THE EFFECT OF MINORITY BANK OWNERSHIP ON MINORITY CREDIT*

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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. Using these 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, exceeds that of minority loan officers, and is more pronounced among low-credit-score borrowers. 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 fraud-induced 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 results are consistent with an information mechanism at the organizational level, whereby minority bank ownership improves soft information transmission, potentially embedding this information into loan policy documents.

JEL classification: G21, J15.

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"Although shapeable by individuals, especially leaders, culture is more than an amalgam of current personalities in the firm; it is a property of the firm" (Hermalin, 2013)

This paper leverages a novel matched dataset spanning almost three decades to investigate the role minority banks play providing credit to minority borrowers. A better understanding of this role is crucial to the establishment of policies or organizational choices that other banks can make to reduce disparities in access to credit. A straightforward organizational choice is hiring minority loan officers, who may collect and act upon more precise information about minority borrowers (Frame et al., 2024). However, officers might be constrained by loan policies setting the terms on how and to whom a bank provides mortgages. In contrast, minority bank ownership and governance may reduce communication frictions, improving information and values' transmission and likely encoding them in loan policy documents. For example, Asian banks may consider red envelopes or hongbao (family gifts) as a source of income, and Hispanic banks might be willing to count the income of all household members in mortgage applications (Goodman et al., 2024).

We find that minority banks are small but are essential credit suppliers in some markets. We also find that minority banks specialize in balance sheet mortgage lending, that most of this lending is allocated to minority borrowers, and that minority banks have a larger impact on minority credit access than loan officer race. Finally, we find that the net mortgage charge-off rate of minority banks is not higher than that of otherwise similar nonminority banks, that the default rate by minority borrowers going to minority banks is not higher than that of otherwise identical minority borrowers going to nonminority banks, and that the default rate by minority borrowers is lower than that for otherwise identical nonminority borrowers at minority banks. The takeaways of these findings are that minority banks expand minority credit without compromising mortgage performance.

This study is a pioneering effort in several aspects. It is one of the first papers to examine the racial composition of minority banks' lending. It is the first to demonstrate that the impact of minority banks is significantly larger than that of minority loan officers and likely reflects an expansion rather than a reallocation of minority credit. Furthermore, it is the first to establish that this expansion of minority credit does not compromise credit performance.

To study minority banks, we assemble the first comprehensive matched data on minority bank ownership and governance, employees, and mortgage borrowers. Our novel data addresses several challenges that have constrained other work. 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 banks from data collected through Freedom of Information Act (FOIA) requests and public sources, using a consistent minority bank definition and collecting unique bank identification numbers. Second, constructing mortgage specialization and performance data from bank balance sheets and income statements over nearly 30 years is challenging due to inconsistencies and definition changes across time and bank types. We address these challenges by developing consistent categorization methods and submitting FOIA requests to obtain original call reports, clarifications, and supplemental data. Third, 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. Fourth, publicly available data on mortgage borrowers lack information on their credit risk, the identity of their loan officers, and defaults. We access three confidential datasets that contain this information and 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, observational designs, and generalized difference-in-differences designs.

In our initial exploration of the data, we shed light on the importance and business model of minority banks. We find that minority banks are a small but growing segment of the banking industry. From 1994 to 2019, the average minority bank holds $252 million in assets—less than a third of the average nonminority bank. By 2019, minority banks grow to over $400 billion in total assets and account for nearly 7% of all banks. Despite their relatively small size, minority banks serve as critical credit suppliers in certain markets, originating a substantial share of mortgages across many census tracts, including those in Los Angeles and Kings (Brooklyn) counties.

Next, we explore what kinds of activities minority banks engage in. They specialize in balance sheet mortgage lending, with close to 50 percent of their assets allocated to real estate loans—50% more than nonminority banks. Minority banks keep 64 percent of their residential mortgages on balance sheet, despite only five percent being balance sheet-intensive (jumbo) loans. By contrast, nonminority banks keep only 43 percent their mortgages on balance sheet, even though they originate a larger share of jumbo loans.

Finally, we examine data on minority banks' employees and borrowers. Over 50 percent of employees in minority banks share the bank owners' race and more than 48 percent natively speak languages other than English. By stark contrast, less than 10 percent of nonminority banks' employees belong to a racial minority group or natively speak languages other than English. We observe similar patterns among mortgage borrowers. Close to 70 percent of minority banks' borrowers are of the same race as the bank owners, whereas less than eight percent of nonminority banks' borrowers belong to any minority group.

The first part of the paper empirically studies whether minority ownership matters for minority credit access. We use an observational 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.

Importantly, we 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 1 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. In addition, we find that the effect of minority bank ownership on minority credit is more pronounced among low-credit-score borrowers and particularly marked among Asian and Hispanic borrowers with credit scores below 700 points.

[Figure 1 here]

Next, we follow a generalized difference-in-differences approach that improves on our fixed-effects design in two dimensions. First, it 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—specifically, the stark difference between the effects of the Abacus near-collapse and the Colonial failure on Asian approvals—are 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 second and last part of the paper studies whether the effect of minority bank ownership compromises credit performance at the bank and borrower level. At the bank level, we compare net charge-off rates of minority and nonminority banks with the same business model, loan loss reserves, and capitalization. We find no statistically significant differences in net charge-off rates between minority and nonminority banks. To better understand this result, we decompose net charge-offs into their two components: gross charge-offs (loans removed from the balance sheet due to severe default) and recoveries (amounts recouped from previously charged-off loans). While gross charge-off rates do not differ meaningfully between minority and nonminority banks, we find that minority banks—particularly Asian and Hispanic banks—exhibit significantly lower mortgage recovery rates.

[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.

Specifically, Hispanic banks recover 0.03 percentage points less than otherwise similar nonminority banks, a difference that is both statistically significant at the 1 percent level and economically meaningful, representing a 60 percent reduction relative to the sample mean. This suggests that minority banks, despite having comparable net charge off rates, recoup less from nonperforming loans.

At the borrower level, we compare 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 importantly, this finding is consistent with improved soft information transmission rather than same-race owners' preferences driving the observed effect on minority credit access.

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 has had to rely on ad hoc assumptions in the past. 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 rationalize their results by assuming that these banks serve mostly minority borrowers.[3] 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) or study only one bank (Stein and Yannelis, 2020).[4] This paper's core contribution is to assemble new microeconomic 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 rate spreads, even when comparing minority and White borrowers that have the same demographic and risk characteristics, mortgages with the same characteristics, and the same bank, loan officer, and underwriting method (Hurtado and Sakong,

[3]See Elyasiani and Mehdian (1992). 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).

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

2024). This literature has identified several plausible sources of racial disparities in this market, including information noise (Blattner and Nelson, 2021), discrimination,[5] 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), loan officers (Fisman et al., 2017; Frame et al., 2024), and venture capitalists (Gompers et al., 2016).[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 and organizations in credit markets. Our study is consistent with minority bank ownership lowering information frictions and improving credit allocations. We 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), embedded in Asian banks' organizational culture and design (Liberti et al., 2016; Skrastins and Vig, 2019). 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

[5] See Bartlett et al. (2022); Bhutta and Hizmo (2021); Giacoletti et al. (2023); Zhang and Willen (2021).

[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. Two exceptions to the trend of finding positive effects in finance settings are Ambrose et al. (2022) and Gompers et al. (2016), who show no or negative effects.

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).

I. Institutional Setting and Data

This paper constructs the most complete data yet applied to study minority banks. 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 A.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: multiracial and Native American banks; minority-board and minority-market banks. Second, we collect banks' unique identification numbers. Finally, we match the resulting datasets. Appendix A.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 A.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 A.1.2.1 lists the languages in each category.

The employee race data contain race predictions constructed using Face Attribute Recognition (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. (2024), which use BIFSG. Appendices A.1.2.1 and A.1.2.2 present an overview and prediction accuracy measures for FAR and BIFSG, respectively. Appendix A.1.2.1 also reports additional details on data sources and construction.

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

[9] Recent papers using these methods include Cook et al. (2022), Frame et al. (2024), and Blattner and Nelson (2021).

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.

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).

[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.

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 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 A.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 E. Appendix A.1.3 presents an overview of the sources and data construction.

E. Minority Banks' Business Model

We begin with a brief exploration of the data that sheds light on minority 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). We use data for minority and nonminority banks from 1994 to 2019. For all the exploratory analyses below, except Figure 2, we use the subset of minority banks in HMDA.

