsianMortgages_{k,2008}},$$

where $AbacusAsianMortgages_{k,2008}$ and $AsianMortgages_{k,2008}$ are the number of Asian mortgages originated by Abacus and all banks in census tract k in 2008, respectively.

Figure 7.3: Asian Borrowers' Exposure to Abacus Federal Savings Bank, 2008

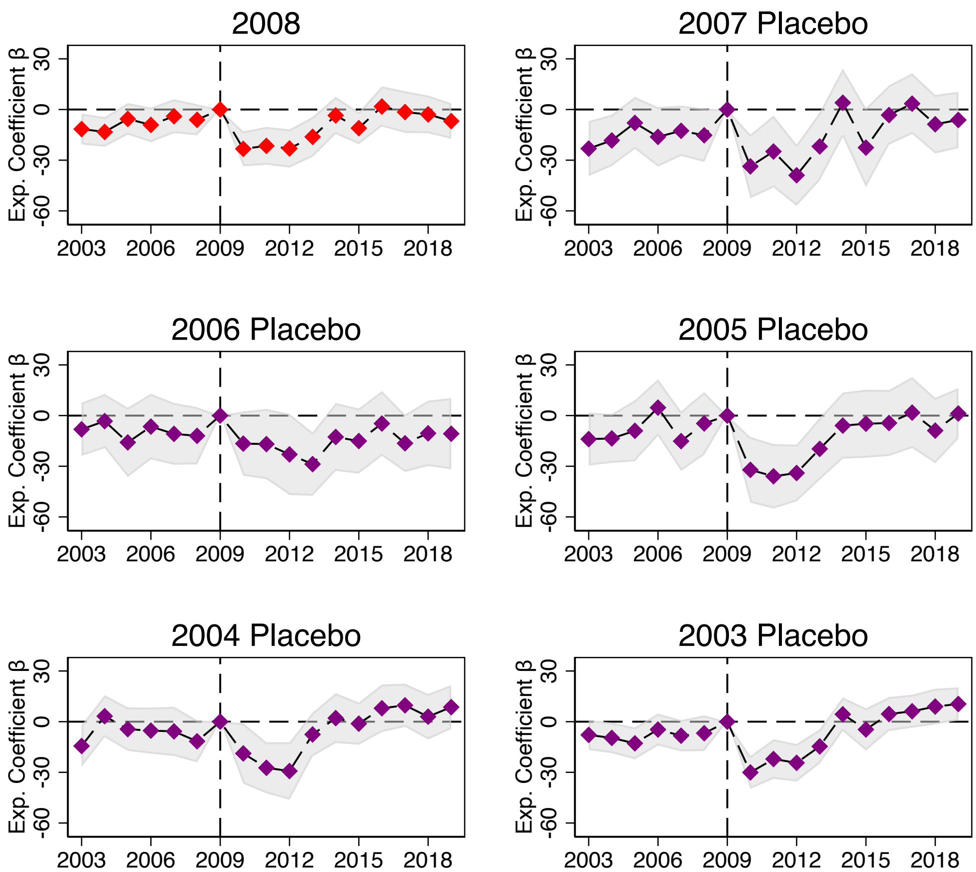


Notes: This figure shows the distribution of Asian borrowers' reliance on Abacus Bank across census tracts in its major markets in 2008, one year before its collapse. Tracts with other non-Abacus, non-failing Asian banks have $AbacusExposure_{k,2008} = 0$, thus forming the pure control group in the research design described in section V.C. The Abacus exposure measure is constructed as:

$$AbacusExposure_{k,2008} = \frac{AbacusAsianMortgages_{k,2008}}{AsianMortgages_{k,2008}},$$

where $AbacusAsianMortgages_{k,2008}$ and $AsianMortgages_{k,2008}$ are the number of Asian mortgages originated by Abacus and all banks in census tract k in 2008, respectively.

Figure 7.4: The Effect of Abacus Bank's Collapse on Credit, Exposure Year Placebos



Notes: This figure plots estimated coefficients and confidence intervals for β_y from the regression:

$$Approval_{ikt} = \alpha_k + \alpha_t + \sum_{y \neq 2009} \mathbb{1}_{t=y} \beta_y AbacusExposure_{k,z} + \gamma X_{ikt} + \xi_{ikt},$$

for borrower i, property's census tract k, and year t. This regression is estimated on a sample of Asian borrowers. $Approval_{ijkt}$ is a mortgage approval dummy and $AbacusExposure_{k,z}$ is computed as:

$$AbacusExposure_{k,z} = \frac{AbacusAsianMortgages_{k,z}}{AsianMortgages_{k,z}},$$

where $AbacusAsianMortgages_{k,z}$ and $AsianMortgages_{k,z}$ are the number of Asian mortgages originated by Abacus and all banks in census tract k in year $z = \{2003, 2004, ..., 2008\}$, respectively. X_{ikt} includes borrower demographics (income-percentile fixed effects; gender and co-borrower dummies) and loan characteristics (loan amount-percentile fixed effects; purpose, type, and occupancy dummies). Standard errors are clustered at the census tract level. Data are constructed from public and commercial sources. Due to legal and time coverage restrictions, we are unable to employ Federal Reserve's confidential data on borrowers and loan officers.