Minority Political Representation, Regulatory Credit Access, and Mortgage Lending

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Abstract

This paper analyzes the impact of electing a black mayor on mortgage access to black households. Using a regression discontinuity design (RDD) to examine US mayoral elections between 1990 and 2014, I find that mortgage lending to black loan applicants increases by three percentage points after black mayors take office. These effects are driven by credit origination in low-income census tracts. To provide a causal mechanism behind this finding, I exploit a double-layered RDD and show that black mayors interact with a federal regulation on fair lending practices, the Community Reinvestment Act (CRA). CRA-eligible neighborhoods experience higher mortgage acceptance rates and lower lending standards compared to non-CRA-eligible census tracts only in cities where black candidates won the mayoral race. These findings imply that a shift in political power on the local level can affect the enforcement of federal financial regulation in terms of fair lending practices and affect the availability of housing credit to minorities.

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1 Introduction

Any policy that attempts to reduce wealth disparities has to understand the reasons for homeownership differences across demographic characteristics. Charles and Hurst (2002) document one particular type of wealth disparity by showing that white renters are much more likely to become homeowners than black renters for two reasons. First, black mortgage applications were 73% more likely to be rejected than white mortgage applications even after controlling for credit score proxies and demographics. Second, black renters exhibit a 20 percentage points lower likelihood of initiating a mortgage application than white renters.[1] Furthermore, homeownership rates for black households have fallen every decade for the last 30 years (Goodman and Mayer, 2018), the racial wealth gap is still as large as it was in the 1950s (Kuhn et al., forthcoming). Bayer and Charles (2018) additionally document a persistent black-white earnings gap since the 1940s. Given these racial disparities, minority political leaders might address and prioritize advances in minorities' economic interests such as equitable credit access or affordable housing. And indeed, this paper shows that black political leadership affects banks' mortgage lending activity in low-income and historically underinvested areas.

This paper analyzes the effects of local black political leadership on mortgage outcomes and lending standards in US cities. I extract exogenous variation from close interracial mayoral elections between 1990 and 2014 by using a regression discontinuity design (RDD) that compares mortgage origination outcomes in US cities where a black candidate barely won a mayoral election with housing credit outcomes in cities where a black candidate barely lost. To provide a mechanism behind the interaction between local politicians and banks, I incorporate a spatial RDD that compares neighborhoods which are barely eligible for fair lending regulations with neighborhoods that are barely not eligible.

This paper utilizes two main data sets. First, I complement existing records on mayoral elections with information on the name, party affiliation, vote return, and the race for each of the top two mayoral candidates. The final data set comprises 331 interracial mayoral elections between 1990 and 2014 in 129 US cities. Second, loan-level application data from the Home Mortgage Disclosure Act (HMDA) contain rich lending contract information on the mortgage

[1] Black households might be discouraged from applying due to systematic racial differences in e.g., down payment constraints, uncertainty about income streams, demographic status, or supply-side borrowing constraints. See Charles and Hurst (2002) on why homeownership constraints might differ by race.

amount applied for, the property location of the applicant, whether the mortgage application got accepted or denied, and most importantly the applicant's race and income.

The findings of the election RDD are twofold. First, marginally-elected African-American mayors lead to an increased origination of home-purchase mortgages for black borrowers. Regression discontinuity estimates document a positive treatment effect of a three to six percentage points increase in the number of accepted black mortgage applications during the first mayoral term. This finding is robust to validity checks and specifications based on different bandwidth choices, alternative functional forms of the assignment variable and controlling for party affiliation. Also, this baseline effect is driven by loan origination in low-income neighborhoods and most pronounced for commercial banks.

Second, to determine whether the effects stem from a relaxation of a lending constraint on the credit supply side, I check whether lending standards are affected by black political leadership. Although overall bank lending standards get slightly stricter in cities where black mayors marginally took office, there is substantial heterogeneity across bank types. Interestingly, the same type of banks, commercial banks, which exhibit an increase in accepted mortgage applications also reduce their credit standards. In contrast, all other bank types exhibit a tightening of lending standards. I follow D'Acunto and Rossi (2017) to measure lending standards with HMDA data by income-to-loan ratios among applicants who got rejected. Distinguishing effects by bank type is crucial because not all banks are equally subject to regulatory constraints.

To provide a mechanism for the former findings, I exploit spatial discontinuities within cities where African-American mayors narrowly won and compare mortgage market outcomes in neighborhoods that are barely eligible for regulatory fair lending practices with neighborhoods that are barely non-eligible. More specifically, I apply a geographical RDD to investigate the role of the Community Reinvestment Act (CRA). This federal law was passed in 1977 to "stimulate" federally insured banks and thrifts to help meet the credit needs of the local communities in which they are chartered (Bhutta, 2011). To check whether lending institutions fulfill their CRA obligations, CRA examiners evaluate the bank's lending performance on the basis of the demographic context and all lenders' aggregate performance in the market using both quantitative and qualitative factors. Essential for this paper is that examiners conduct interviews

with local community stakeholders such as mayors, commissioners, or city council members. Econometrically, I exploit a discontinuous income eligibility rule that defines a census tract to be eligible for CRA lending agreements if its median family income is less than 80% of the Metropolitan Statistical Area (MSA) median family income. Specifically, I identify the causal impact of the CRA on mortgage lending outcomes by taking all election-year pairs in which black mayors barely won and compare mortgage outcomes in CRA-eligible census tracts just below the income cutoff with CRA-non-eligible census tracts that are just above the threshold. I find significant effects of black mayors interacting with regulatory credit access of the CRA on mortgage lending outcomes. First, mortgage acceptance rates significantly increase by 2.6 percentage points across the CRA-income eligibility cutoff in cities where black mayors barely won. In contrast, acceptance rates are not significantly affected in cities where white mayors narrowly won. Second, lending standards decrease by 3.7 percentage points in CRA-eligible census tracts compared to census tracts where the lending regulation is not binding. As before, this result is only statistically significant in cities where black mayors barely won. Since the CRA only covers commercial banks and thrift institutions, credit unions and independent mortgage lenders are legally not affected by the CRA and serve as a natural placebo sample. Interestingly, only banks subject to the CRA decrease their lending standards, while placebo institutions do not show any statistically significant effects. The differential response in this placebo test also reduces concerns that my findings are mainly driven by credit demand. Otherwise, placebo lenders would also react.

Finally, I provide evidence that the effects on mortgage origination are mainly driven by credit supply variation. Estimates from an event analysis show that a close victories of a black mayoral candidates do not affect post-election borrower incomes. Even if local politicians enact policies that might affect future borrower income expectations, it is unlikely that this effect exactly stops at the spatial discontinuity. Furthermore, I show that African-American political leadership does not lead to an application encouragement effect since there is no change in the application propensity of black households.

This paper is related to three strands of literature. The first strand of literature on the "direct" economic effects of local political leadership has investigated city policy outcomes such as public spending, employment, crime rates, or education (Ferreira and Gyourko, 2009, 2014; Hopkins and McCabe, 2012; Meyersson, 2014). The second strand of literature focuses on the impact of hard

political power, such as US federal laws or regulations, on mortgage lending outcomes. Despite numerous efforts of legislative acts[2] to expand credit access and reduce disparate treatment in the mortgage market, evidence on the success of these government actions is mixed (Agarwal et al., 2014; Agarwal and Evanoff, 2016; Bayer et al., 2018; Munnell et al., 1996). This paper is mostly related to the third strand of literature on the nexus between soft political power and the mortgage market. Akey et al. (2021) show that turnover in Senate committee chairs is associated with a considerable reduction in the availability of consumer credit in the ascending Senator's state. Antoniades and Calomiris (2016) exploit the US presidential election in 2008 to show that voters punish Presidential candidates for local mortgage supply contractions but do not reward them for local mortgage supply expansions. Chavaz and Rose (2019) demonstrate that receivers of the 2008 liquidity assistance program TARP increased bank lending by 23% to 60% more in areas located inside their home representative's district than elsewhere. I contribute to this third strand of literature in two distinct ways. First, no attention has been paid to political influence on bank lending at the very local level: city mayorships. This is an important angle since political power might be most effective in municipal environments where spatial proximity between politicians and banks is closest. Second, no understanding has been established on whether and how local politicians have an impact on mortgage access of minority groups.

This paper reveals two implications. On the one hand, a shift in political power on the local level can affect the enforcement of federal financial regulation in terms of fair lending practices and ultimately affect the availability of housing credit to minorities. On the other hand, increasing loans to low-income neighborhoods might have important financial stability implications since financial shocks have a positive differential impact on default rates of minority households (Bayer et al., 2016).

The remainder of the paper is structured as follows. Section 2 describes the institutional setting and develops the hypothesis. Section 3 describes the data sets, explains the empirical methodology, and tests for the validity of the research design. Section 4 presents the RD baseline results and the underlying mechanism. I conclude in section 5.

[2]See for example the Fair Housing Act of 1968, the Equal Credit Opportunity Act of 1974, the Community Reinvestment Act of 1977 or the Home Mortgage Disclosure Act of 1975.

2 Hypotheses and Institutional Setting

After the end of the Civil War in 1865, the 15th Amendment to the US constitution made it possible for black men to vote by giving Congress the power to enforce "The right of citizens of the United States to vote shall not be denied or abridged by the United States or by any State on account of race, color, or previous condition of servitude".[3] Despite this de jure enfranchisement of black political representation, mostly Southern States found legal loopholes and passed "Jim Crow" laws that enacted viable minority voting restrictions.[4] Furthermore, a dispute between Republicans and Democrats around the 1876 presidential election resulted in the Compromise of 1877 that led to an withdrawal of troops deployed in the South and essentially ended the Reconstruction Era.[5] That instance further disenfranchised black voters because the violence directed towards African-Americans could spread even more without federal troops' protection. While the 15th Amendment only guaranteed that people could vote, the Voting Rights Act (VRA) in 1965 enforced the 15th Amendment. The VRA prohibited electoral discrimination against racial minorities and implied an increase of the black American electorate and made politicians responsible to black voters. Looking at the numbers, the VRA indeed increased the responsiveness of black political power at the local level to the policy interests of racial minorities. While no US city had ever experienced an African-American mayor in the year 1960, out of the top 100 most populous cities in that year, 46 would elect an African-American city leader by 2010 (Vogl, 2014).

Racial disparities in the housing market are historically rooted in the actions of private actors like banks and real estate agencies but also in laws and policy decisions passed by local, state and federal governments (Rothstein, 2017). While Section 2 of the Thirteenth Amendment authorized Congress in 1866 to "pass all laws necessary and proper for abolishing all badges and incidents of slavery in the United States", a landmark decision by the Supreme Court in 1883 disagreed that exclusions from housing markets could be a "badge or incident" of slavery. Consequently, Civil Rights protections in housing markets were ignored for a century until 1968 when the Supreme Court rejected its 1883 decision in the case of Jones v. Alfred H. Mayer Company. That reinterpretation ultimately validated the 1866 Civil Rights Act's declaration

[3] See section 1 and 2 of the Amendment XV.

[4] See Perman (2001) on the history of post-civil War South and the legal disenfranchisement devices of black Americans such poll taxes, literacy tests or white primaries.

[5] See for example, https://www.politico.com/story/2008/02/presidential-election-deadlocks-congress-feb-1-1877-008243.

and empowered Congress to regulate the sale of private property to prevent racial discrimination. Simultaneously, the Fair Housing Act was signed into law by President Lyndon B. Johnson and gave the government the power to prohibit discrimination concerning the sale, rental, and financing of housing based on race, religion and national origin. However, the century between 1866 and 1968 was characterized by unequal access to housing wealth through Redlining that induced systematic credit rationing and residential segregation (Appel and Nickerson, 2016), blockbusting[6], or restricted access to loans insured by the Federal Housing Agency. But even after passing additional anti-discrimination laws in the post-civil-rights era like the Fair Housing Act of 1968, the Equal Credit Opportunity Act of 1974, the Home Mortgage Disclosure Act of 1975, or the Fair Housing Amendments Act of 1988, African American borrowers still face unequal mortgage credit conditions (Bartlett et al., 2019; Bayer et al., 2018; Charles and Hurst, 2002; Munnell et al., 1996). Moreover, the US Department of Justice charged a total of $500 million in settlements against several of the largest lenders due to overcharging black and Hispanic borrowers during the housing boom (Bhutta and Hizmo, 2019). Given the historical persistence of racial housing wealth disparities in the US, advances in minorities' housing market interests should be at the top of the black political power agenda. But how can black politicians effectively change housing credit availability? If the financial intermediation chain is characterized by either credit supply frictions (e.g. statistical discrimination or market power) or credit demand-side frictions (e.g. application discouragement despite being credit-worthy), politicians can address these frictions either *directly* or *indirectly*.

Direct political influence can be interpreted from a political economy's point of view and breaks down to exerting leverage on banks by affecting credit supply frictions. For example, the first African-American mayor of Atlanta, Maynard Jackson defeated his white competitor Sam Massel in the 1973 mayoral election. Despite a contentious electoral campaign where the incumbent mayor Sam Massel used the "Atlanta, Too Young to Die" slogan to suggest that a black mayor would lead to Atlanta's economic downfall, Maynard Jackson finally won the election with a majority of 60%. As Bayor (2001) documents, Atlanta always has been a city where business leaders from banking, utility, insurance, law and real estate companies ran city hall. Such a white business-oriented power structure had conflicting interests with the priorities of

[6]Blockbusting was a business practice by real estate agents in the period around the Great Migration that produced panic sales at undervalued prices in white areas to sell these discount homes at exploitative and overvalued prices to African Americans.

black communities and saw affirmative action in minority hiring and promotion as a subordinate priority. Nonetheless, Maynard Jackson pressured white-run banks to appoint black as executives and used deposits of city money to exert pressure on banks. In an interview, Maynard Jackson stated equal opportunity as motivation for "moving a half-million account out of a bank that would not comply with the city policy to a bank that had come in on the twenty-ninth day of a thirty-day ultimatum" (Bayor, 2001). Unfortunately, data on public deposits are not readily available. Another possibility for local politicians to influence banks is to tighten regulatory constraints that were previously non or less binding or to enforce lax regulation. This paper investigates such regulation on fair credit access, the Community Reinvestment Act. According to Bhutta (2011), bank regulators periodically monitor CRA compliance by collecting CRA exam ratings and take these records into account when evaluating bank applications for mergers, acquisitions, or new branches. More specifically, to understand perceptions on the performance of financial institutions in helping meet local credit needs, CRA examiners conduct interviews with local community contacts such as mayors, commissioners, tribal chiefs, city council members, and tribal council members (FDIC, 2020). Consequently, there is some discretionary power for local politicians to reduce the slackness of regulatory credit access. Besides the soft sanctioning mechanism of CRA examination ratings, these lending agreements have no legal enforcement mechanism in case of non-compliance. In section 4.3, I hypothesize that local politicians exert leverage on banks by relaxing lending constraints towards African-American households via this federal law on fair credit access.