Minority banks are small but a growing part of the banking industry. Panel A of Figure 2 shows that, on average, minority banks hold \$252 million in assets, whereas nonminority banks are more than three times larger. Panel B indicates that minority banks account for nearly 5% of all banks but hold just over 1% of total banking assets. Appendix Figure A.2.1 illustrates the increasing importance of minority banks over time. By 2019, minority banks had grown to over \$400 billion in assets, on average, and comprised close to 7% of all banks. Despite their modest but growing size and importance, minority banks are essential credit suppliers in some markets. For example, as illustrated in Figure 3, they account for a substantial share of mortgage originations across many census tracts in Los Angeles and Kings counties.

[Figures 2 and 3 here]

Minority banks specialize in mortgage lending. Panel A of Figure 4 shows that the weighted average mortgage share in minority banks is 47.16%. By contrast, the average mortgage share is only 32.17% in nonminority banks. In other words, minority banks' average mortgage share is almost 50% higher than that of nonminority banks.

Balance sheet retention partly explains the substantial difference in mortgage shares between minority and nonminority banks. Panel B of Figure 4 reports the weighted average share of mortgages retained on balance sheet. Minority banks retain 64.28% of their mortgages on balance sheet, compared to 43.10% for nonminority banks.[11] Appendix Figure A.2.3 confirms that this difference is not due to minority banks originating a larger share of jumbo mortgages, which are harder to securitize (Buchak et al., 2024). Quite the opposite, jumbo mortgages account for only 5.46% of loans at minority banks, compared to 6.90% at nonminority banks.

[Figure 4 here]

Minority banks employ a much higher share of same-race employees compared to nonminority banks. Panel A of Figure 5 shows that, on average, 52.97% of employees in minority banks share the bank owner's race. This share varies by group, reaching 51.42% in Asian banks, 39.13% in Black banks, and 54.41% in Hispanic banks. Panel B highlights the stark contrast in nonminority banks, where only 2.25% of employees are Asian, 0.78% are Black, and 8.29% are Hispanic.

Language representation follows a similar pattern. Panel C of Figure 5 shows that 48.38% of employees in Asian banks speak an Asian language, whereas this share is below 3% in other minority banks and nonminority banks. Similarly, Panel D reports that 53.39% of employees in Hispanic banks speak a Hispanic language, compared to less than 8% in other banks.

Minority banks also serve predominantly same-race borrowers. Panel E of Figure 5 indicates that 68.59% of mortgage borrowers at minority banks have the same race as the bank owners, with shares of 62.95% in Asian banks, 51.70% in Black banks, and 78.55% in Hispanic banks. By contrast, Panel F shows that nonminority banks serve a far lower share of same-race borrowers, with only 6.69% of borrowers being Asian, 4.62% Black, and 7.58% Hispanic.

[Figure 5 here]

These patterns indicate that, despite their relatively small size, minority banks are a growing segment of the banking industry and a critical source of credit in certain markets. Their business model is distinct, characterized by a high share of same-race mortgage balance sheet lending and a workforce that reflects their borrowers' racial and linguistic composition. Their greater reliance on balance sheet retention allows for more relationship driven lending, as off balance sheet mortgages are more transactional in nature (Boot and Thakor, 2000).[12]

F. Analyses Samples and Summary Statistics

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

[11] See Appendix Figure A.2.2 for mortgage and balance sheet share breakdowns by race and ethnicity.

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

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 I and II present details on the data and analysis.[13]

Panel B of Table II 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 I and III.C 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 II. Mean approval rates are similar in both datasets; 67 and 68 percent in the Abacus and Colonial samples, respectively. Section III.C presents further details on sample construction and the analyses.

[Table II here]

II. Does Minority Bank Ownership Matter?

A. Observational 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

[13] Appendix A.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.

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

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 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 nonminority 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.

Selection issues. The primary selection issue in this design arises from the nonrandom matching between mortgage borrowers and banks. We worry about two cases in which 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 issue 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. Observational Design: Findings

Main Findings. We estimate specification (1) for 1990-2019 to test whether minority bank ownership matters. Results are presented in Figure 6 and Appendix Table A.3.1.

The first bar of Figure 6 reports the effect of minority ownership when minority borrowers are pooled in a single category.[14] 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

[14] In this case, $MinorityOwnedBank_{jkt}$ in (1) is equal to one for same-race minority banks, and zero otherwise.

in other-race banks.

[Figure 6 here]

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 from 2018 to 2019. Results are presented in Figure 1 and Appendix Table A.3.2. The first bar of Figure 1 indicates that minority borrowers applying for mortgages at same-race minority-owned banks are 9.1 percentage points more likely to get approved than minority borrowers with the same credit risk and loan officers' race at other banks. The second, third, and fourth bars indicate that this effect is 6.3, 16.5, and 8.5 percentage points for Asian, Black, and Hispanic borrowers at same-race banks.

Appendix Table A.3.2 shows estimated effects do not meaningfully change after controlling for controlling for risk and loan officers' race, whereas R-squared values increase. This suggest that the degree of selection on unobservables relative to observables might be modest.[15] 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 (A.12) in Appendix A.5 details its calculation. We report δ statistics in the last row of Table A.3.2. Column 2 shows that the influence of unobservables would need to be 1.4 times that of observables for the minority-ownership effect to be zero; columns 4, 6, and 8 indicate that it would need to be 2.3, 5.1, and 1.3 times the influence of observables for the Asian, Black, and Hispanic ownership effects to be zero.[16]

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 in Appendix Table A.3.3.

First, we scale coefficients in the even-numbered columns in Table A.3.2 by the mortgage approval mean and the gap between White and minority approvals. Column 1 of Appendix Table A.3.3 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

[15] Odd-numbered columns in Table A.3.2 report baseline results similar to Appendix Table A.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.

[16] In Appendix A.3, we estimate (1) using interest rate spread as outcome. We measure spread as the difference between the mortgage's annual percentage rate and the average prime offer rate for a comparable transaction. For more details, see Appendix and Hurtado and Sakong (2024). We find that minority borrowers with mortgages from same-race minority-owned banks exhibit slightly higher spreads than minority borrowers with the same credit risk and loan officers' race at other banks, although this effect is statistically indistinguishable from zero.

minority bank to credit score coefficients.[17] Column 3 of Appendix Table A.3.3 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.[18] Column 4 of Appendix Table A.3.3 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. (2024) shows that minority borrowers having a minority loan officer are more likely get their mortgage applications approved than nonminority 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.[19] As detailed in section I and Appendix A.1.2.1, we address this concern by using loan officers' professional headshots from LinkedIn and a face-attribute recognition algorithm with accuracy rates of over 90 percent (Karkkainen and Joo, 2021). Even-numbered columns in Table A.3.2 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

Motivation. Our findings so far do not provide direct evidence that minority-owned banks expand credit for minority borrowers. In section E, we show that the default rate of minority banks' minority borrowers is lower than that of their nonminority borrowers. In addition, in section II.B, we show the effect of minority bank ownership is particularly marked among low-credit-score minority borrowers. These facts might be consistent with minority banks having superior information. However, if this superior information leads to minority banks being better at cream-skimming the best low-credit-score minority borrowers, other low-credit-score minority borrowers may find obtaining credit even more challenging. In a counterfactual without minority banks, the best low-credit-score minority borrowers would still obtain mortgage credit.

We can approach this counterfactual world using bank failures or near-failures, which can also provide a valuable setting to study information and relationship lending theories, because failures exacerbate market-wide information frictions (Bernanke, 1983). A bank's ability to lend is tied to the breadth and depth of the relationships with its borrowers. When a bank fails, lending relationships and the specialized information embodied in the organization and its loan officers are

[17]Table A.3.4 in Appendix A.3 reports the results for this specification. The credit-score coefficient is 0.12.

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

[19]Table A.3.5 shows that race predictions constructed using Frame et al. (2024)'s method induce attenuation in loan-officer coefficients in all specifications. Furthermore, the Black-loan-officer effect is not statistically significant.

destroyed. Ex-ante information frictions increase intermediation costs and hamper the formation of new lending relationships. If the minority-ownership effect is driven by superior information and relationships, the impact of a minority bank failure on minority 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 nonminority bank failure might have a more limited and short-lived effect on minority mortgage borrowers, given the transactional nature of the mortgage market.

Ideal Experiment. We use the Asian category to illustrate the 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 an approval dummy. In the case of an Asian bank failure, $\beta < 0$ would be consistent with the bank expanding credit thanks to information and relationships. By contrast, $\beta \geq 0$ 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 might be driven by local economic conditions. Changes in credit access and exposure to bank failures may be jointly determined by an omitted variable such as household income shocks. Shocked households can weaken their banks' balance sheets through non-performing loans or deposit withdrawals, and cause failures.

We use a bank failure and a near-failure induced by unexpected fraud cases to address this challenge. In the latter case, the owners of Abacus Federal Savings Bank, a Chinese bank in New York, discovered that an employee 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.[20]

Abacus unexpectedly collapsed in 2010. Figure 7 shows that the investigations and the legal case disrupted Abacus's mortgage lending, its main line of business.[21] From 2003 to 2009, Abacus closely followed other Asian banks' lending patterns. Abacus's originations declined by 50 percent

[20]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.

[21]Figure 7 and Appendix Figure A.4.1 use data constructed from public and commercial sources. Due to legal and time coverage restrictions, we are unable to employ Federal Reserve's confidential mortgage data.

in 2010, completely dried up in 2011, and barely recovered after the bank's owners were acquitted.[22]

[Figure 7 here]

The other case is one of the largest bank fraud schemes in US history and caused the failure of Colonial Bank, a nonminority bank headquartered in Alabama.[23] The fraud 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.

Empirical Setup. We attempt to replicate the ideal experiment using a generalized difference-in-differences design around the collapse of Abacus and Colonial. In the Abacus setting, 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 8 shows the geographical distribution of this exposure measure in New York City—Abacus's primary market—and indicates that census tracts in NYC Chinatown were the most exposed to the Abacus Collapse.[24]

[Figure 8 here]

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 demographic and loan characteristics described in section II.A. 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

[22] Figure A.4.1 shows that Abacus's mortgage lending after the collapse concentrated on non-Asian borrowers.

[23] In 2011, Department of Justice Criminal Division's Attorney General stated "Lee Farkas...masterminded one of the largest bank fraud schemes in history." For details, see the Department of Justice's press release.

[24] Figures A.4.2 and A.4.3 show Abacus exposure across census tracts in New York state and the East Coast.

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 a similar generalized difference-in-differences design around Colonial Bank's failure, which compares Asian borrowers with the same demographics, applying for mortgages with the same characteristics, before and after the failure, whose only observable difference is their exposure to Colonial before its collapse. Estimates from this design provide a benchmark for the effect of the Abacus collapse on Asian credit.[25]

Validity. The validity of this design hinges on three assumptions. First, no anticipation. The nature of the fraud cases 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 customer bribes. Second, it is unlikely that Abacus's owners, employees, or customers could have anticipated the disproportionate legal response to the purported fraud case–the Manhattan DA office brought 184 charges against Abacus and its owners. Furthermore, Abacus and its owners were all acquitted. Third, Figure 7 shows a sharp and persistent decline in Abacus's lending to Asian borrowers after the Manhattan DA office launched its investigation. A similar argument supports the no-anticipation assumption in the Colonial design: The prompt closure of the bank by its regulators after discovering the scheme is consistent with no anticipation.

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 10 indicates smooth pretrends before the Abacus and Colonial failures and a sharp and persistent decline in Asian approvals only after the Abacus collapse.

Third, our difference-in-differences design features continuous treatment intensity, and Callaway et al. (2021) show that a critical assumption in these designs is homogeneity in gains from treatment. This assumption would be violated if census tracts' selection into treatment is related to potential outcomes. The risk of violating this assumption is limited because the Abacus and Colonial collapses were induced by unexpected fraud cases and caused a sudden and persistent decline in Asian approvals only in census tracts exposed to Abacus. We do not observe such a decline in census tracts unexposed to Abacus or those exposed to Colonial in markets served by other Asian banks. We will 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 A.4.4 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

[25]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.

in specification (3), and present the data in a binscatter plot. Figure A.4.4 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 9 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.

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 9 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).

[Figure 9 here]

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 9 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 A.4.5 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 10 features smooth pretrends around both bank collapses, but Asian mortgage approvals declined in exposed tracts only after the Abacus collapse. Consistent with Figure A.4.5, Panel B of Figure 10 depicts a slight but non-significant increase in Asian approvals in 2011 and 2012 in tracts fully exposed to Colonial.

[Figure 10 here]

While large relative to both benchmarks above, the estimated effect of the Abacus collapse on Asian credit likely underestimates the true effect because low-financial-trust Asian borrowers might have been discouraged from applying to other banks (Brown et al., 2019). To explore this possibility, we study the effect of the Abacus collapse on Asian mortgage applications per capita by estimating

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

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 A.4.6 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 9, mortgage approvals for other race groups should exhibit smooth pretrends and a sharp decline after Abacus collapsed. Figure 11 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.

[Figure 11 here]

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 Appendix Figure A.4.7. 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.

III. Why Does Minority Bank Ownership Matter?

A. Observational Design I: Setup

Motivation. Minority banks play a significant role in expanding credit access for minority borrowers. Their effect on minority mortgage credit is substantial, exceeding that of minority loan officers and reflecting an expansion rather than a reallocation of credit. This suggests that minority banks provide mortgages to borrowers who might otherwise be excluded from traditional mortgage markets. These borrowers may have different credit profiles than those typically served by nonminority banks.

This naturally raises the question of whether the expansion of minority credit compromises mortgage performance at the bank level. If minority banks systematically extend credit to borrowers with weaker credit profiles or higher unobservable risk, this could manifest in higher default rates or charge-offs, raising concerns about the long-term sustainability of their lending model. Alternatively, if minority banks have informational advantages in screening and monitoring these borrowers, they may mitigate these risks through more effective relationship lending. To assess this, we measure mortgage performance using net charge-off rates at the bank level.

We use net charge-off rates to measure mortgage performance at the bank level. When borrowers miss payments, loans progress through delinquency stages, leading to gross charge-offs (loans written off as losses) and recoveries (amounts recouped through collections or settlements). The net charge-off amount is the difference between gross charge-offs and recoveries, and the net charge-off rate is this amount divided by the total mortgage portfolio on balance sheet.

Figure 12 shows average mortgage net charge-off rates by bank type from 1994 to 2019. We find similar net charge-off trends for minority and nonminority banks, with no persistent differences except during the financial crisis. Both bank types experienced a sharp rise in charge-offs from 2008 to 2010, reflecting widespread mortgage distress. However, this comparison does not account for differences in bank business models and other characteristics, which we address next.

[Figure 12 here]

Empirical Setup. We examine minority banks' relative mortgage performance by comparing them to nonminority banks headquartered in the same state, in the same year, with the same business model and financials:

$$CO_{jt} = \alpha_{st} + \beta MinorityBank_{jt} + \gamma X_{jt} + \xi_{jt},$$

for bank j and year t. $MinorityBank_{jt}$ is a dummy variable equal to one if bank j is a minority bank and zero otherwise. X_{jt} includes bank-level controls, discussed below. All regressions include state-by-year fixed effects α_{st} to absorb time-varying regional factors that could influence mortgage charge-offs. We cluster standard errors at the lender and state levels to account for within-bank correlation across states.

X_{jt} includes business model and financial controls, consistent with previous research (Rajan, 1994). Business model controls include size, mortgage and balance sheet shares. The rationale for their inclusion is that mortgage specialization and sales affect screening incentives. For example, banks that sell a larger share of their loans may have weaker screening incentives, leading to lower observed charge-off rates if riskier loans are offloaded. (Keys et al., 2010; Purnanandam, 2011).

Financial controls include mortgage loss reserves and capital as a share of assets. Loan loss reserves are an indicator of prudence in risk management and risk taking in lending decisions, which impact default and charge off rates. Capitalization levels also drive risk taking, impacting default and charge off rates (Jiménez et al., 2014; Dell'Ariccia et al., 2014). We include all controls nonparametrically as percentile fixed effects.

The coefficient of interest β measures whether minority banks have systematically different mortgage net charge-off rates compared to otherwise identical nonminority banks.