Indirect political influence could work through policy actions that, for example, affect or encourage credit demand. Referring again to Atlanta, in his first year, mayor Jackson appointed twelve whites and fifteen black to head city departments and agencies. He also established a city Minority Business Enterprise (MBE) program to ensure that a significant level of city contracts would be awarded to black-owned firms.[7] Another policy action was to shift city hall priorities and resources away from downtown business district to protect residential areas, especially supporting low-income housing policies. Further, he secured funds from the Community Development Block Grants administered by the U.S. Department of Housing and Urban Development (HUD) to revitalize deteriorating neighborhoods. The money went to housing rehabilitation, housing code enforcement, sewers, streetlight, recreation centers and social services, especially in black

[7]The ratio of city contracts that went to black-owned firms relative to all firms went up from 19% to 34% between the first year in office and the last year in office.

neighborhoods.

3 Data and Empirical Strategy

3.1 Data Description

Electoral data. Data on mayoral elections come from two main sources: Ferreira and Gyourko (2009) and Vogl (2014).[8] Merging these two data sets and hand-collecting missing information on both elections after 2010 and the race of the top two candidates leads to a final data set on 7,000 mayoral elections in over 1,000 US cities between 1950 and 2014. To identify the missing race of each candidate, I follow (Vogl, 2014) and rely on the reporting of candidates' races by newsmedia and advocacy organizations.[9] The final dataset contains information on the name, vote share, party affiliation and the race of winner and runner-up candidate. Two data constraints reduce the number of observations: (i) the outcome variables (mortgage activity) is available from 1990 until 2018 and (ii) the RD design requires to analyze interracial elections[10], i.e. a black candidate runs against a non-Hispanic white candidate. This produces a regression sample with 331 interracial elections in 129 cities that enter the RD estimation. Table 1 shows some key city characteristics of all cities above 25,000 inhabitants as of the year 2000 in column (1). Column (2) and (3) contrasts displays city characteristics for the whole election sample and the interracial election sample that enter the baseline regression. Apparently, interracial elections take place disproportionately in the southern region of the US and in large cities. Also, the fraction of African-American people living in these cities is higher compared to cities in the first column. The over-representation of the sample in the southern part of the United States might also explain the lower median family income, lower house prices and the higher poverty rate.

– Insert Table 1 here –

Mortgage data. Data on mortgage origination and applications come from the Home Mortgage Disclosure Act (HMDA). It provides loan-level information on the year and the number of mortgage applications and the decision of the bank (denial or acceptance of the loan). A rich set of applicant information like income, race, ethnicity and the location of the property allow

[8] The sample period for (Ferreira and Gyourko, 2009) ends in 2005 and for (Vogl, 2014) ends in 2010.

[9] See Appendix A.I for details on the data collection process and a list of sources.

[10] The motivation behind this constraint is to compare cities where black mayoral candidates barely won with cities where black mayoral candidates barely lost. As a consequence, the RD design disregards all elections where the mayor and the runner-up have the same race.

me not only to track each mortgage application at the census tract level but also to identify loans from black applicants.[11] Loan level data are aggregated to the census tract-year level. The main outcome variable measures mortgage origination activity by taking the logarithm of the number of accepted mortgage applications. Although variable scaling should not be an issue because population size of census tracts is evenly distributed between treatment and control groups around the threshold, I also look at the number of accepted mortgages to black borrowers relative to total accepted mortgages. The second set of outcome variables are bank lending standards, mortgage acceptance rates and application ratios defined as:

- Lending standards$_{ctract,t} = \frac{\sum_{i \in rejected} \frac{Applicant\ Income_{i,ctract,t}}{Mortgage\ volume_{i,ctract,t}}}{All\ rejected\ applications_{ctract,t}}$,
- Acceptance rates$_{ctract,t} = \frac{\sum Accepted\ mortg.\ nr^{b}_{i,ctract,t}}{\sum Total\ mortg.\ nr^{b}_{i,ctract,t}}$
- Application ratio$_{ctract,t} = \frac{\sum Applications^{b}_{i,ctract,t}}{\sum Total\ Applications^{total}_{i,ctract,t}}$

where b stands for African-American applicants, i for bank, $ctract$ for census tract and t for year. The components of the lending standard variable are based on rejected mortgage applications only. Intuitively, higher income-to-loan ratios among denied mortgage applicants reflect stricter lending standards since banks are rejecting wealthier applicants given the same loan amount applied for (D'Acunto and Rossi, 2017). Normalizing accepted loan volumes by the total mortgage flow (accepted plus declined loan applications) is one way to "control" for loan demand (Loutskina and Strahan, 2009). Application ratios are defined as the sum of applications by African-American households over total applications by white and black applicants.

To clean the data I use the following filter criteria. I drop both home refinance and home improvement mortgage applications to concentrate on home-purchase loans only. In addition, I consider both conventional and unconventional loan applications that keeps also Federal Housing Agency (FHA) insured loans. For more details on the loan data construction, see Appendix A.I and Table OA1.[12]

[11] Between 1990 and 2003, applicants and lenders are required to chose among six racial or ethnic classifications (white, black, Hispanic, Asian or Pacific Islander, American Indian and Alaska Native, or "other". If the applicant does not want to disclose this information the lender is required to make a selection based on visual inspection (Avery et al., 2007). Reporting rules changed in 2004 allowing the applicant to report both ethnicity (Hispanic or non-Hispanic) and race (white, black, Asian, American Indian and Alaska Native, Hawaiian or other Pacific Islander).

[12] Especially after the Great Recession, most African American borrowers have FHA loans (Bhutta et al., 2017).

3.2 The RD Design

Since black mayorships are not randomly assigned to US cities, identifying the causal effect of black political leadership is challenging. Comparing housing market outcomes in black governed cities with housing market outcomes in white governed cities is biased because e.g. demographic developments, that are unobserved by the researcher, can both lead to the black candidate's victory but also to higher mortgage origination. Cities with high support for a black mayor might be systematically different from cities where black communities are not that strong resulting in white mayorship. According to Lee (2008) and Lee and Lemieux (2010), narrowly decided interracial elections provide quasi-random variation in election winners because which race wins is likely to be determined by idiosyncratic factors as long as contestants cannot systematically manipulate the election outcome.

The RD design embodies the reasoning above by assigning the treatment (black mayorship) deterministically to those units whose running variable (black win margin) is above the cutoff, $c = 0$, while leaving units with vote margins below the cutoff as untreated. Black candidates with a win margin below the cut-off are assigned to the control group (white mayoralty). In the context of interracial elections, the RD design holds constant the conditions that give rise to black mayoralties and thereby reduces omitted variable bias (OVB).

The RD treatment effects of black political leadership on housing market outcomes are estimated as follows:

$$M_{ctract,c} = \beta_0 + \theta_1 blackwin_c + P(\beta, margin_c) + \epsilon_{ctract,c}, \quad (1)$$
$$\forall\ margin_c \in (\text{cutoff} - h, \text{cutoff} + h),$$

where $M_{ctract,c}$ represents the average mortgage lending to census tract *ctract* in city c during the post-election period which lasts for the duration of a mayor's first term.[13] The variable $blackwin_c$ is a dummy with value one in each year of the first term indicating whether the black candidate won the mayoral election in city c and zero if the black candidate lost the mayor's race. The running variable $margin_c$ is the vote margin of the black candidate defined as the vote

[13]The choice of a mayor's term duration for the outcome variable is motivated by Dell (2015). For every census tract I pool yearly mortgage outcomes over the respective term length after the focal election date. In my sample, 78% of all cities have a 4-year term length, 2% of cities have a 3-year term length and 20% a 3-year term of office.

percentage obtained by the black candidate minus vote percentage obtained by it's strongest white opponent. P stands for an n-order polynomial in the vote share to control for different functional forms (linear, quadratic and cubic). $\epsilon_{ctract,t}$ is an idiosyncratic error. Standard errors are robust and clustered at the census tract level to account for serial correlation over time since observations are pooled over the first term. [14] I also cluster at the city level to allow for correlation between census tracts located in the same city which doesn't affect robustness but decrease standard errors substantially.

Covariates. In order to increase the precision of the estimator of the RD treatment effect, I include predetermined control variables (Calonico et al., 2019). Census-tract level covariates come from the US Census and contain log(population), % of black households, log(median family income), share of population with age 65+. Since US Census data are in decennial frequency, I follow (Vogl, 2014) and linearly interpolate between census years to include controls based on the election year. Referencing the covariates to the election year is motivated by the fact that RD designs should include only predetermined covariates Lee and Lemieux (2010). See Table OA1 for details on all variables used in this paper.

Bandwidth and polynomial order. To analyze close elections, I conduct local linear regressions in a neighborhood, h, around the cutoff (Meyersson, 2014; Imbens and Lemieux, 2008; Cattaneo et al., 2020) and drop observations that are far away from the cutoff since identification in this region is not feasible. The bandwidth h^* is calculated according to the bandwidth algorithm developed by Calonico et al. (2014) for each outcome with a linear control function of the assignment variable.[15] Since this bandwidth-selection algorithm is a data driven approach, each outcome variable produces a different bandwidth. This bandwidth-selection algorithm is a modification of the conventional algorithm developed by Imbens and Kalyanaraman (2012).[16] I

[14] More specific, I apply cluster-robust nearest neighbor variance estimation via the STATA rdrobust command.

[15] Low-order (linear) polynomial approximation is substantially more robust and less sensitive to boundary and overfitting problems (Cattaneo et al., 2020). Further, such local polynomial methods employ only observations close to the cutoff, and interpret the polynomial used as a local approximation, not necessarily as a correctly specified model.

[16] Although standard in the literature as it harmonizes the variance-bias trade-off by calculating a RD point estimator that is mean-squared-error optimal, the Imbens and Kalyanaraman (2012) algorithm is biased (Calonico et al., 2014). The confidence intervals are based on t-statistics that contain a bias since the true regression function, i.e. the functional form of the assignment variable, is not known leading ultimately to a misspecification error. Hence the critical values to build the confidence intervals are biased. As remedy, Calonico et al. (2014) developed a robust bias-correction approach which estimates the bias, manually removes it from the point estimator and within an appropriate bandwidth. This method is implemented via the "rdrobust" STATA package according to Cattaneo et al. (2016). However, all my results do also hold when applying the algorithm by Imbens and Kalyanaraman (2012).

employ a triangular Kernel scheme gives more weight to the observations that are close to the cutoff. All results are insensitive to applying alternative weighting schemes such as a uniform kernel or the Epanechnikov kernel.

Unit mismatch. In contrast to the explanatory variables which are measured at the city-year level, observations of the outcome variable vary at a much finer level of granularity: census-tract-year level.[17] Applying the conventional data-driven bandwidth selection procedure based on this sample would yield a bandwidth that is, by construction, too narrow since mass points artificially inflate the number of observations although the masspoint sub-units belong to the same limited set of cities. Therefore, I collapse all the observations from the census-tract-year level to the city-year level and determine the optimal bandwidth based on the collapsed city-level mortgage data. Specifically, I proceed in two steps for every outcome variable of interest. First, I determine the bandwidth, h^* based on the city-level as unit of analysis for both the explanatory and the outcome variables. Second, I calculate RD treatment effects with city-level explanatory variables and census-tract-level outcome variables within the neighborhood h^* from the first step.

3.3 Internal Validity

Density of the running variable. A standard validity check in the RD literature is to test for discontinuity of the assignment variable at the cut-off (Imbens and Lemieux, 2008). Intuitively, a discontinuous jump of the vote shares around zero might indicate that certain candidates might have systematic advantage or differential resources to influence the outcome and self-select into treatment. This endogenous sorting around the threshold would be a serious threat to internal validity.[18] Figure 1 shows no statistically significant discontinuous jump of the assignment variable as indicated in both the upper panel that plots the density of the assignment variable via a histogram (upper panel) and a local density plot (bottom panel). In addition, the statistical manipulation test by McCrary (2008) based on local polynomial density estimation technique yields a p-value of 0.23.[19] Therefore, it fails to reject the null hypothesis of no difference in the

[17] I collapse the HMDA loan-level data at the Census-tract-year level. The average city in my sample consists of 561 census tract.

[18] Vogl (2014) shows that black candidates might disproportionately have control over the outcomes of close elections since they mobilize large groups of previously unregistered and unincorporated electorates. However, his sample ranges from 1965 to 2010 while my sample starts in 1990, a year in which voter suppression and voter mobilization are less of an issue compared to the period right after the voting rights act. The more time passed by since the Civil Rights Movement the less African-Americans were excluded from political life in their local communities and the less important an untapped pool of eligible voters play (Hajnal, 2010).

[19] The STATA package used for this test comes from Cattaneo et al. (2018).

density of treated and control observations around the cut-off.

– Insert Figure 1 here –

Balance of predetermined covariates. Another standard validity check in the RD literature is to inspect whether, near the cutoff, treated units are similar to control units in terms of observable and predetermined covariates that are later used in the regression analysis for covariate adjustment. Figure 2 plots all covariates as local averages (in 8-percent bins) against the black win margin within the optimal bandwidth h^* (Calonico et al., 2014). In addition, the graph shows regression lines that are predicted values with separate cubic vote margin trends estimated separately on each side of the cut-off. The shaded areas are 95% confidence intervals. None of the RD panels exhibit significant jumps in the predetermined covariates.

– Insert Figure 2 here –

Pre-election balance of treatment and control groups. Due to the panel structure of the data set, I am able to check for pre-election trends in the outcome variable, a feature which most of conventional RD settings are not able to test. Intuitively, if the RD design really exploits plausibly exogenous variation in black election winners, then random election results should by definition not have any explanatory power for predicting pre-election mortgage lending outcomes. One possible interpretation of random election outcomes predicting pre-election mortgage lending is reverse causality: banks are strategically changing their lending behavior in order to affect election outcomes (Dinç, 2005; Englmaier and Stowasser, 2017). To check for this, I follow Cellini et al. (2010) and pool observations from two years before through four years after the election for each electoral (c,t) combination to estimate the following "intent-to-treatment" (ITT)[20] effects. Intuitively, ITT investigates mortgage lending outcomes in cities where the black candidate won or lost a specific initial electoral (c,t) combination controlling for the black vote share in this election but not for any subsequent years or other control variables:

$$M_{b,c,t,\tau} = \theta_{\tau}^{ITT} black_{c,t} + P(\beta_{\tau}, margin_{c,t}) + \alpha_{\tau} + \kappa_t + \gamma_{ct} + \delta_b + \epsilon_{b,c,t,\tau} \tag{2}$$

[20]This is a reduced form IV approach where the black mayoralty is instrumented with the black candidate being "eligible" to get elected and the ITT measures the effect of a black candidate that might get elected. Originally proposed by Cellini et al. (2010), the dynamic RD design is also adapted by Ferreira and Gyourko (2014) in the context of female mayors affecting city outcomes.

where $M_{b,c,t,\tau}$ represents the mortgage lending outcome for bank b in city c in the election year t and the number of years elapsed between the election date and the date the outcome was measured τ. $black_{c,t}$ is a dummy variable equal to one if city c elected a black mayor in year t and zero if the black candidate lost the election or if there was no election. The running variable $margin_{c,t}$ is the vote margin of the black candidate defined as described above. P stands for an n-order polynomial in the vote share to control for different functional forms (linear, quadratic and cubic). I also include year fixed effects (FE) (κ_t), years relative to the election FE (α_τ), election FE (γ_{ct}) and bank FE (δ_b). $\epsilon_{b,c,t}$ is an idiosyncratic error term.