B. Observational Design I: Findings

Main Findings. Results presented in Table III examine differences in mortgage net charge-off rates between minority and nonminority banks. Column 1 reports results for all minority banks pooled in a single category. It shows that the average minority bank has a net mortgage charge-off rate 0.02 percentage points higher than the average nonminority bank with the same business model and financials, but this difference is not statistically significant. Column 2 presents estimates separately for Asian, Black, and Hispanic banks, showing similar results.

As described above, net charge-off rates are equal to gross charge-off rates minus recovery rates, so we decompose the effects in columns 1 and 2 into these components in columns 3 through 6. Columns 3 and 4 show no statistically significant differences in gross charge-off rates between minority and nonminority banks. However, column 5 indicates that minority banks exhibit a mortgage recovery rate 0.01 percentage points lower than comparable nonminority banks, and this difference is statistically significant at the 10 percent level. Column 6 further shows that Asian and Hispanic banks drive this result, with recovery rates 0.02 and 0.03 percentage points lower than otherwise identical nonminority banks, with the Hispanic bank difference being statistically significant at the 1 percent level.

[Table III here]

Economic Magnitudes. To assess the magnitude of the recovery rate differences, we scale the coefficients in columns 5 and 6 of Table III by the average recovery rate. The 0.01 percentage point lower recovery rate for minority banks represents a 20 percent reduction relative to the sample mean. This effect is driven by Asian and Hispanic banks, which exhibit 0.02 and 0.03 percentage point lower recovery rates, translating to reductions of 40 percent and 60 percent of the average recovery rate, respectively. The Hispanic bank effect is the largest in magnitude and is statistically significant at the 1 percent level.

We focus on recovery rate magnitudes because they are the only statistically significant results. Differences in net and gross charge-off rates are not economically nor statistical meaningful. These findings suggest that minority banks, particularly Hispanic banks, recover significantly less from defaulted mortgages than comparable nonminority banks.

C. Observational Design II: Setup

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 II is consistent with reduced information asymmetry or preferences. In section E, 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 the same minority bank.

This ideal experiment abstracts away from off-balance sheet lending. Appendix A.6 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 nonminority 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 demographic and loan characteristics described in section II.A. 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.

D. Observational Design II: 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 I, 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 IV. 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 IV, 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]

[Table IV here]

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 A.7, 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 lack of statistical power due to 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 follow an approach similar to that of Alesina and La Ferrara (2014) and 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 IV 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 IV. 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

[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.

4, are valid for the average borrower. Addressing these limitations is work in progress.

IV. Conclusion

This paper assembles unique matched data to answer two first-order questions in banking, household finance, and organizational economics: *whether* 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' preferences, at least in the case of Asian banks. Our evidence is consistent with Asian bank ownership alleviating communication frictions and improving soft information transmission and encoding within banks' organizational structure. 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 critical 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, tend to be more informationally opaque and credit rationed than nonminority borrowers.

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

This table presents summary 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 minority borrowers applying for mortgages between 1990 and 2019 and between 2018 and 2019 for confidential variables. The data are derived from HMDA. $\mathbb{1}$(Minority Bank)* and $\mathbb{1}$(Minority Loan Officer)* indicate same-race minority bank and loan officer, respectively. 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. $\mathbb{1}$(Minority Borrower)* indicate same-race minority borrower.

	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 II. Summary Statistics: All Analyses Samples (continued)

This table presents summary statistics for all analyses in this paper. The unit of observation in all panels is a mortgage borrower. 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 I, II, and C provide data construction details.

	Mean	P10	P50	P90	Observations
Panel C. Abacus Collapse Sample					
Key Variables					
$\mathbb{1}$(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
$\mathbb{1}$(Female)	0.31				492,576
$\mathbb{1}$(Co-borrower)	0.41				492,576
Loan Variables					
Amount ($1K)	312.53	86	280	540	492,576
$\mathbb{1}$(Home Purchase)	0.51				492,576
$\mathbb{1}$(Conventional)	0.95				492,576
$\mathbb{1}$(Principal Residence)	0.90				492,576
Panel D. Colonial Failure Sample					
Key Variables					
$\mathbb{1}$(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
$\mathbb{1}$(Female)	0.34				888,964
$\mathbb{1}$(Co-borrower)	0.42				888,964
Loan Variables					
Amount ($1K)	294.93	80	250	528	888,964
$\mathbb{1}$(Home Purchase)	0.43				888,964
$\mathbb{1}$(Conventional)	0.95				888,964
$\mathbb{1}$(Principal Residence)	0.86				888,964

Table III. Charge-Off and Recovery Rates: Minority vs. Nonminority Banks

This table reports estimates of net charge-off rates, gross charge-off rates, and recovery rates for mortgage loans at minority and nonminority banks. Rates are in percentage points. Columns (1)-(2) present net charge-off rates, Columns (3)-(4) report gross charge-off rates, and Columns (5)-(6) display recovery rates. All variables are expressed as a percentage of total mortgage amounts at the bank level. All regressions include bank headquarter state×year fixed effects and controls, which account for differences in bank business models, including mortgage share (mortgage amounts over total loan amounts), on balance sheet mortgage share (on balance sheet mortgages over total mortgages), and size (total assets). Loan loss reserves as a share of total assets are also included as a control. Controls are applied nonparametrically using percentile fixed effects, which are computed separately for each year. Standard errors clustered at the bank and state levels are in parentheses. ***, **, and * indicate coefficient estimates statistically distinct from 0 at the 1%, 5%, and 10% levels, respectively. The data covers both minority and nonminority banks and is sourced from pur minority bank census, call reports and public HMDA. See Appendix A.1.4 for sample construction and Appendices A.5 and A.7 for computation details.

	Net Charge Offs		Gross Charge Offs		Recoveries	
	(1)	(2)	(3)	(4)	(5)	(6)
Minority Bank	0.02		0.00		–0.01*	
	(0.02)		(0.02)		(0.01)	
Asian Bank		0.02		–0.00		–0.02*
		(0.02)		(0.02)		(0.01)
Black Bank		0.03		0.04		0.02
		(0.04)		(0.04)		(0.02)
Hispanic Bank		0.00		–0.02		–0.03***
		(0.03)		(0.03)		(0.01)
Outcome Mean	0.16	0.16	0.22	0.22	0.05	0.05
Sample Banks	All	All	All	All	All	All
Observations	164,861	164,861	164,861	164,861	164,861	164,861
R-squared	0.14	0.14	0.17	0.17	0.14	0.14

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

This table reports mortgage default rate regressions for borrowers at minority-owned banks. Columns (1)-(2) pool borrowers at Asian and Hispanic banks. Columns (3)-(6) focus on Asian-owned banks, while Columns (7)-(8) present results for Hispanic-owned banks. Odd-numbered columns include borrower demographics and loan characteristics, while even-numbered columns add confidential controls, such as credit scores and loan-to-value ratios. Columns (5)-(6) restrict the sample to Asian borrowers near the margin of approval, identified through automated underwriting rejections later approved by the minority bank. Default rates are in percentage points, and standard errors clustered at the bank level are in parentheses. ***, **, and * indicate coefficient estimates statistically distinct from 0 at the 1 percent, 5 percent, and 10 percent levels, respectively. 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 issued between January 2018 and March 2019. See Appendix A.1.4 for sample construction and Appendices A.5 and A.7 for computation details.

	(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				

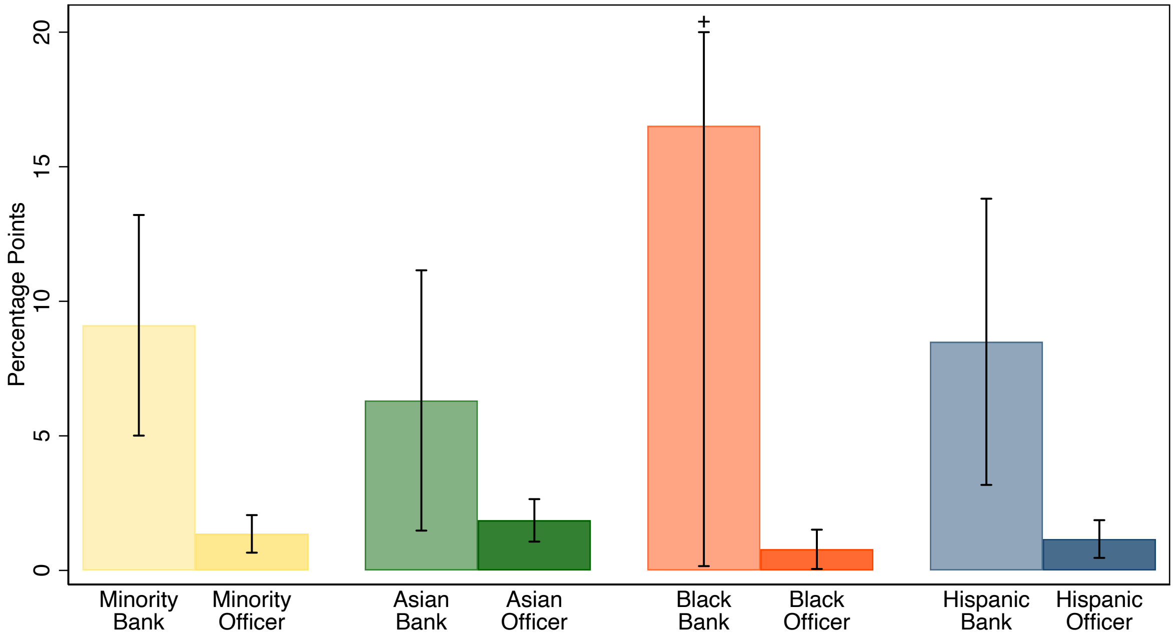

Figure 1. The Effect of Minority-Owned Banks and Loan Officers on Minority Credit. This figure plots $\hat{\beta}$s and their 95% confidence intervals from (1). See Appendix A.3.2 for details.

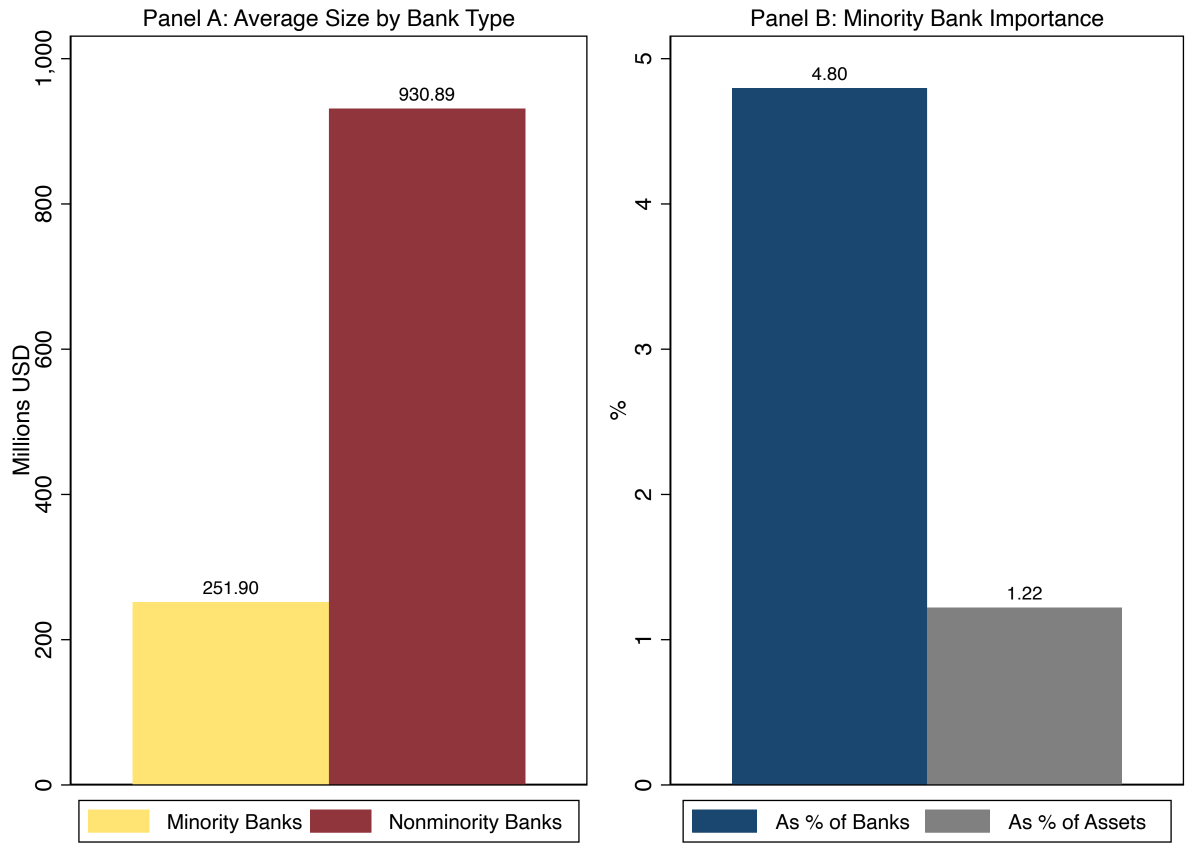

Figure 2. Minority Bank Size and Importance. This figure reports the average size of minority and nonminority banks (Panel A) and the relative importance of minority banks in the banking sector (Panel B). Minority banks include those classified as Asian, Black, or Hispanic, while nonminority banks serve as a comparison group. Vertical axes represent total assets (Panel A), expressed in millions of dollars in 2019 values, and minority banks' share of total banks and total assets (Panel B). Data are based on call reports from 1994-2019.

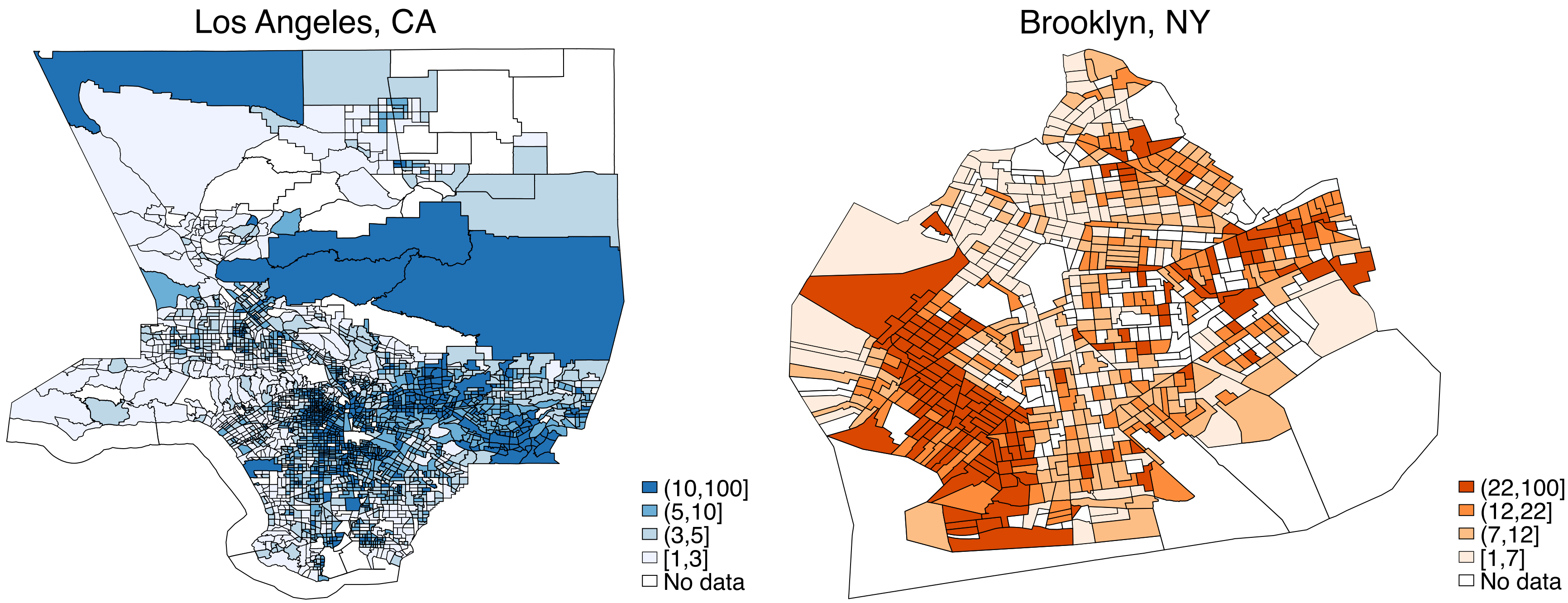

Figure 3. Minority Bank Mortgage Market Shares by Census Tract. This figure illustrates the distribution of minority bank mortgage market shares across census tracts in Los Angeles County, CA (left), and Kings County (Brooklyn), NY (right). Darker shades indicate census tracts where minority banks originate a larger share of total mortgages. Both maps use HMDA data from 2012-2019.