Table 4 shows the corresponding results for regressing pre-election mortgage outcomes on a dummy variable of whether the black candidate won or lost the election. Columns 1 and 2 only use observations in the year before the election. The parsimonious specification in the first column is basically a difference-in-means test with year fixed effects and indicates no statistically significant difference in the pre-election mortgage outcome for black versus white governed cities. The inclusion of a cubic vote shares in column 2 does not alter the results. It means that treatment and control groups do have different mortgage market outcomes before elections. In columns 3 and 4, I pool observations from two years before through four years after the election for each electoral (c,t) combination, but additionally considering effects in the year of and the year before the election. Table 4 reports the coefficients θ_{-1} of equation (2). Irrespective of adding election fixed effects, γ_{ct}, and bank fixed effects, δ_b, in column 4, there are no pre-election outcome differences. The rejection of differences in trends between cities that elect and fail to elect a black mayor still hold if pre-election growth rates of mortgage origination are investigated. Columns 5 to 7 regress the annual growth rate of accpeted mortgages between year $t-2$ and $t-1$ on year fixed effects and the indicator for whether the black candidate won or lost the mayoral election. Column 6 also contains cubic vote shares. Also here, no pre-treatment trends in the outcome variable are detected, which validates the randomness of the treatment variable (Lee and Lemieux, 2010) with respect to lending outcomes.

– Insert Table 4 here –

4 Main Results

4.1 RD Effects on Mortgage Origination

Graphical results. Before proceeding to the formal regression analysis, I start with the visual RD representation. RD graphs divide the assignment variable, black win margin, into a number of bins and plots average values of mortgage outcome variables in the post-election period against the binned vote margin (Lee and Lemieux, 2010). Comparing mean outcomes just to the left and right to the cutoff provides an indication of the magnitude of the jump or fall in the regression function in the neighborhood around this point, i.e. the treatment effect. Figure 3 plots mortgage lending outcomes against the black win margin. I follow Meyersson (2014) and plot unconditional means of mortgage outcomes against the black vote margin assignment variable in 5-percent bins. The solid line is a local linear smoother based on raw data fitted separately on the left and right hand side of the cutoff. To inspect overall trends in the regression function, I do not confine the graphical RD on the narrow election sample dictated by the bandwidth but instead look at broader window ($margin_c \in [c - 0.5, c + 0.5]$). The vertical distance between the two fitted lines approximates the RD treatment effect. The upper panel shows a jump by roughly 1.2 log units at the cutoff of mortgages originated suggesting that mortgage lending increases in cities where black candidates barely won relative to cities where white mayors barely won the mayoral election.[21] The right-sided U-shaped functional form can be explained by an obvious positive relationship between definitive election victories and economic outcomes.[22] However, the left-sided inverted U-shape of the regression function is harder to explain since it is not driven by outliers (i.e. black candidates systematically losing very small cities and thereby showing lower extensive margin of mortgage lending activity.). The large effect is mainly due to this left-sided inverted U-shape feature. The lower panel of figure 3 also shows a significant jump in mortgage origination to black applicants relative to total originated mortgages by roughly 10 percentage points. Note that this scaled version of mortgage origination has much milder left-sided inverted U-shape. Overall, the graphical RD representation usually applies higher-order polynomials and is therefore not suited to infer RD treatment effects because of overfitting or biases at boundary points (Calonico et al., 2014). Treatment effects in RD settings are rather taken from nonparametric regressions allowing for different linear slopes.

[21] This is a large effect since it corresponds to one standard deviation.

[22] For example, if the Democratic candidate wins an election by a wide margin, this city might be more progressive and exhibit higher per capita government spending than cities where Democrats and Republicans are evenly distributed among the electorate.

Regression results. This paragraph presents the nonparametric local estimation results for the RD treatment effects of black political leadership based on Equation 1. Table 5 presents the RD regression results of the baseline scenario. All dependent variables are pooled across years within the first mayoral term. Column 1 displays the RD estimate of regressing mortgage outcomes on the dummy variable $BLACKwin$ for the global sample and a cubic vote margin showing statistically significant effects on mortgage origination. The remaining columns perform local RD regressions in order to focus on close elections within the distance from the cutoff where the running variable $margin_c \in [c - h^*, c + h^*]$. Columns 2 employs the optimal bandwidth h^* according to Calonico et al. (2014) with a triangular Kernel weighting scheme and report a positive RD treatment effect of 8 percentage points, respectively, which is significant both in a statistical and economic sense. While adding covariates in column 3 reduces the magnitude of the point estimator, the RD treatment effect is still statistically significant at the 1% level in this preferred specification.[23] In terms of economic significance, African-American city leaders increase mortgage origination by 6 percentage points in the post-election period.[24] The last three columns investigate the effect on mortgage origination to black borrowers scaled by total mortgage origination. Column (6) reveals that black mayors lead to an increase in scaled mortgage lending by three percentage points. [25]

– Insert Table 5 here –

4.1.1 Robustness

Functional form sensitivity. Although it has become standard to use local linear regressions in RD designs, the literature has not yet developed a clear-cut selection rule for the polynomial order of the assignment variable (Hall and Racine, 2015). Pei et al. (2018) surveyed the top 8 economics journals and found that 70% of RD papers use local polynomial regressions as main specifications and the rest report global regression estimators. Further, out of the paper that use local polynomial regressions, 60% of these studies employ linear functional forms. According to Cattaneo et al. (2020), despite the fact that higher-order polynomials generally improve the

[23] All effects remain robust to different weighting schemes such as Epanechnikov or uniform Kernels and to alternative bandwidths. See Figure 7 for details.

[24] In RD settings with a logarithmic outcome variable, the effect can be expressed in relation to the control group mean, which is the estimate of $E[\log(Y(0))|X = \text{cutoff}]$. Accordingly, an increase of log(accepted mortgages) by 0.561 relative to 8.7 results in an economic effect of 6 percentage points. I calculate the estimate of control group mean by the STATA command rdrobust.

[25] Also, I check robustness for a higher aggregation level. Unreported results find that the significance of RD treatment effects of table 5 remain unchanged, quantitatively and qualitatively, when collapsing the outcome variable at the city level.

accuracy of the approximation it also increases the variability of the treatment effect estimator. Also, higher-order polynomials lead to data overfitting and unreliable results near boundary points.

However, in order to show that my results are not born out of ad-hoc fashion selection procedures, Figure 7 presents RD estimations based on the specification in column (2) of Table 5 with alternative polynomial orders of the assignment variable. Employing a quadratic or a cubic control function does not systematically change the baseline results.

Bandwidth sensitivity. As the bandwidth choice represents a crucial decision within the RD methodology (Imbens and Lemieux, 2008), Figure 7 depicts a falsification test by plotting the RD treatment effects coefficients of the baseline specification (equation 1) based on different bandwidths ranging between $(h^*/2, h^* * 2)$ choices. Intuitively, increasing the bandwidth will decrease the variance, and so the size of the confidence intervals, but increase the bias of the estimator. Figure 7 shows that the RD point estimators remain statistically significant in a neighborhood around the optimal bandwidth h^* of 0.17.

4.2 Income Heterogeneity and Lending Standards

This section analyzes potential credit demand channels and heterogeneities underlying my results. I hypothesize that the positive RD treatment effects on mortgage originations should be more pronounced in low-income areas.

Income effects. I collect census tract level information from FFIEC Census to find out which neighborhoods are in the lower end of the income distribution. Specifically, I define poor neighborhoods to have an median family income below 80% of the median family income of the respective Metropolitan Statistical Area. Rich neighborhoods are above 80%. Table 6 shows the effects of black political leadership on the share of mortgages going to black borrowers relative to overall mortgage origination in low versus high neighborhoods based on the preferred specification as in column (3) and (6) of table 5. Column 1 presents the effects on mortgages for applicants that received loans in low-income census tracts. In contrast, column 2 shows the effects on mortgages for high-income census tract sub-sample. While political black victories increase mortgage origination to black borrowers in both income groups, only low-income census tracts experience a statistically significant increase. Further, the economic significance of the

low-income effect is more than twice as large as the high-income effect.[26] Due to sample splits, each effect should reported relative to the mean of the control group. An increase of mortgage origination by 4.8 p.p. in low-income neighborhoods corresponds to an economic effect of 1.3% and the effect for high-income neighborhoods breaks down to 0.5%.

Bank type heterogeneity. Taking into account the literature on political economy in banking (Dinç, 2005; Englmaier and Stowasser, 2017), one would expect more pronounced effects of politicians on banks whose business model are more locally oriented. It should be rather the local community banks who are closer the local mayor to affect mortgage access. After all, why would the headquarter of Bank of America in Charlotte (North Carolina) care about a local political leader in the middle of nowhere and adjust bank lending policies locally. On the other side, if different bank types are differentially affected by fair lending regulations, one might expect effects for banks where the regulatory constraints are de-jure more binding. To investigate effect heterogeneity across different bank types, I exploit the HMDA lender file by Robert Avery that identifies commercial banks, thrifts, credit unions and non-depository institutions (hereafter shadow banks). Columns 3 to 6 of Table 6 show the effects of black political leadership on mortgage origination by different bank types. While thrifts, credit unions and shadow banks exhibit negative credit responses, only credit unions contract mortgages in a statistical significant way. In contrast, commercial banks increase the share of mortgages to black household relative to total lending by almost 2 percentage points. A possible explanation for these results might lie in regulatory constraints. While commercial banks, thrifts and credit unions are all federally insured lending institutions, only the first two are subject to the Community Reinvestment Act.

– Insert Table 6 here –

Bank lending standards. In order to find out whether the effects stem from a relaxation of a lending constraint on the credit supply side, I check whether lending standards are affected by black political leadership. Table 7 investigates effects of black political leadership on bank lending standards defined as the ratio of rejected applicant income to the loan volume being rejected.[27] Column 1 shows that overall lending standards are getting stricter after black mayors take office. Interestingly, the largest group of banks, commercial banks, are relaxing their lending

[26] Both coefficients are statistically different from each other. P-values from SUR tests of coefficient equality between these two estimates indicate a statistically significant difference.

[27] See details in the data section.

standards while all other bank types tighten them. Also here one might expect a role for the Community Reinvestment Act to explain this result, because only commercial banks and thrifts are subject to the lending regulation and the others not. Section 4.3 will shed light on this.

– Insert Table 7 here –

4.3 The Community Reinvestment Act

This section investigates the mechanism behind the positive effects on mortgage origination. I hypothesize that local politicians exert leverage on banks by relaxing lending constraints towards African-American households via a federal law on fair credit access.

Institutional Background. The Community Reinvestment Act (CRA) was passed by Congress in 1977 in order to encourage lending institutions to extend credit to low-and moderate-income (LMI) borrowers.[28] One rationale behind such government intervention is that banks lack the incentives to gather more information on low-income and minority neighborhoods because the information and potential profits produced via an improved screening process cannot be kept private: potential increasing appraisal values of homes are public knowledge and competitor banks could benefit (Bhutta, 2011). The CRA stipulates that banks are examined periodically to find out whether they are meeting the credit needs of the communities in which they operate. Specifically, four federal agencies[29] assess whether depository institutions serve the credit needs of LMI neighborhoods and LMI population within their assessment area.[30] Although the CRA does not impose hard sanctions for non-compliance with the law, banks have two main incentives not to fail CRA-examinations (Ding et al., 2018). First, banks' CRA performance can be an important criterion for the federal regulator to evaluate the same bank's application for a merger or acquisition, expansion of branch network or other business plans. Second, the availability of HMDA data enables community activists and public interest groups to monitor bank lending behavior in LMI neighborhoods.

[28] Low-income areas are defined as census tracts with a median family income of less than 50% of the median income of the surrounding Metropolitan Statistical Area. Moderate-income areas are census tracts with a ratio between 50% and 79.9%.

[29] The Federal Reserve, the Office of the Comptroller of the Currency (OCC), the Federal Deposit Insurance Corporation (FDIC), and the Bureau of Consumer Protection.

[30] Assessment area is defined as geographic area in which lending institutions have their main office, branch and deposit-taking ATMs.

Although there is no literature on how local politicians interact with the CRA, there is recent anecdotal evidence on the importance and meaning of this federal law for city leaders. During the COVID-19 pandemic, the Office of the Comptroller of the Currency (OCC) issued a proposal to reform the CRA without the support of the two other banking regulators. Some observers claim that the new rules weaken the CRA to the detriment of low-income communities and communities of color. Lori E. Lightfoot, the first female African-American mayor of Chicago, explained her concern about the future of this civil rights law:

> "While Chicago is battling against a historic threat to our health and economy, the Trump Administration is busy attempting to gut laws meant to drive resources to lower-income communities - the very families and small businesses that need our help the most," [...] "It is another example of this administration's misplaced priorities. This great city, whose activists birthed the movement against redlining, will continue to fight so that banks meet the needs of all our neighborhoods, not just the wealthy ones."

Further, under command of Ron Nirenberg, mayor of San Antonio, a coalition of 70 mayors wrote a letter to Jerome H. Powell on November 2018:

> "We request that you engage with the mayors of America to have an open conversation about how to improve the Community Reinvestment Act. The deep scars of neighborhood segregation and housing discrimination are still visible today, and we invite you to come from Washington D.C. to our cities and learn about our challenges."