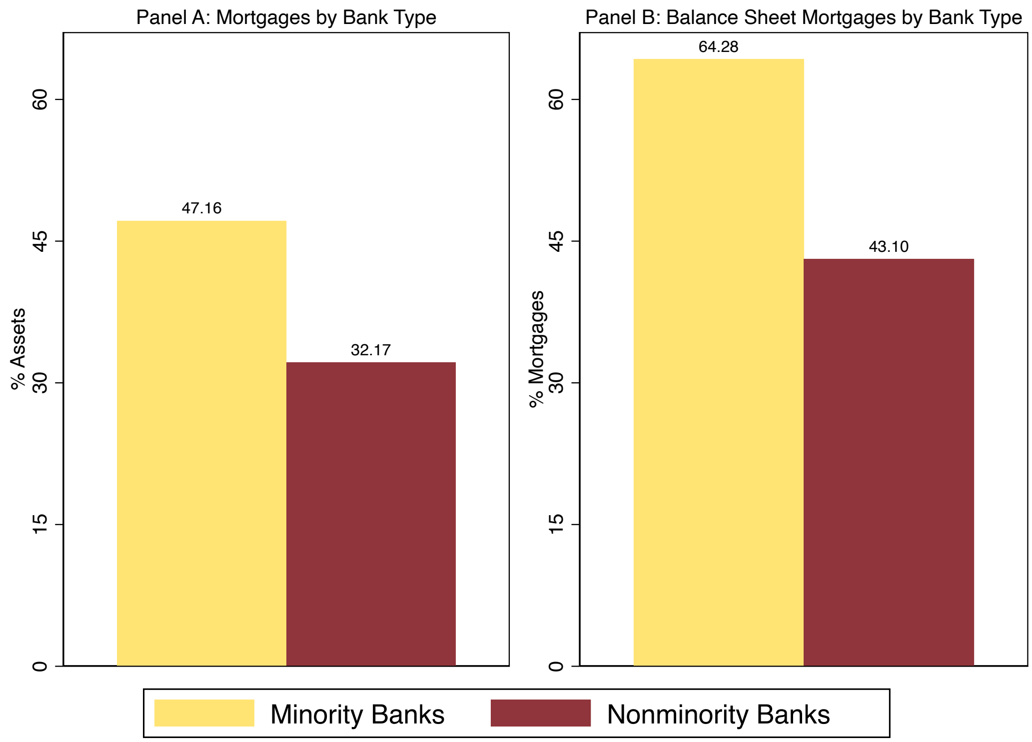

Figure 4. Asset and Mortgage Composition by Bank Type. This figure reports weighted average mortgage shares (Panel A) and balance sheet mortgage shares (Panel B) for different bank types. "Minority" banks include those classified as Asian, Black, or Hispanic, while nonminority banks serve as a comparison group. Vertical axes represent mortgages as a share of total assets (Panel A) and balance sheet mortgages as a share of total mortgages (Panel B). Panel A is based on call report data from 1994-2019, while Panel B uses HMDA data from 1994-2019.

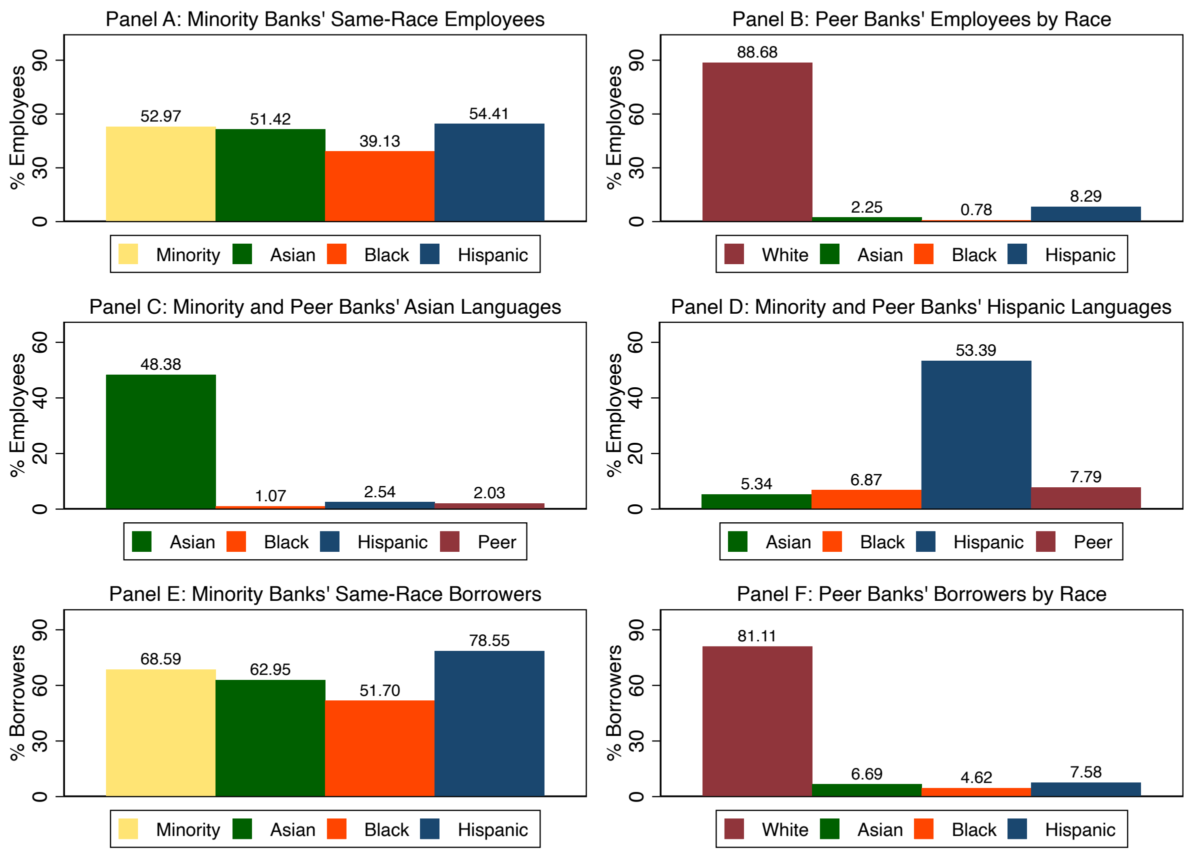

Figure 5. Employees, Languages, and Borrowers in Minority and Peer Banks. This figure reports weighted average same-race employee shares (Panels A and B), language shares (Panels C and D), and same-race borrower shares (Panels E and F) for different bank types. "Minority" banks include those classified as Asian, Black, or Hispanic, while nonminority banks serve as a comparison group. Employees and borrowers are considered same-race if they share the bank owner's race. Panels A and B show same-race employee shares for minority and nonminority banks, respectively. Panels C and D report Asian and Hispanic language shares, defined as the percentage of employees speaking specified Asian or Hispanic languages in addition to English. Panels E and F present same-race borrower shares for minority and nonminority banks. Vertical axes are in percent. Panels A-D use LinkedIn data as of December 2019, while Panels E-F use public HMDA data as of 2019.

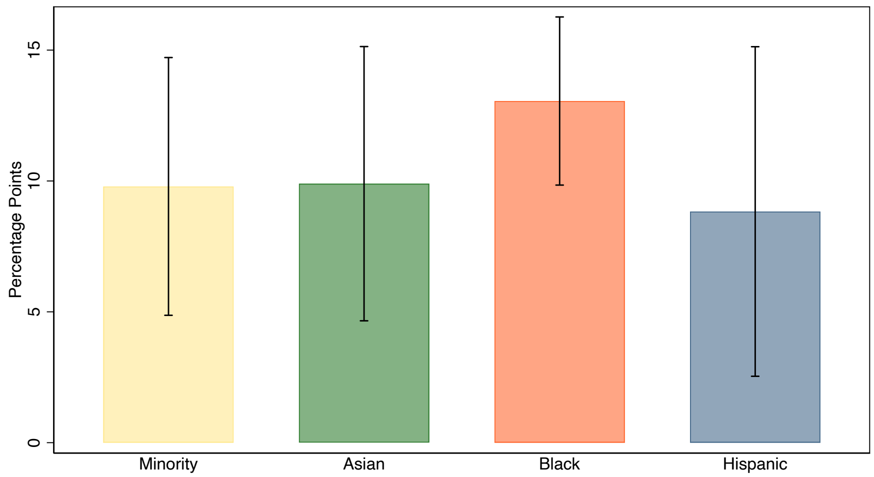

Figure 6. The Effect of Minority Bank Ownership on Minority Credit

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 A.3.1 for more details.

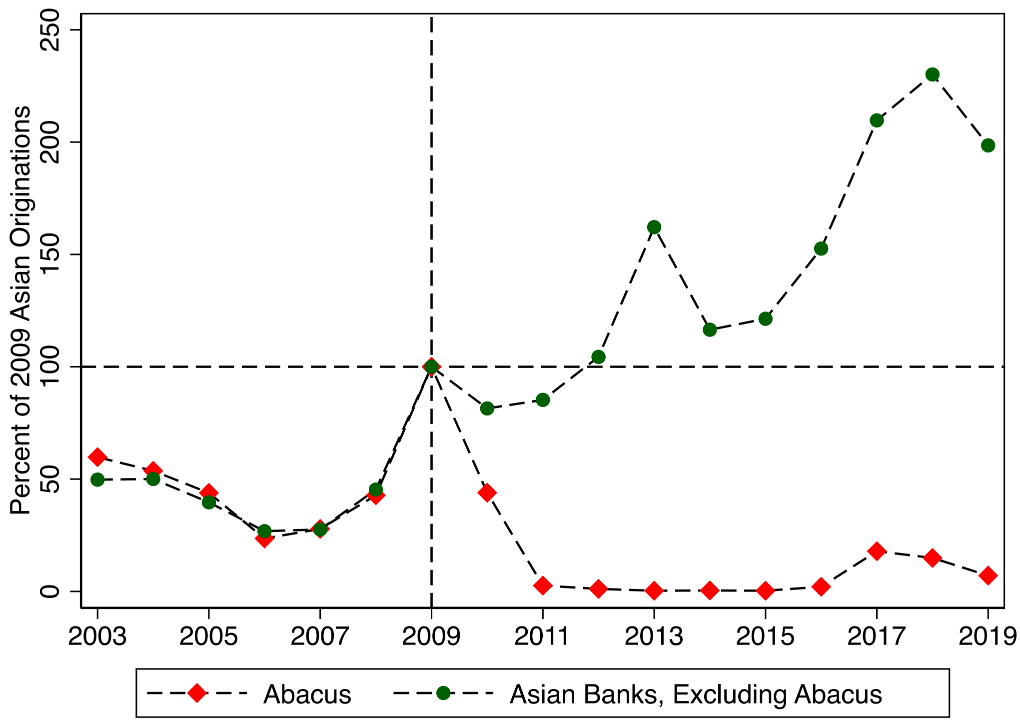

Figure 7. Asian Mortgage Originations by Abacus and other Asian Banks

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 restrictions, we are unable to employ Federal Reserve's confidential data on borrowers and loan officers.

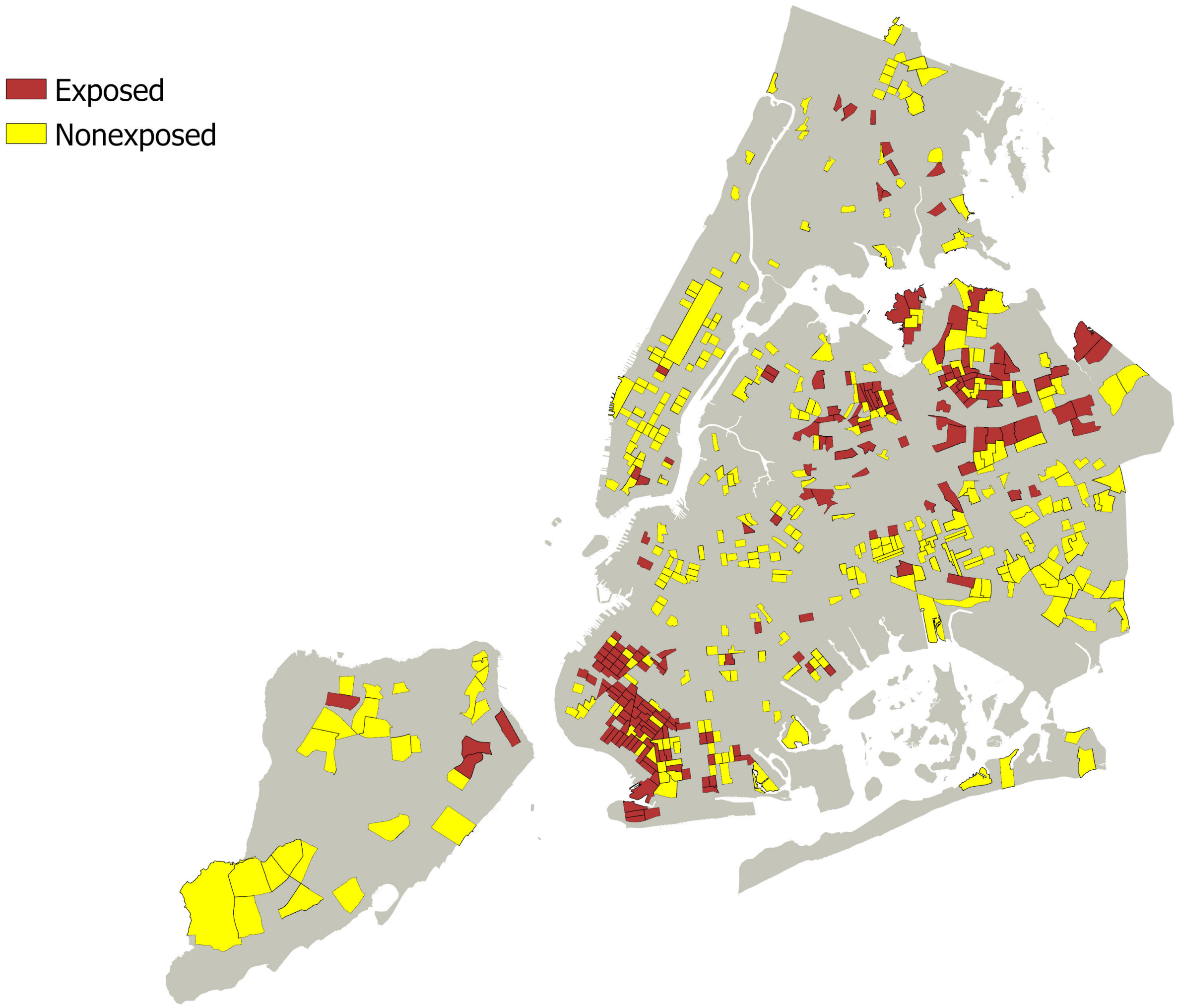

Figure 8. Asian Borrowers' Exposure to Abacus Federal Savings Bank in New York City, 2008

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 III.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 restrictions, we are unable to employ Federal Reserve's confidential data on borrowers and loan officers.