While this anecdotal evidence does not provide a precise understanding of how local politicians use the CRA as leverage to influence bank lending behavior, it nevertheless shows that mayors value the role of the Community Reinvestment Act in helping to ensure more equitable credit access and invest in affordable housing. A possible channel could work through the contact between politicians and CRA examiners. The Consumer Compliance Examination Manual describes the review process of CRA examiners. A big part of their job is to conduct interviews with local community, civic, or government leaders in order to understand public perceptions about how well local institutions are responding to the community's credit needs.[31]

[31] On page 2(6/07) it states: "An examiner can use information obtained from these interviews to balance his or her understanding of the institution's performance context. Community contact interviews normally take the form of personal meetings, but telephone conversations or larger group meetings may also be appropriate."

Empirical Implementation. To investigate whether African-American mayors utilize the Community Reinvestment Act to improve the access to mortgages for their constituents, I apply a double-layered regression discontinuity design and create additional treatment and control groups to minimize the possibility of confounding factors. Intuitively, think of an interaction model where two shocks, the electoral shock and a regulatory shock, happen at the same time and significantly affect economic outcomes in one sub-sample but not in the other. More specific, I define the set of cities where black candidates barely won as treatment group cities and the set of cities where black candidates barely lost as control group cities.[32] Within each set, I define additional treatment and control group census tracts that are either eligible for CRA or not. I follow Bhutta (2011) and define the assignment variable as a share of census tract median family income to MSA median family income. Census tracts below 80% of MSA median family income are in the treatment group since they are eligible for the Community Reinvestment Act (CRA) and census tracts above are not eligible for the CRA. In essence, this identification strategy compares mortgage outcomes in census tracts that are just below and above CRA-eligibility cutoff in black-governed cities. Such a strategy ensures that census tract characteristics converge at the cutoff in expectation and are thus comparable. In a final step I compare the resulting evidence with effects in cities where white candidates barely won. Figure 4 graphically summarizes the procedure for the double-layered RD setting.

For each set of cities, the RD treatment effects of the CRA on housing market outcomes are estimated as follows:

$$M_{ctract,c} = \beta_0 + \theta_1 \text{CRA}_{ctract} + P(\beta, \text{CRAmargin}_{ctract}) + \epsilon_{ctract,c}, \tag{3}$$
$$\forall\ \text{CRAmargin}_{ctract} \in (\text{cutoff} - h, \text{cutoff} + h),$$

where $M_{ctract,c}$ represents the average mortgage lending to census tract *ctract* in city c during the post-election period which lasts for the duration of a mayor's first term. The variable CRA_{ctract} is a dummy with value one indicating whether the census tract is CRA eligible and zero if census tract is not CRA-eligible. The running variable $\text{CRAmargin}_{ctract}$ is the CRA-eligibility margin defined as the percentage of census tract median family income to MSA median family income. The cutoff for distinguishing treatment from control groups is defined at 80%. It means that census tracts with median family income (MFI) less than 80 percent of the metropolitan

[32] Which cities enter each group is determined by the bandwidth algorithm that was applied to the baseline specification.

statistical area (MSA) MFI are CRA eligible. For the sake of clarity, I invert and center the running variable around zero such that census tracts with a CRA eligibility margin greater than zero belong to the treatment group affected by the regulation. Conversely, census tracts that are not affected by the CRA regulation have a CRA eligibility margin smaller than zero. P stands for an n-order polynomial in the vote share to control for different functional forms (linear, quadratic and cubic). $\epsilon_{ctract,t}$ is an idiosyncratic error. Standard errors are robust and clustered at the city level.

Validity. Figure 6 presents the manipulation/validity test for the CRA RD analysis. The panels on the left illustrate the set of cities where black candidates won and the panels on the right side depict the set of cities where white candidates won. Note that the number of cities for each set is determined by optimal bandwidth from the previous section. The unit of observation is a census tract. As expected, neither set of cities displays a discontinuity of the CRA eligibility margin around the cutoff suggesting that self-selection or manipulation of a census tract into treatment is not happening.

Results. Table 8 presents the results for mortgage acceptance rates. The first three columns show RD treatment effects for cities where black candidates barely won and the remaining three columns show RD estimates for close winner cities. As in the baseline scenario, columns 3 and 6 depict the preferred specification. For close black winner cities, the CRA has a positive and statistically significant impact on mortgage acceptance rates by 2.6 percentage points in census tracts that are barely eligible for regulatory credit access compared to census tracts that are not CRA-eligible. The CRA however has no effect on mortgage access in close white winner cities.

Table 9 presents the results for lending standards. The first three columns show RD treatment effects for cities where black candidates barely won and the remaining three columns show RD estimates for close winner cities. As in the baseline scenario, columns 3 and 6 depict the preferred specification. As expected, for close black winner cities the CRA decreases bank lending standards by 3.7 percentage points in census tracts that are barely eligible for the credit stimulation program compared to census tracts that are not CRA-eligible.[33] The effect of the CRA on lending standards close white winner cities is statistically not significant.

[33]The estimated mean for the control group is 4.08.

Next I conduct a placebo test by introducing an additional layer of treatment and control groups such that the CRA effect can vary for banks for which the CRA is binding versus banks where CRA is not binding.[34] So for each treatment group, i.e. CRA-eligible census tract, we have a sub-treatment units (CRA banks) and sub-control units (non-CRA banks). Figure 4 illustrates that logic. Table 10 strengthen the previous results by showing that lending standard decrease only for banks subject to the Community Investment Act while credit unions and independent mortgage companies do not show a statistically significant effect on credit standards. Above all, neither CRA banks nor non-CRA banks show any statistically significant effects on lending standards in white winner cities.

These results suggest that black mayors *remind* the banks to recognize the "affirmative obligation to help meet the credit needs of the local communities in which they are chartered" as officially stipulated in the act. Intuitively, if hard political power lacks a legal enforcement mechanism, soft political power at the local level can be complementary monitoring/enforcement tool.

4.4 Discussion of Results

External validity. The empirical findings in this paper are not only based on the selection of interracial elections but are also derived from the focus on close elections. These methodological constraints lead to local treatment effects and thereby reducing the external validity of the results. Table 1 indeed shows that interracial elections take predominantly take place in the South with a larger share of black population, lower incomes and house values. While these cities provide limited evidence for wealthier communities, black political representation is not only relevant but also has the highest marginal value on exactly the cities under investigation.

Political party. One confounding factor is party affiliation since candidates' race is strongly correlated with their party affiliation. The majority of black mayors is affiliated with the Democratic party. I collected party membership information of mayors and runner-up candidates and included a democrat party dummy variable as covariate for the baseline specification.[35] The

[34] As discussed before, the CRA applies only to commercial banks and thrifts but not for credit unions or independent mortgage companies.

[35] I was able to collect information on party affiliation for 322 elections. In 216 elections, the runnerup candidate or the mayor are affiliated either with the Democrats or the Republicans. The rest are elections where at least one candidate is either independent, member of the Green party or explicitly not party affiliated. Out of the 216 elections, 89% of both African-American mayors and runner-up candidates are affiliated with the Democratic party

results are unchanged after controlling for partisanship. The first three columns of table 12 show that Democratic party affiliation does not alter the baseline findings. Note that the amount of observations is smaller than in Table 5 because of missing information on partisanship for some candidates. In a further validity check, I disentangle the race from the partisan effect by splitting the sample into two sub-samples: elections where both white and black candidates are from the same party (Democrat vs. Democrat, Republican vs. Republican), and elections where both candidates coming from different parties (Democratic vs. Republican). While the last three columns of table 12 reveal that the RD treatment effect on mortgage origination is positive for elections involving candidates from different parties, the effect for the same party sub-sample is also positive and significant. Therefore, I conclude that the race effect is not contaminated by the partisan effect.

Further, I exploit 3,500 elections between Democratic and Republican mayoral candidates to rule out that positive RD treatment effects on loan origination for black applicants are driven by party affiliation. Unreported results (available upon request) document no significant effects of party affiliation on mortgage outcomes, irrespective of the bandwidth choice, polynomial order of the assignment variable, sample period or control variables added.

– Insert Table 12 here –

Demand versus supply. Finding out whether the effects of political leadership on credit origination is driven by demand or supply side factors is important from a policy perspective. Since every bank is lending to multiple cities at the same time, in the future I plan to disentangle supply from demand factors via an augmented RD setting by incorporating the Khwaja and Mian (2008) fixed-effects estimator. As further robustness check, I plan to look at the ratio of originated mortgages that are insured by the Federal Housing Agency (FHA) since the supply side of lending carries no credit risk with these mortgages.

If banks are lending more to black applicants because of improving borrowing capacities, then the baseline findings might be driven by credit demand factors. Suppose that the new mayor in town enacts policies that differentially improves the labor market condition of some constituents, improving income conditions and thereby increasing both credit demand and solvency of the borrower. In order to investigate this channel, I conduct an event analysis to see whether the income situation of black mortgage applicants improves after a black mayor won an election by a

and 11% with the Republicans. 49% of both white mayors and runnerups are Democrats and 51% are affiliated with the GOP. In 41% of elections, the two top candidates come from the same party,

narrow margin. In contrast to the RDD setting before, the event analysis exploits time-series variation before and after the treatment event focusing only on the sub-sample of close black election winner cities. The observation window of the dependent variable black loan applicant income is restricted between $t-1$ and $t+4$ whereas the election year, t, serves as reference period. I estimate the following specification:

$$Y_{ctract,t} = \sum_{-1}^{4} \beta_j d_{c,t-j} + \mu_{ctract} + \theta_t + \epsilon_{ctract,t},$$

where $d_{ct} = 1[e_c = 1]$ is the event indicator that takes the value one in the election year, e_c and zero otherwise. Census tract fixed effects are depicted by μ_{ctract} and year fixed effects by θ_t. The coefficient β_j is the dynamic treatment effect j years after or before the election.

Figure 8 shows the dynamic effects of electing an African-American leader on reported income of black loan applicants. The event study estimates do not show a statistically significant effect on applicant income suggesting that relative to pre-election periods, there is no change in credit demand-side factors such as borrowing capacity or solvency effects.

Another plausible demand-side effect comes from the pool of black applicants that were discouraged to apply for a mortgage in the past and now are encouraged to apply because they see their acceptance chances higher. As a consequence one should see sorting of black applicants around the cutoff with black applications relative to total applications rising in census tracts that are eligible for CRA relative to those census tracts in CRA non-eligible tracts. To investigate this channel, I go back to the geographical RDD and test for the effects on application activity. Table 11 shows the effect of the CRA on application differentials. All specifications show no effect on the applications of black households relative to total applications implying that minority households are not encouraged to apply.

5 Conclusion

This paper identifies effects of black political leadership on mortgage access of African-American households. I implement a regression discontinuity design to investigate interracial elections in 129 US cities between 1990 and 2014. The first finding suggests that black mayors lead to higher home-purchase mortgage lending to black households. This finding is driven by lending activity in low-income areas. Second, although overall lending standards marginally increase I find substantial heterogeneity across bank types. Lenders subject to the Community Investment Act not only decrease their credit standards but also originate relatively more mortgages to minorities than other bank types where regulatory credit access laws are not binding. Third, the effects on mortgage lending are driven by the Community Reinvestment Act. The CRA causally increases mortgage access and decreases lending standards in cities where black mayors barely won but not in cities where black candidates barely lost the mayoral race.

The main implication of the paper is that a shift in political power on the local level can affect the enforcement of federal financial regulation in terms of fair lending practices and ultimately affect the availability of housing credit to minorities. On the other hand, increasing loans to low-income neighborhoods might have important financial stability implications since financial shocks have positive differential impact on default rates of minority households (Bayer et al., 2016).

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Tables and Figures

Table 1: Sample representativeness.

	Cities		
	All	Election	Interracial Election
	(1)	(2)	(3)
Population	61,262	128,911	338,956
% White	76	71	52
% Black	11	15	34
% Homeownership	62	56	47
% West	24	23	13
% South	36	24	43
% Midwest	19	27	26
% Northeast	20	26	19
Median Family Income	54,306	51,822	43,782
Median House value	144,988	137,192	115,856
% Poverty Share	11	13	18
Nr Cities	3,965	914	129

Note: This table shows mean city characteristics for different city categories. Column 1 depicts US cities with more than 25,000 people as of year 2000. Column 2 highlights cities where I was able to gather and complement election information necessary for the RD design. The last column presents cities that have interracial elections between 1990 and 2014 that enter the baseline regression.

Table 2: Summary statistics - Electoral RDD

	Obs.	Mean	S.D.
(A) Outcome variables			
Log(accepted loans)	105,180	2.03	1.56
Mortg. (black) / Total mortg.	105,180	0.21	0.25
Mortg. (black)/Total mortg. (Low income ctracts)	57,389	0.28	0.27
Mortg. (black)/Total mortg. (High income ctracts)	47,791	0.14	0.20
Mortg. (black)/ Total mortg. (commercial banks)	70,293	0.30	0.28
Mortg. (black)/Total mortg. (thrifts)	48,066	0.35	0.31
Mortg. (black)/Total mortg. (credit unions)	12,474	0.58	0.38
Mortg. (black)/Total mortg. (shadow banks)	65,533	0.35	0.29
Lending standards	92,780	0.80	1.46
Lending std. (banks)	80,572	0.82	1.58
Lending std. (thrifts)	56,159	0.79	1.31
Lending std. (credit unions)	11,185	0.84	1.86
Lending std. (shadow banks)	59,134	0.71	1.70
(B) Explanatory variable			
Black win margin	331	0.01	0.40
(C) Covariates			
Log population	105,180	8.03	0.65
Minority population %	105,180	54.81	35.03
Log family income	105,180	10.62	0.22
Population 65+ %	105,180	12.26	6.71
Mayor Democrat Share	215	0.84	0.37

Note: This table presents the summary statistics of the census-tract and city-level data for the sample of the baseline scenario. I collapse HMDA loan-level data across banks to get mortgage outcome variables in panel (A) at the census-tract-year level. Loan nr and loan vol correspond to the number or volume of accepted mortgage applications of home purchase loans. Bank types are defined as in the HMDA lender file kindly provided by Robert Avery. Panel (B) depicts the summary statistics of the assignment variable which is measured at the city level. The black win margin is defined as the difference in the vote share of the black candidate and the vote share of the white competitor. A negative margin indicates an electoral defeat of the black candidate and a positive margin indicates an election victory of the black mayoral candiate. Census-tract level control variables in panel (C) are log of total population, share of minority population, the log of median family income and the share of people over 65.

Table 3: Summary statistics - Geographical RDD

	Obs.	Mean	S.D.
A. Close black winner cities			
1.1 Outcome variables			
Loan acceptance rate	20,248	0.84	0.20
Lending standards	18,898	0.92	6.93
Lending std. (CRA banks)	18,029	0.94	7.10
Lending std. (non-CRA banks)	13,970	0.79	1.42
Application ratio %	20,248	0.27	0.25
1.2 Explanatory variable			
CRA eligibility margin	20,248	-0.02	0.43
1.3 Covariates			
Log population	20,248	8.10	0.58
Minority population %	20,248	53.37	34.72
Log family income	20,248	10.59	0.25
Population 65+ %	20,248	12.77	6.55
B. Close white winner cities			
2.1 Outcome variables			
Loan acceptance rate	18,608	0.83	0.24
Lending standards	16,462	0.77	1.71
Lending std. (CRA banks)	15,244	0.79	1.30
Lending std. (non-CRA banks)	10,780	0.68	2.54
Application ratio %	18,608	0.28	0.26
2.2 Explanatory variable			
CRA eligibility margin	18,608	-0.10	0.45
2.3 Covariates			
Log population	18,608	8.06	0.59
Minority population %	18,608	58.94	34.94
Log family income	18,608	10.61	0.20
Population 65+ %	18,608	12.05	6.40

Note: This table presents the summary statistics for all variables used in the geographic RDD shown separately for the sub-sample of close black election winners (sub-panel A) and close white election winners (sub-panel B). I collapse the HMDA mortgage lending variables in both panels at the census-tract/year level. Loan acceptance rates are defined as the ratio of accepted mortgage applications to total mortgage applications based on home purchase loans. Lending standards are defined as the ratio of the income that rejected mortgage applicants report to declined mortgage volume applied for. CRA banks comprise bank types that are subject to the Community Reinvestment Act: commercial banks and thrift institutions. Non-CRA banks correspond to banks which are not subject to the Community Reinvestment Act: credit unions and independent mortgage lenders. CRA eligibility margin is defined as the percentage of census-tract level median family income to median family income in the surrounding metropolitan statistical area standardized and centered around zero. A negative CRA margin indicates that this census tract has more than 80% of MSA median family income and is not eligible for CRA. Census tracts with a positive CRA margin are eligible for CRA and have a share of MSA-level median family income lower than 80%. Census-tract level control variables are log of total population, share of minority population, the log of median family income and the share of people over 65.

Table 4: Differences in pre-election trends.

	Log(accepted mortgages) in t-1				Change in mortgages between t-2 and t-1		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Black win	-0.046	-0.121	-0.112	-0.041	-0.706	0.282	0.720
	(0.07)	(0.08)	(0.08)	(0.03)	(0.85)	(1.80)	(2.01)
Obs	31,188	31,188	212,274	210,660	17,819	17,819	122,494
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cubic vote share	No	Yes	Yes	Yes	No	Yes	Yes
Sample (-2,4)	No	No	Yes	Yes	No	No	Yes
Election FE	No	No	No	Yes	No	No	No
Bank FE	No	No	No	Yes	No	No	No

Note: Column 1 to 7 reports estimated effects of the black winner dummy variable on pre-election mortgage outcomes. Each entry represents a separate regression for each of the outcome variable. The first four columns depict the mortgage outcome in log-levels one year before the election. Columns 5 to 7 analyze the annual growth rate of accepted mortgage from t-2 to t-1. Columns 3, 4 and 7 uses the pooled observation ITT setting with keeping two years before through four years after the election for each electoral (c,t) combination including high order polynomial of the vote share, year and relative year fixed effects. Column 4 additionally adds election and bank fixed effects. Robust standard errors (in parentheses) are clustered at the city level. Significance levels are *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5: RD effect on mortgage outcomes

	Log(accepted mortgages)			$\frac{Mortgages(black)}{Total\ mortgages}$		
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: Ctract level			
Black win	1.423***	0.819***	0.558***	0.092***	0.083***	0.031***
	(0.043)	(0.074)	(0.066)	(0.006)	(0.012)	(0.008)
Obs	105,180	105,180	105,180	105,180	105,180	105,180
Eff. Obs	105,180	45,524	45,524	105,180	45,863	45,863
Covariates	Yes	No	Yes	Yes	No	Yes
Polynomial order	Cubic	Linear	Linear	Cubic	Linear	Linear
Bandwidth	100.00	0.17	0.17	100.00	0.18	0.18
Mean C-group	1.23	1.65	8.87	2.10	0.17	2.72

Note: This table presents regression discontinuity treatment effects based on local polynomial regressions using the rdrobust command in Stata. The assignment variable is the black vote margin defined as the difference in the vote share of the black candidate and the vote share of the white competitor. The bandwidth is calculated by the mean-squared-error (MSE) bandwidth selector (Calonico et al., 2014). The polynomial order describes the functional form of the assignment variable. The dependent variable is the log of total number or volume of accepted mortgages for the first three columns and the ratio of originated mortgages to black applicants relative to total mortgage origination for the last three columns in a respective census tract pooled in the first term. The estimated mean for the control group, $E[\log(Y(0))|X = \text{cutoff}]$, is 8.87. Standard errors are in parentheses and refer to cluster-robust nearest neighbor variance estimation at the census tract level. The covariates are all measured in the election-year and consist of: log(population), percentage of minority population, the percentage of median MSA family income and the share of persons at age 65+. ***p < .01, **p < .05, *p < .1

Table 6: RD effect on mortgage outcomes by income and bank group

	$\frac{Mortgages(black)}{Total\ mortgages}$					
	Low income Ctracts	High income Ctracts	Commercial Banks	Thrifts	Credit Unions	Shadow Banks
	(1)	(2)	(3)	(4)	(5)	(6)
Black win	0.048***	0.012	0.019**	-0.015	-0.236***	-0.016
	(0.012)	(0.010)	(0.010)	(0.011)	(0.021)	(0.010)
Obs	57,389	47,791	70,293	48,066	12,474	65,533
Eff. Obs	22,322	23,425	31,404	25,122	6,143	27,428
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Polynomial order	Linear	Linear	Linear	Linear	Linear	Linear
Bandwidth	0.18	0.18	0.21	0.29	0.24	0.20
Mean C-group	3.65	2.19	3.53	2.87	7.21	1.75

Note: This table presents regression discontinuity treatment effects based on local polynomial regressions using the rdrobust command in Stata. The assignment variable is the black vote margin defined as the difference in the vote share of the black candidate and the vote share of the white competitor. The bandwidth is calculated by the mean-squared-error (MSE) bandwidth selector (Calonico et al., 2014). The polynomial order describes the functional form of the assignment variable. The dependent variable is the ratio of originated mortgages to black applicants relative to total mortgage origination in a respective census tract pooled in the first term by income and bank type. Poor census tracts are defined as the median family income being below 80% of family income in the corresponding Metropolitan Statistical Area. Bank type are defined as in the HMDA lender file kindly provided by Robert Avery. Standard errors are in parentheses and refer to cluster-robust nearest neighbor variance estimation at the census tract level. The covariates are all measured in the election-year and consist of: log(population), percentage of minority population, the percentage of median MSA family income and the share of persons at age 65+. ***p $<$ .01, **p $<$ .05, *p $<$ .1

Table 7: RD effect on lending standards

	Lending standards ($\frac{Income^{reject}}{mortgage\ volume^{reject}}$)				
	All	Commercial Banks	Thrifts	Credit Unions	Shadow Banks
	(1)	(2)	(3)	(4)	(5)
Black win	0.4514*	-0.0879**	0.5594	0.4823***	0.2046***
	(0.2743)	(0.0378)	(0.5176)	(0.1073)	(0.0704)
Obs	93,119	80,764	56,239	11,220	59,218
Eff. Obs	49,729	38,025	24,756	5,028	25,957
Covariates	Yes	Yes	Yes	Yes	Yes
Polynomial order	Linear	Linear	Linear	Linear	Linear
Bandwidth	0.27	0.23	0.23	0.18	0.21
Mean C-group	5.49	7.05	5.08	5.13	4.00

Note: This table presents regression discontinuity treatment effects based on local polynomial regressions using the rdrobust command in Stata. The assignment variable is the black vote margin defined as the difference in the vote share of the black candidate and the vote share of the white competitor. The bandwidth is calculated by the mean-squared-error (MSE) bandwidth selector (Calonico et al., 2014). The polynomial order describes the functional form of the assignment variable. The dependent variable is bank lending standard defined as income-to-loan ratio based solely on rejected mortgage applications. The estimated mean for the control group, $E[\log(Y(0))|X = \text{cutoff}]$, is 5.49. Standard errors are in parentheses and refer to cluster-robust nearest neighbor variance estimation at the census tract level. The covariates are all measured in the election-year and consist of: log(population), percentage of minority population, the percentage of median MSA family income and the share of persons at age 65+. ***p < .01, **p < .05, *p < .1

Table 8: RD effect on mortgage acceptance rates by CRA eligibility.

	Mortgage acceptance rates					
	Close black winner cities			Close white winner cities		
	(1)	(2)	(3)	(4)	(5)	(6)
CRA	0.022***	0.024**	0.026***	0.003	0.014	0.010
	(0.008)	(0.010)	(0.009)	(0.011)	(0.012)	(0.012)
Obs	20,248	20,248	20,248	18,608	18,608	18,608
Eff. Obs	19,608	5,397	5,421	17,989	4,545	4,615
Covariates	Yes	No	Yes	Yes	No	Yes
Polynomial order	Cubic	Linear	Linear	Cubic	Linear	Linear
Bandwidth	1.00	0.13	0.13	1.00	0.12	0.13

Note: This table presents regression discontinuity treatment effects based on local polynomial regressions using the rdrobust command in Stata. The assignment variable is the share of census tract median family income to MSA median family income. Census tracts below 80% of MSA median family income are in the treatment group since they are eligible for the Community Reinvestment Act (CRA) and census tracts above are not eligible for the CRA. For the sake of exposition, the assignment variable is centered around zero and inverted so that values above zero indicate CRA-eligibility and values below zero reflect non-CRA-eligibility. The bandwidth is calculated by the mean-squared-error (MSE) bandwidth selector (Calonico et al., 2014). The polynomial order describes the functional form of the assignment variable. The dependent variable is mortgage acceptance rates defined as the ratio of accepted number of mortgage applications to total number of mortgage applications (sum of accepted plus denied mortgages) in a respective census tract pooled in the first term. Standard errors are in parentheses and refer to cluster-robust nearest neighbor variance estimation at the census tract level. The covariates are all measured in the election-year and consist of: log(population), percentage of minority population, the percentage of median MSA family income and the share of persons at age 65+. ***p $<$ .01, **p $<$ .05, *p $<$ .1

Table 9: RD effect on mortgage lending standards by CRA eligibility.

	Lending standards (Income/mortgage volume)					
	Close black winner cities			Close white winner cities		
	(1)	(2)	(3)	(4)	(5)	(6)
CRA	0.019	-0.140***	-0.142***	0.000	-0.013	-0.034
	(0.089)	(0.051)	(0.050)	(0.048)	(0.051)	(0.048)
Obs	23,472	23,472	23,472	26,168	26,168	26,168
Eff. Obs	22,588	3,670	3,755	24,823	9,544	9,964
Covariates	Yes	No	Yes	Yes	No	Yes
Polynomial order	Cubic	Linear	Linear	Cubic	Linear	Linear
Bandwidth	1.00	0.08	0.08	1.00	0.19	0.19

Note: This table presents regression discontinuity treatment effects based on local polynomial regressions using the rdrobust command in Stata. The assignment variable is the share of census tract median family income to MSA median family income. Census tracts below 80% of MSA median family income are in the treatment group since they are eligible for the Community Reinvestment Act (CRA) and census tracts above are not eligible for the CRA. For the sake of exposition, the assignment variable is centered around zero and inverted so that values above zero indicate CRA-eligibility and values below zero reflect non-CRA-eligibility. The bandwidth is calculated by the mean-squared-error (MSE) bandwidth selector (Calonico et al., 2014). The polynomial order describes the functional form of the assignment variable. The dependent variable is bank lending standard defined as income-to-loan ratio based solely on rejected mortgage applications in a respective census tract pooled in the first term. Standard errors are in parentheses and refer to cluster-robust nearest neighbor variance estimation at the census tract level. The covariates are all measured in the election-year and consist of: log(population), percentage of minority population, the percentage of median MSA family income and the share of persons at age 65+. ***p $<$ .01, **p $<$ .05, *p $<$ .1

Table 10: Placebo test - RD effect on lending standards.

	Lending standards (Income/mortgage volume)			
	Close black winner cities		Close white winner cities	
	non-CRA Banks	CRA Banks	non-CRA Banks	CRA Banks
	(1)	(2)	(3)	(4)
CRA	-0.034	-0.221***	-0.078	-0.004
	(0.062)	(0.073)	(0.062)	(0.063)
Obs	14,396	21,669	12,674	24,309
Eff. Obs	5,379	2,788	5,074	8,678
Covariates	Yes	Yes	Yes	Yes
Polynomial order	Linear	Linear	Linear	Linear
Bandwidth	0.17	0.06	0.20	0.18

Note: This table presents regression discontinuity treatment effects based on local polynomial regressions using the rdrobust command in Stata. The assignment variable is the share of census tract median family income to MSA median family income. Census tracts below 80% of MSA median family income are in the treatment group since they are eligible for the Community Reinvestment Act (CRA) and census tracts above are not eligible for the CRA. For the sake of exposition, the assignment variable is centered around zero and inverted so that values above zero indicate CRA-eligibility and values below zero reflect non-CRA-eligibility. The bandwidth is calculated by the mean-squared-error (MSE) bandwidth selector (Calonico et al., 2014). The polynomial order describes the functional form of the assignment variable. The dependent variable is bank lending standard defined as income-to-loan ratio based solely on rejected mortgage applications in a respective census tract pooled in the first term and disaggregated by banks that are either affected by the CRA regulation (commercial banks and thrift institutions) or not (credit unions and independent mortgage lenders). Standard errors are in parentheses and refer to cluster-robust nearest neighbor variance estimation at the census tract level. The covariates are all measured in the election-year and consist of: log(population), percentage of minority population, the percentage of median MSA family income and the share of persons at age 65+. ***p $<$ .01, **p $<$ .05, *p $<$ .1

Table 11: RD effect on application ratios.