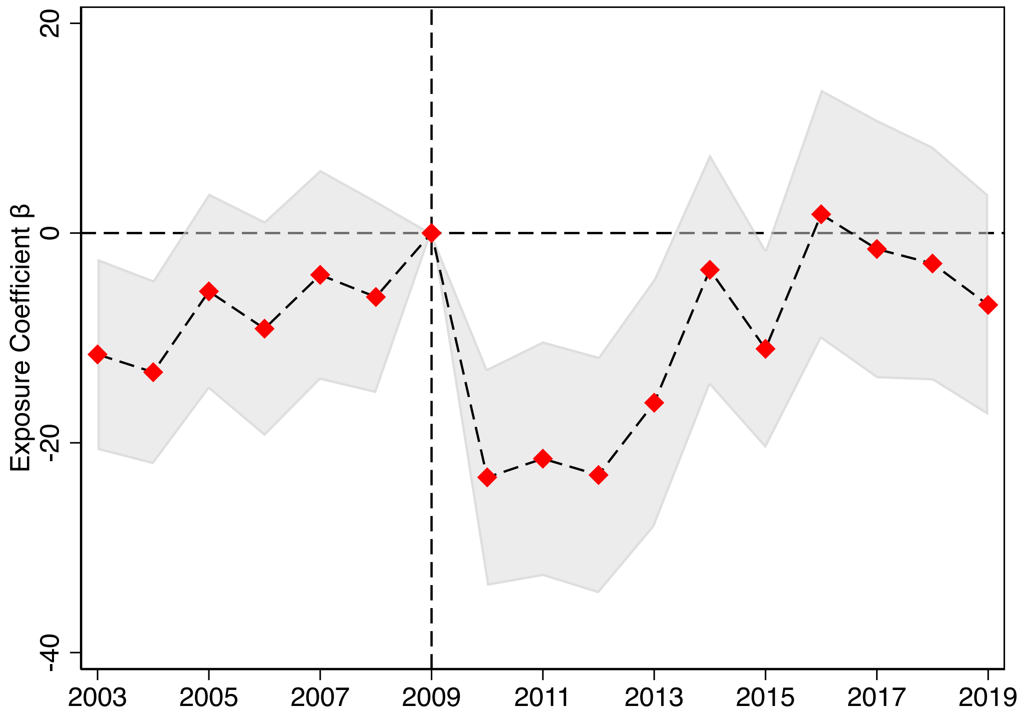

Figure 9. The Effect of Abacus Bank's Collapse on Asian Credit

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 restrictions, we are unable to employ Federal Reserve's confidential data on borrowers and loan officers.

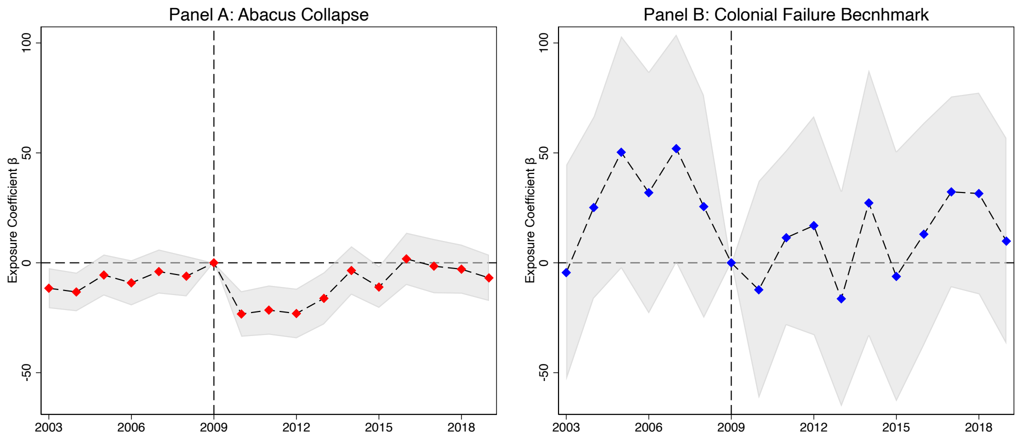

Figure 10. The Effect of Abacus Bank's Collapse, Colonial Benchmark
Notes: This figure plots estimated coefficients and confidence intervals for β_y from the regression:

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

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 restrictions, we are unable to employ Federal Reserve's confidential data on borrowers and loan officers.

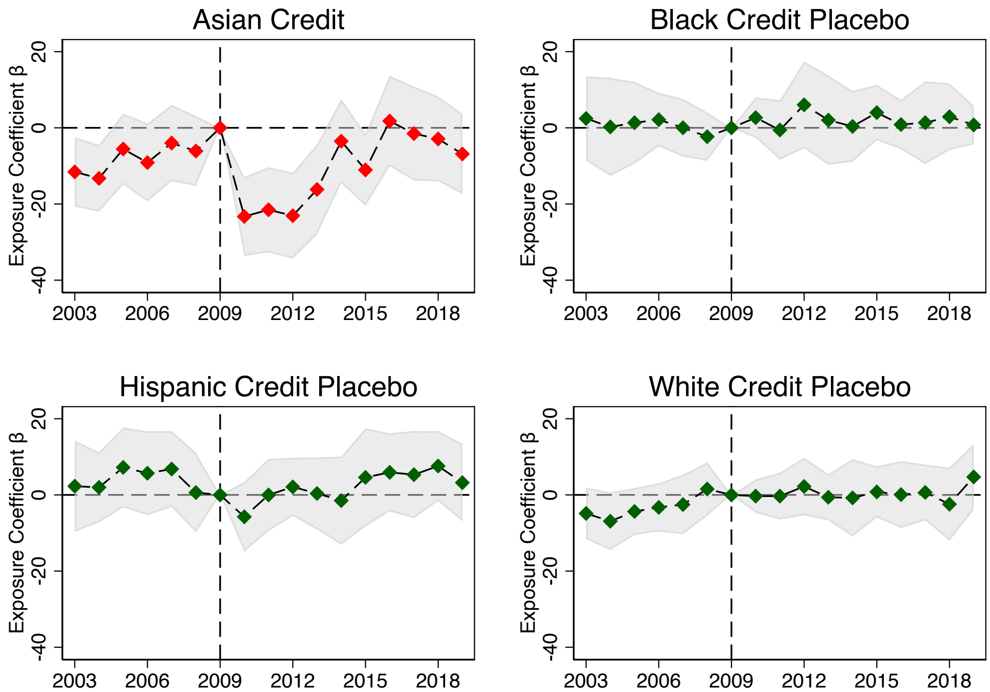

Figure 11. The Effect of Abacus Bank's Collapse on Credit, Group Placebos

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 restrictions, we are unable to employ Federal Reserve's confidential data on borrowers and loan officers.

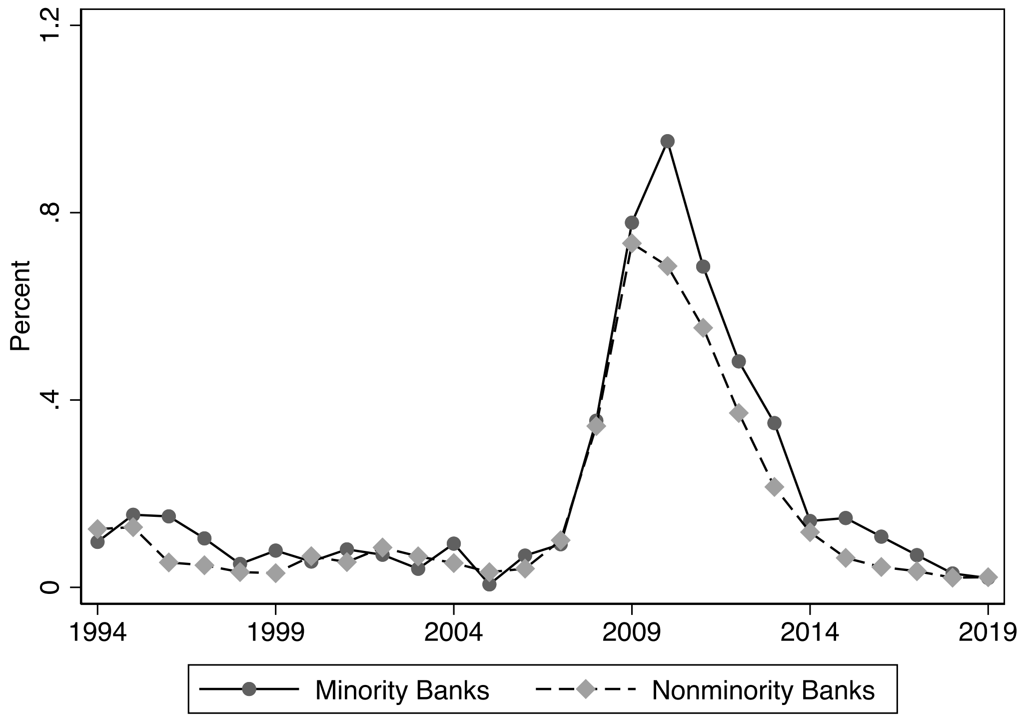

Figure 12. Mortgage Net Charge Off Rates by Bank Type. This figure reports average mortgage net charge-off rates for different bank types. "Minority" banks include those classified as Asian, Black, or Hispanic, while nonminority banks serve as a comparison group. Vertical axes represent mortgage net charge off amounts as a share of total mortgage amounts on balance sheet. Data are based on call reports from 1994-2019.