	Application ratios					
	Close black winner cities			Close white winner cities		
	(1)	(2)	(3)	(4)	(5)	(6)
CRA	0.009	0.023	0.002	0.011	0.006	0.017
	(0.011)	(0.017)	(0.011)	(0.013)	(0.013)	(0.013)
Obs	20,110	20,110	20,110	25,795	25,795	25,795
Eff. Obs	19,300	5,659	8,136	24,467	10,718	7,742
Covariates	Yes	No	Yes	Yes	No	Yes
Polynomial order	Cubic	Linear	Linear	Cubic	Linear	Linear
Bandwidth	1.00	0.15	0.21	1.00	0.22	0.16

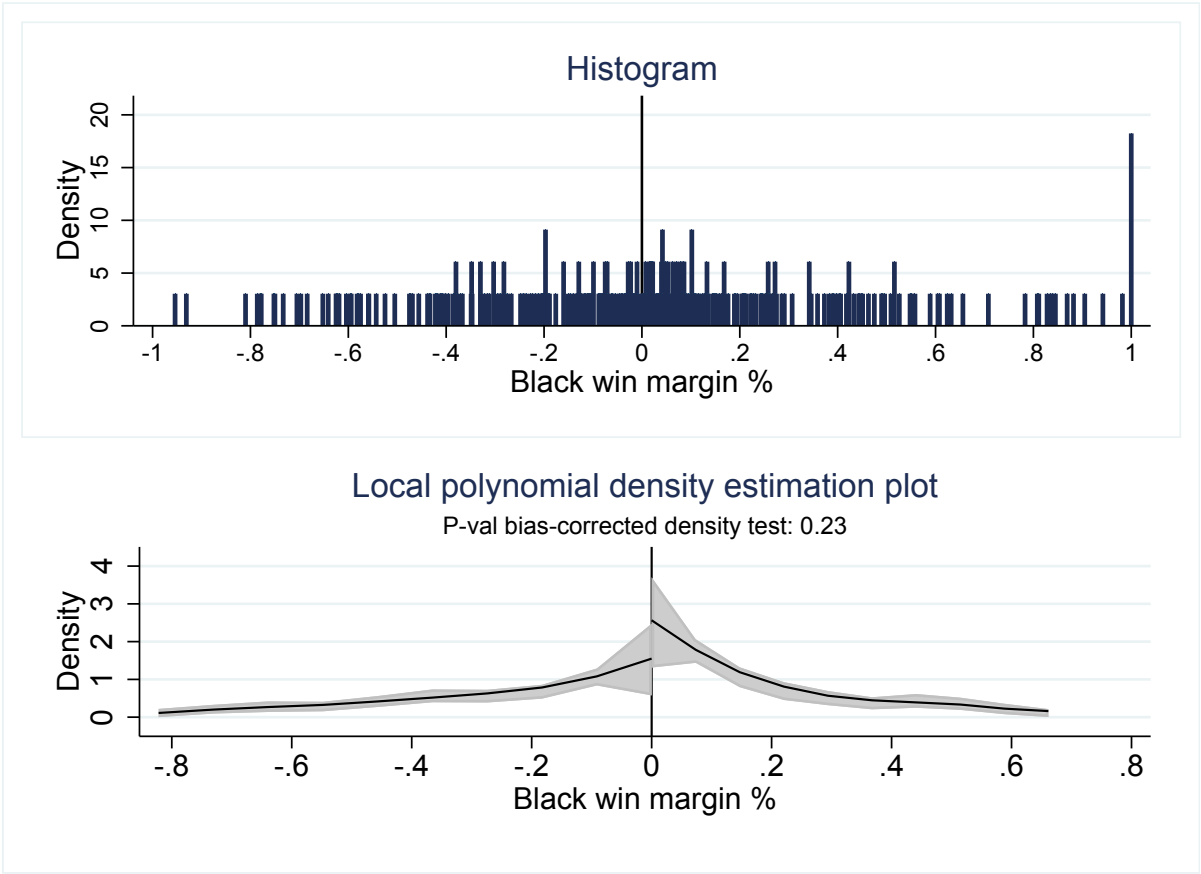
Note: This table presents regression discontinuity treatment effects based on local polynomial regressions using the rdrobust command in Stata. The assignment variable is the share of census tract median family income to MSA median family income. Census tracts below 80% of MSA median family income are in the treatment group since they are eligible for the Community Reinvestment Act (CRA) and census tracts above are not eligible for the CRA. For the sake of exposition, the assignment variable is centered around zero and inverted so that values above zero indicate CRA-eligibility and values below zero reflect non-CRA-eligibility. The bandwidth is calculated by the mean-squared-error (MSE) bandwidth selector (Calonico et al., 2014). The polynomial order describes the functional form of the assignment variable. The dependent variable is mortgage application ratio defined as the sum of applications by African-American households over total applications in a respective census tract pooled in the first term. Standard errors are in parentheses and refer to cluster-robust nearest neighbor variance estimation at the census tract level. The covariates are all measured in the election-year and consist of: log(population), percentage of minority population, the percentage of median MSA family income and the share of persons at age 65+. ***p $<$ .01, **p $<$ .05, *p $<$ .1

Table 12: RD effect on mortgage outcomes - party affiliation

	$\frac{Mortgages(black)}{Total\ mortgages}$				
	Democrat control			Sample split	
				Same party	D vs. R
	(1)	(2)	(3)	(4)	(5)
Black win	0.176***	0.131***	0.096***	0.044**	0.100***
	(0.007)	(0.014)	(0.010)	(0.017)	(0.010)
Obs	80,352	80,352	80,352	38,929	41,423
Eff. Obs	80,352	32,782	32,782	12,816	22,491
Covariates	Yes	No	Yes	Yes	Yes
Democrat control	Yes	No	Yes	Yes	Yes
Polynomial order	Cubic	Linear	Linear	Linear	Linear
Bandwidth	100.00	0.18	0.18	0.16	0.26

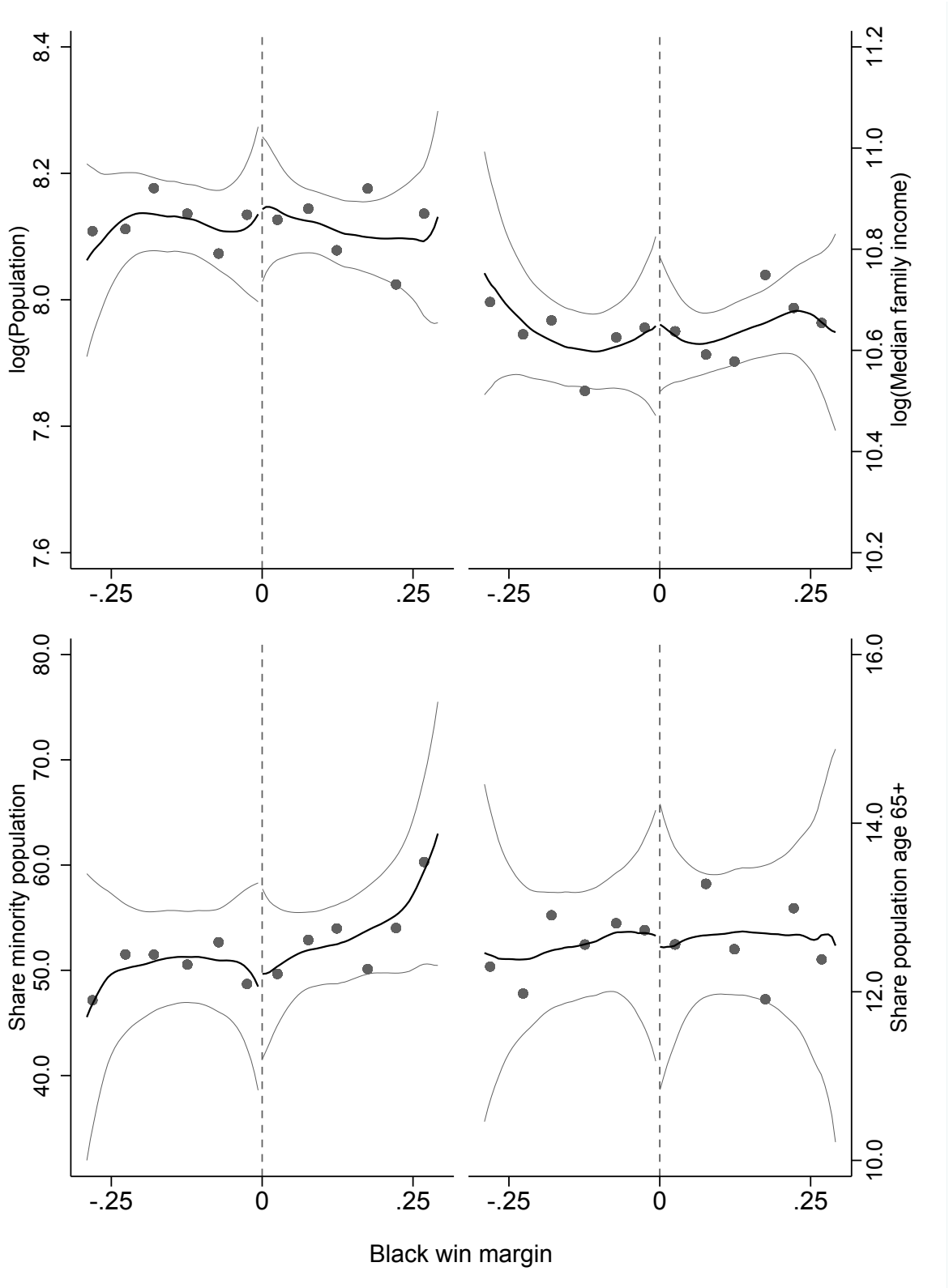
Note: This table presents regression discontinuity treatment effects based on local polynomial regressions using the rdrobust command in Stata. The assignment variable is the black vote margin defined as the difference in the vote share of the black candidate and the vote share of the white competitor. The bandwidth is calculated by the mean-squared-error (MSE) bandwidth selector (Calonico et al., 2014). The polynomial order describes the functional form of the assignment variable. The dependent variable is the ratio of originated mortgages to black applicants relative to total mortgage origination in a respective census tract pooled in the first term. Standard errors are in parentheses and refer to cluster-robust nearest neighbor variance estimation at the census tract level. The covariates are all measured in the election-year and consist of: log(population), percentage of minority population, the percentage of median MSA family income and the share of persons at age 65+. The first three columns additionally include a democrat control variable that is one for Democratic mayors and zero for Republican mayors. Column (4) estimates RD treatment effets of black mayors on mortage outcomes based on a sub-sample where the two candidates share the same party affiliation. The last column is estimated based on a sub-sample where both candidates have an opposite party affiliation. D stands for Democrat and R for Republican. ***p $<$ .01, **p $<$ .05, *p $<$ .1

Figure 1: Validity Test I.



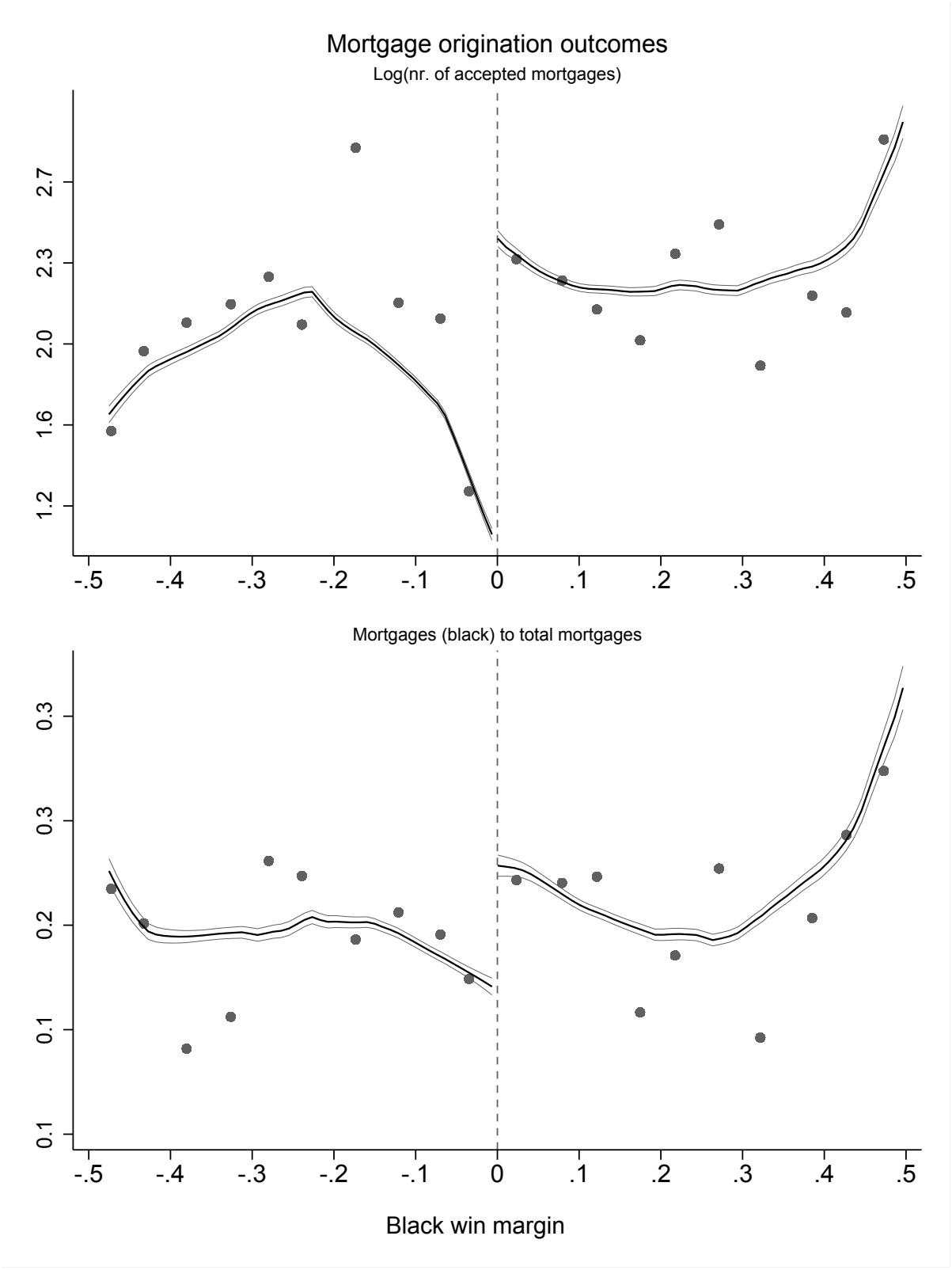
Notes: This graph shows the distribution of the assignment variable for all interracial elections. The assignment variable is the black win margin with the cut-off being at zero. A negative margin indicates that a black candidate lost the mayoral election while positive values represent an election victory. Panel (a) displays the histrogram of the black win margin. Panel (b) reports a local polynomial density plot of the black vote margin with 95% confidence intervals to show whether there is a discontinuity at the winner threshold. Vertical lines in both panels denote the cut-off at zero.

Figure 2: Balanced Covariate Checks.



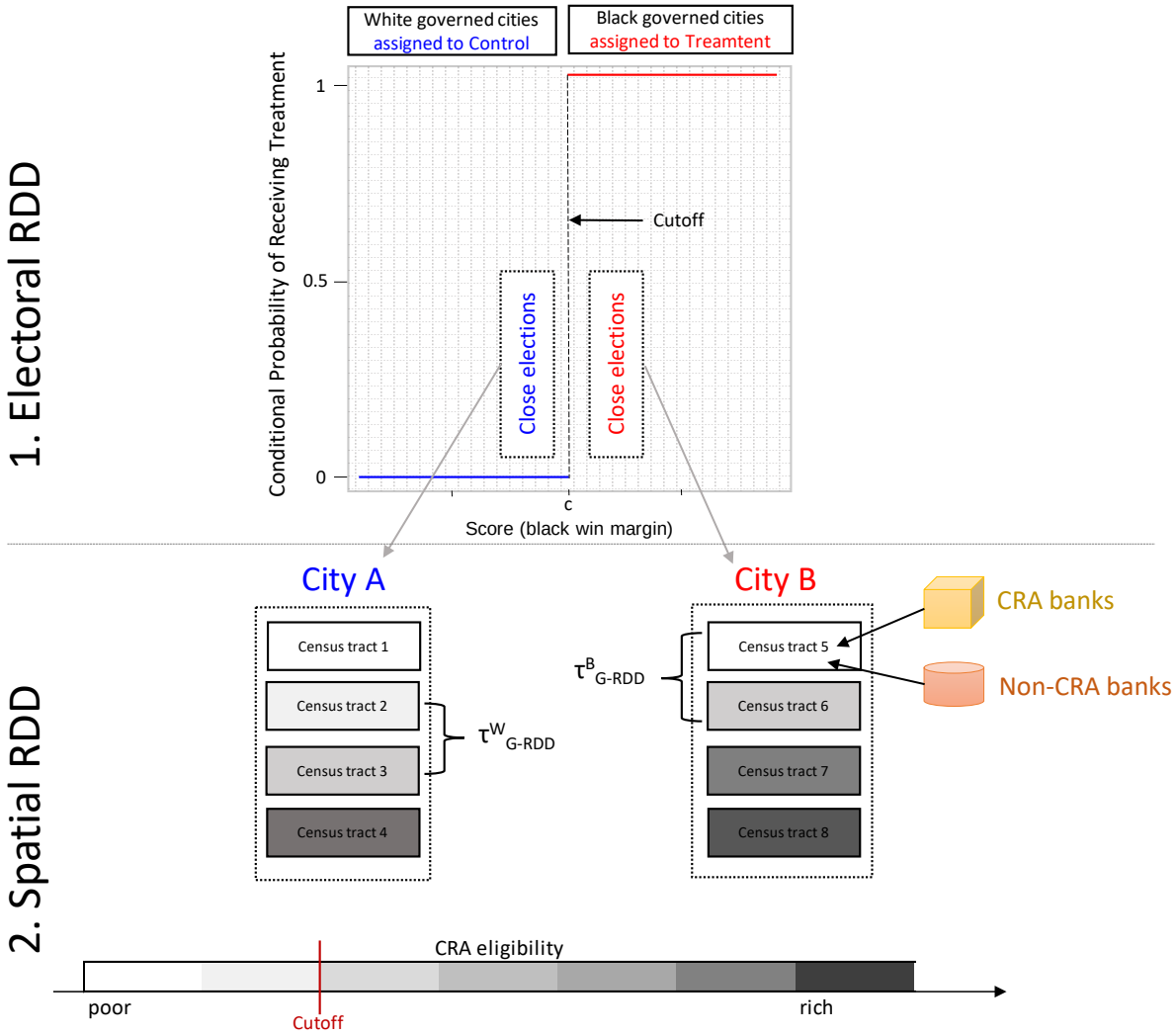
Notes: This graph plots the covariate measures against the black win margin whereby a negative margin indicates an election loss of a black candidate and a positive margin an election victory for the black mayoral candidate. Each of the dots is the average value of the covariate in 8-percent vote margin bins. The graph-panel shows the following covariates: log(population), % of black households, log(median family income), and the share of people with age 65+. The solid black lines are approximations to the unknown regression functions based on a Kernel-weighted local polynomial smoother, fitted separately above and below the cutoff at zero by using the raw data. The shaded area shows 95% confidence intervals.

Figure 3: Regression Discontinuity Plot.



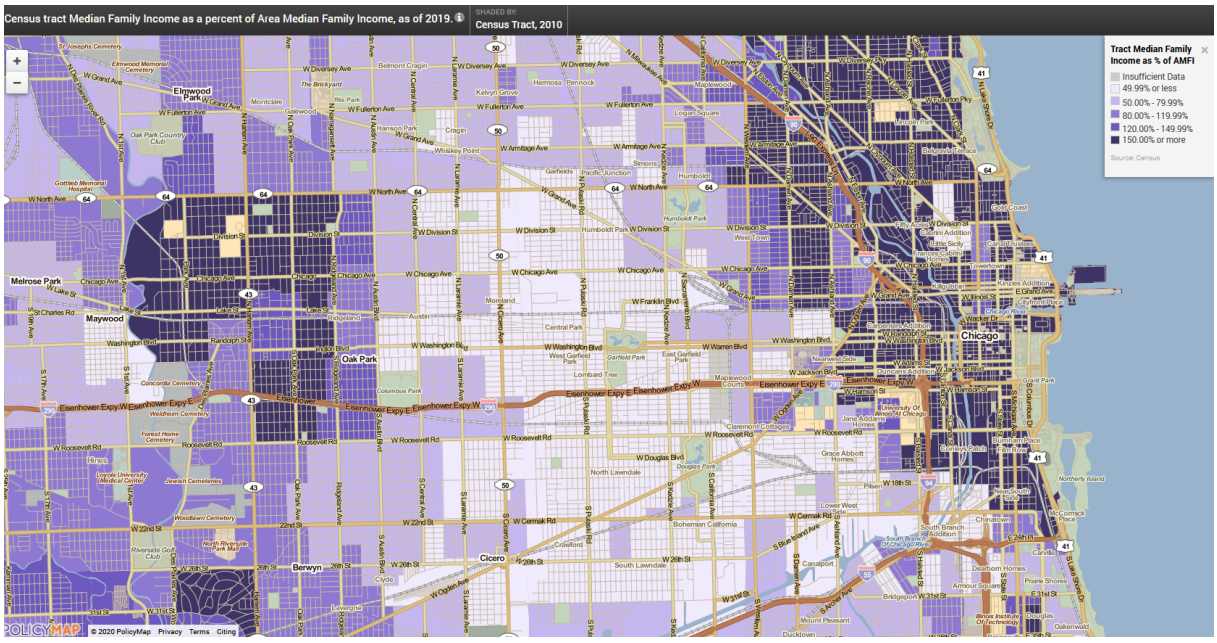
Notes: This RD graph plots mortgage outcome variables against the black vote margin of victory. A negative margin indicates that a black candidate lost the mayoral election while positive values represent an election victory. Each of the dots is the average value of the outcome in 5-percent vote margin bins. The outcome variables are the log number of originated mortgages and the ratio of mortgages originated to black applicants to total originated mortgages during the first mayoral term. The solid black lines are approximations to the unknown regression functions based on a Kernel-weighted local polynomial smoother, fitted separately above and below the cutoff at zero by using the raw data. The shaded area shows 95% confidence intervals.

Figure 4: Double layered RDD - Identification scheme.

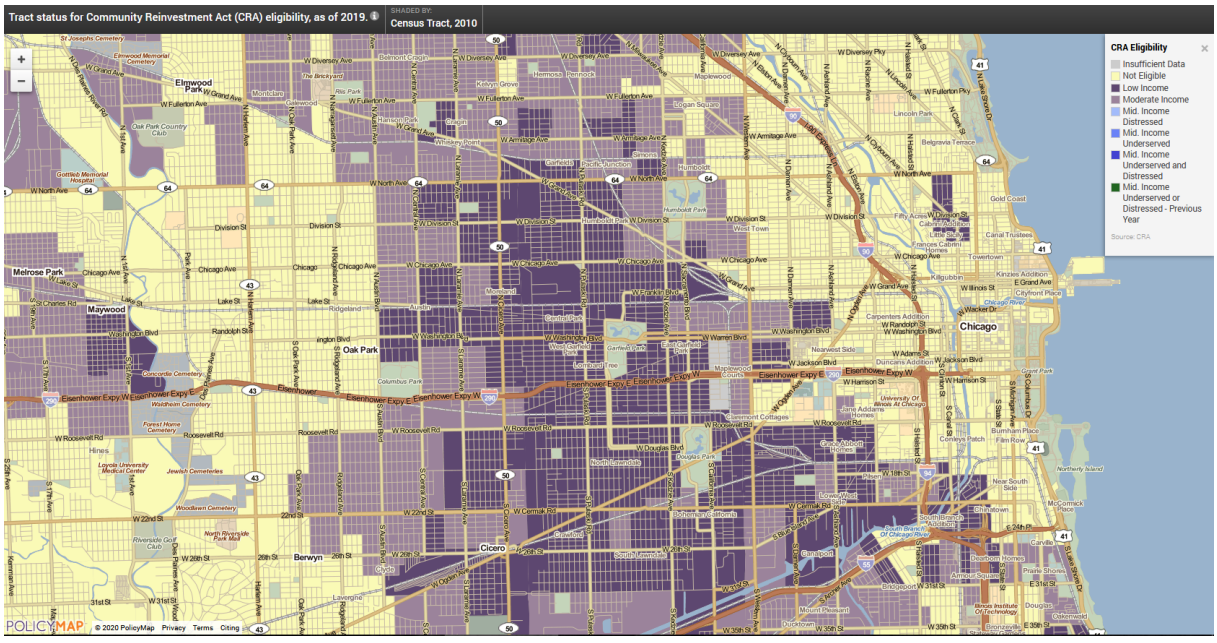


Notes: This graph shows a stylized explanation of the double-layered RD setting. The upper part shows the electoral regression discontinuity design. The bottom part shows the geographic regression discontinuity design.

Figure 5: Chicago - Census Tract Community Reinvestment Act Eligibility.



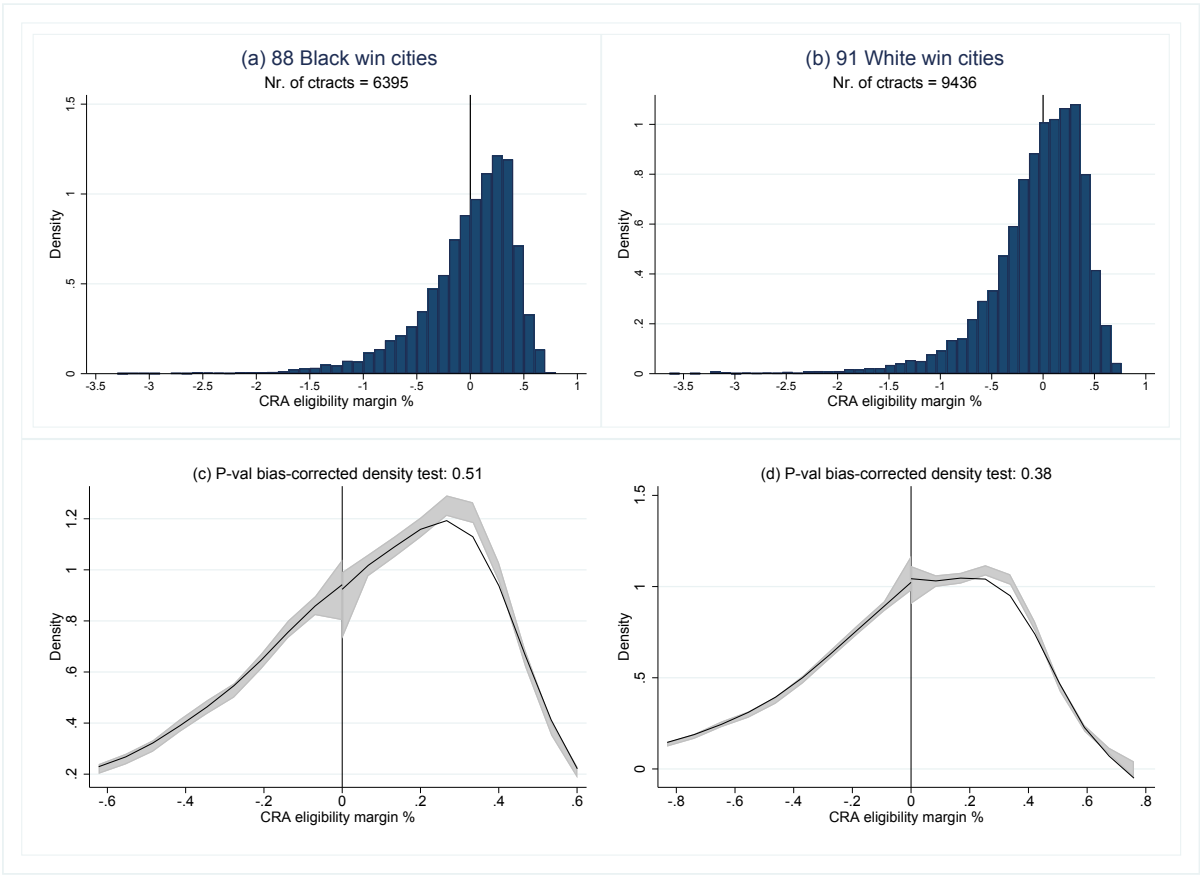
(a) Census Tract Median Family Income



(b) Census Tract CRA Eligibility

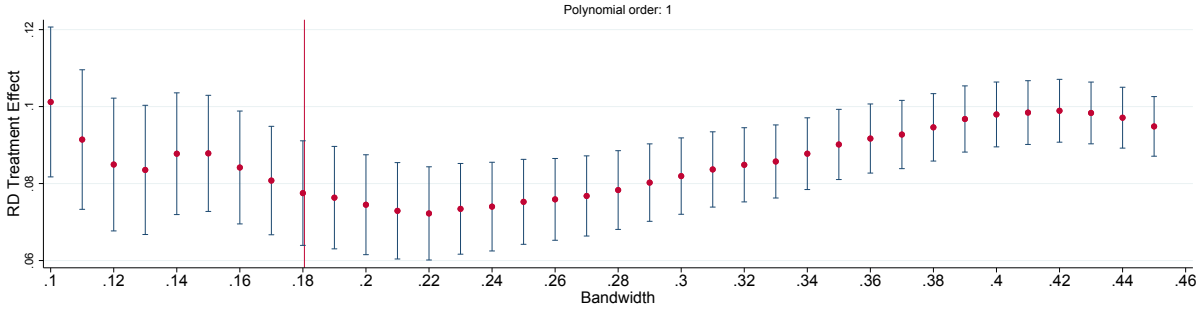
Notes: This graph shows a map extract of Chicago. Subgraph (a) shows Census tract median family income as percent of Metropolitan Statistical Area median family income as of 2019. Subgraph (b) depicts census-tract status of Community Reinvestment Act eligibility as of 2020. Source: www.policymap.com

Figure 6: Validity Test II.

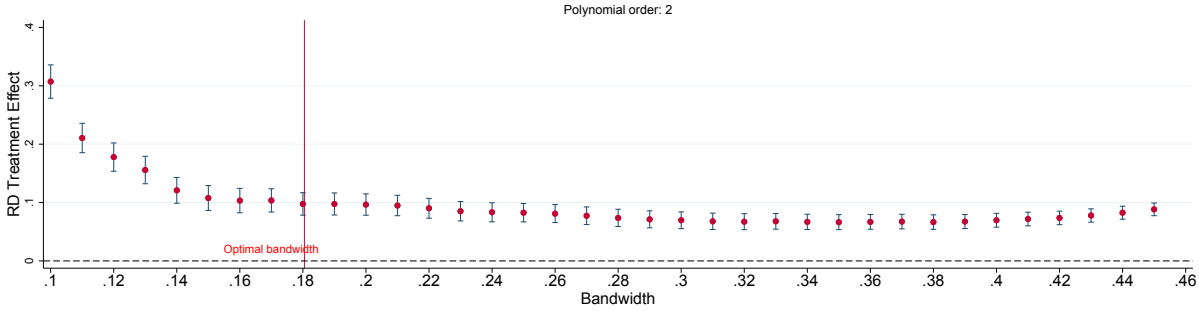


Notes: This graph illustrates the validity of the CRA assignment variable. Panel (a) shows the distribution of the CRA-eligibility margin for the set of cities where black candidates barely won and panel (b) shows the distribution of the CRA-eligibility margin for white-governed cities. A census tract is eligible for CRA compliance if its median family income is less than 80 percent of the metropolitan statistical area (MSA). For the sake of exposition, the assignment variable is centered around zero and inverted so that values above zero indicate CRA-eligibility and values below zero reflect non-CRA-eligibility. Panel (a) displays the histrogram of the CRA-eligibility margin. Panel (b) reports a local polynomial density plot of the CRA-eligibility margin with 95% confidence intervals to show whether there is a discontinuity at the eligibility cutoff. Vertical lines in both panels denote the cut-off at zero.

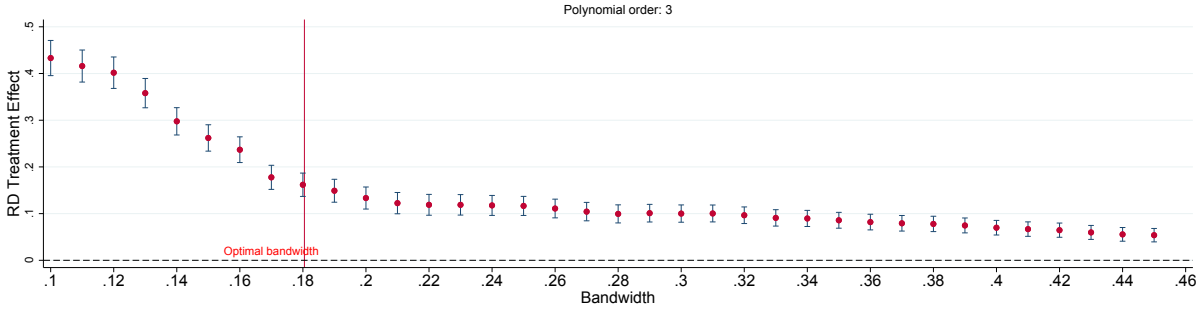
Figure 7: Bandwidth and control function sensitivity.



(a) Linear control function



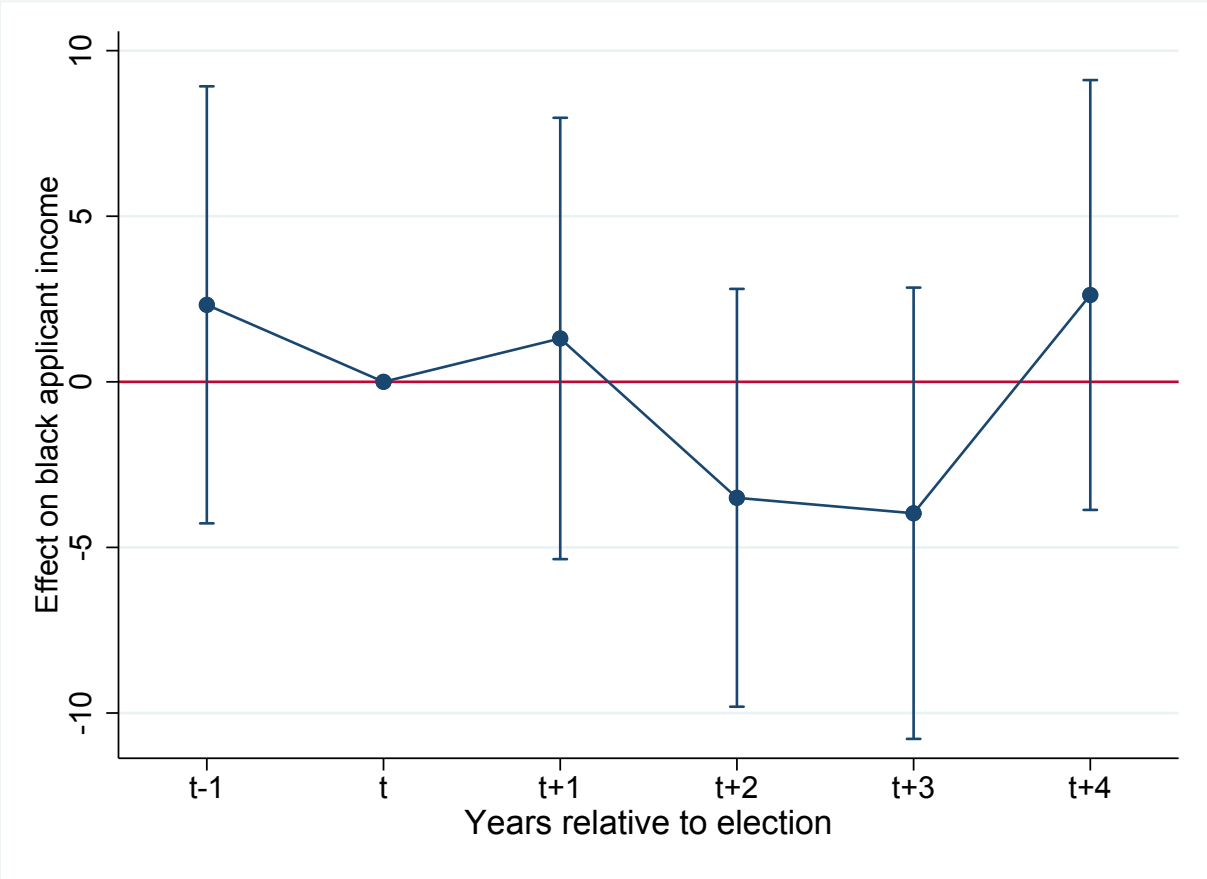
(b) Quadratic control function



(c) Cubic control function

Notes: This graph shows local linear RD point estimates with 95% confidence intervals for several bandwidths on the x-axis based on the outcome variable log of number of mortgages. Each dot is the RD point estimate of the BLACK win dummy equal to one if a black candidate won the mayoral election and zero if the black candidate lost corresponding to column (2) of Table 5. Several versions of the black win margin are depicted in the respective panels. The weighting scheme of observations close to cut-off is a uniform Kernel. The optimal bandwidth h^* is depicted as red vertical line and computed according to Calonico et al. (2014) based on a linear control function.

Figure 8: Close election winner event analysis.



Notes: This graph shows point estimates and 95%-confidence intervals according to the event-analysis specification $Y_{ctract,t} = \sum_{-1}^{4} \beta_j d_{c,t-j} + \mu_{ctract} + \theta_t + \epsilon_{ctract,t}$. It plots the dynamic effect of narrowly electing an African-American mayor on black mortgage applicant income. The bandwidth, 0.17, to select narrow elections is taken from the baseline regression in table 5. This results in 36,042 census-tract-year observations and 89 narrow elections where black candidates won. The model is estimated in levels with census tract and year fixed effects. The effect window is restricted between $[-1, 4]$. Standard errors are clustered by cities.

Online Appendix

This Appendix is for Online Publication and provides further details on the data and the results of the paper “The Great Equalizer? Banking Competition and Black Mortality".

OA1 Figures and Tables

Table OA1: Variable description

Variable name	Description	Source
	Census-tract level variables	
Outcome variables		
Mortgage origination (unscaled)	Number of newly originated mortgages to black applicants. Loans are home purchase loans only and excludes home improvement loans and refinancing loans. The property types are 1-4 family houses, manufacturing houses and multifamily houses. Accepted mortgage loans at the bank-household-year level are aggregated at the census-tract-year level.	HMDA
Mortgage origination (scaled)	Number of newly originated mortgages to black applicants scaled by mortgage origination to black and non-Hispanic white applicants. Numerator and denominator at the bank-applicant-year level are aggregated at the census-tract-year level.	HMDA
Mortgage approval	The number of accepted mortgages is divided by total number of mortgage applications, i.e. accepted plus denied loans.	HMDA
Lending standards	The applicant income of all denied mortgage applications is divided by rejected mortgage volume according to D'Acunto and Rossi (2017).	HMDA
Application ratio	The share of total applications from black households to total applications from both white and non-Hispanic white households. Total applications are the sum of both accepted and rejected mortgage applications. Numerator and denominator at the bank-applicant-year level are aggregated at the census-tract-year level.	HMDA
Applicant income	The income of both accepted and rejected mortgage applications from black applicants.	HMDA
CRA eligibility	The CRA eligibility threshold is defined as the percentage of census tract median family income to median family income at the Metropolitan Statistical Area level. The income data are based on decennial Census data.	FFIEC
CRA treatment	The CRA treatment dummy variable indicates in which census tract the Community Reinvestment Act is binding and where not. The CRA law applies to every census tract with median family income less than 80 percent of the metropolitan statistical area (MSA) median family income. For these census tracts the indicator takes on the value one and zero for census tracts with more than 80% of MSA median family income.	FFIEC
Covariates		
Population	The total population count in a given census tract based on decennial census data and interpolated between census years.	FFIEC
Family income	Decennial median family income in a given census tract is interpolated between census years.	FFIEC
Population 65+	The share of population with median age over 65 in a given census tract.	FFIEC
Minority population	The share of minority population to total population in a given census tract. Minority population is defined as Hispanic, African-American, American Indian, Eskimo, Aleut, Asian or Pacific Islander and Other.	FFIEC
	City level variables	
Vote margin	The assignment variable or vote margin is defined as the difference between the vote share of the African-American candidate and the vote share of the strongest white candidate.	Own data
Election winner	The treatment indicator or black win dummy is defined as one for African-American mayors and zero for white mayors.	Own data
Democrat	Dummy variable that is one for a mayor being affiliated with the Democratic party and zero for Republican mayors.	Own data

A.I Appendix A: Data

This paper merges different data sets with information on mayoral elections, mortgage application data and home ownership data. The following section describes the data sources and data preparation in detail.

Mayoral elections. For the regression discontinuity design to work, I need year and city of the election, vote shares of the mayor and the runner-up candidate and their races. These information come from three data sources: Ferreira and Gyourko (2009), Vogl (2014) and own hand-collection. Ferreira and Gyourko (2009) sent surveys to all US cities with more than 25,000 inhabitants as of the year 2000 and received the date of the election, the name of the mayor and the runner-up, vote totals for each candidate, type of election and some additional information for 2,000 mayoral elections in 413 cities between 1950 and 2000. Unfortunately, this data set does not contain information on the race of the top two candidates. Vogl (2014) collects 1,196 elections between 1965 - 2010 with information on names, vote counts and the race for the top-two candidates. Given that the mortgage data start in 1990 and I can only exploit interracial elections, I increase the amount of observations by complementing these two data sets and extend the sample period to 2014. Sources of my manual search, especially for the race information, include the following:

- www.ourcampaigns.com
- Wall Street Journal Online, Washington Post Online
- Nexis®
- EBSCO - Academic Search Premier
- Bayor (2001)
- Black Elected Officials - A National Roster 1990, 1991, 1993-1997 and 1999
- https://blackdemographics.com/culture/black-politics/black-mayors/
- https://www.ourmayors.org

Mortgage origination data. Data on mortgage applications come from the Home Mortgage Disclosure Act (HMDA). This regulation was enacted in 1975 and requires approximately 80% of

all mortgage lending institutions nationwide to disclose information on their mortgage lending activity (Avery et al., 2007). It provides loan-level application data on rich borrower characteristics like applicant's income, race, sex, loan amount, location of the borrower's house and whether/why the loan application was denied or accepted. The granularity of the HMDA data enables to me to track each mortgage application at the census tract level. The geographic area of each city in the United States consists of several census tracts. Therefore, I collapse loan-level information at the city level for each banks that lend to borrowers who have their home property in the respective city. Since information on race and income of the borrower is only available from 1990 onwards, I have to restrict the sample period from 1990 to 2018 although electoral data start in 1950. Note that discrepancy between election data ending in 2014 and the mortgage data ending in 2018 is explained by the fact that mortgage outcomes are defined as post-election outcomes up to four years.

I drop all loans if income or mortgage amount is zero or negative and keep loan applications where applicant race contains values "Non-Hispanic White" and "Black" or "African-American". I keep only "Conventional" and "FHA-insured" loans and drop "Veterans Administration", "Farm Service Agency" or "Rural Housing Service" loans. Since the paper focuses on home ownership decisions, I select only home purchase loans and disregard refinance and home improvement loans. I keep only owner-occupied loans and banks which had at least one African-American loan application. Based on this filter, I collapse HMDA loan-level data across banks and loans to get mortgage outcomes for the RD specification at the census tract-year level.

Classifying bank types. HMDA data contains an agency code variable that identifies the regulator overseeing the respective bank. Although commercial banks are assigned to one of the three commercial bank regulators, thrift institutions are assigned to the Office of Thrift Supervision (OTS), credit unions report to the National Credit Union Administration (NCUA), and independent mortgage companies file with the U.S. Department of Housing and Urban Development (HUD), these classifications are not necessarily systematic.[36] To properly classify banks, I use the bank type indicator variable from the HMDA lender file kindly provided by Robert Avery.

[36]For example, some thrift institutions file with the Federal Deposit Insurance Institution and not with the OTS. Furthermore, HMDA reporting errors or merger and acquisitions make it hard to exactly identify the bank type (Avery et al., 2007).