Partisan Loan Officers and the Racial Gap in Mortgage Lending

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Abstract

This paper examines how loan officers' political ideology shapes racial disparities in mortgage lending, using a novel dataset linking voter registration records to mortgage origination data. Democratic loan officers originate 30 percent more loans to minority borrowers than Republican loan officers, a gap that persists after controlling for branch location, demand-side characteristics, and loan officer fixed effects. At the individual loan level, Democratic officers are more likely to approve loans with high debt-to-income ratios for minority applicants, yet these loans exhibit lower ex post delinquency rates, ruling out differential favoritism as an explanation. A complementary email correspondence experiment reveals that Republican loan officers are 27 percentage points less likely to respond to low-credit-score minority applicants than Democratic counterparts, confirming that the partisan-racial gap originates largely at the pre-application stage.

Keywords: Political Affiliation, Racial Gap, Lending Discrimination, Mortgage, Statistical Discrimination

JEL Code: G21, G23, G28, J15, D72

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1 Introduction

Political ideology increasingly shapes economic decisions far beyond the ballot box. Recent research documents how partisan affiliation affects beliefs about the economy (Cookson et al. 2020; Kempf and Tsoutsoura 2021; Dagostino et al. 2023), home buying and selling decisions (McCartney et al. 2024; Chu et al. 2024); portfolio choice (Meeuwis et al. 2022; Ke 2024); entrepreneurship (Engelberg et al. 2025a); and patenting activities (Engelberg et al. 2025b). The interconnectedness raises a critical question: how does political affiliation manifest in seemingly non-political contexts, and what are its downstream consequences? In this paper, I examine how loan officers' political ideology affects their lending decisions and ultimately shapes minority borrowers' access to mortgage credit.

The mortgage market provides an ideal laboratory for this analysis for three reasons. First, loan officers exercise substantial discretion during the pre-screening phase, where they can influence which applications ultimately receive formal underwriting reviews (Ross et al. 2008; Hanson et al. 2016). Second, the stark partisan divide on racial equity issues creates clear predictions about how political ideology might manifest in lending behavior (Tesler 2013; Schickler 2016; Valentino et al. 2018). Third, mortgage lending represents a high-stakes economic decision with significant consequences for wealth accumulation and intergenerational mobility.

The institutional context amplifies the potential impact of loan officer discretion. As gatekeepers in the mortgage origination process, loan officers evaluate prospective borrowers, collect documentation, and recommend loan products. Their compensation structure, which is primarily based on loan volume, creates incentives to screen applications based on the perceived likelihood of approval (Giacoletti et al. 2023). This screening process is particularly consequential for marginal borrowers, including many minorities, who may require additional effort to compile the necessary documentation or overcome deficiencies in traditional credit metrics. If political ideology shapes loan officers' perceptions of minority borrower creditworthiness, these beliefs could systematically affect lending outcomes, even in the absence of explicit taste-based discrimination. Alternatively, political ideology could

affect loan officers' specialization in serving certain borrowers or their marketing efforts in attracting them.

To test this hypothesis, I construct a novel dataset linking CoreLogic mortgage origination records with North Carolina voter registration data to identify loan officers' political affiliations. I supplement this core dataset with information from the Nationwide Mortgage Licensing System (NMLS), Home Mortgage Disclosure Act (HMDA) records, and McDash loan performance data to conduct comprehensive analysis at both the loan officer and individual loan levels.

By aggregating mortgage origination at the loan officer-county-year level, I examine whether loan officers with different political affiliations make different lending decisions for minority applicants. The identification assumption is that loan officers with different political affiliations face similar applicant pools. Unconditionally, this assumption could easily be violated if Democratic loan officers live or work near areas with larger minority populations. To satisfy the identifying assumption, I include granular fixed effects to control for demand side factors, loan officer location, and the potential endogenous match between loan officers and borrowers. Specifically, I use loan officer location (branch) by year by minority group fixed effects to control for the potential impact of loan officer location. For example, if the branches of Democratic loan officers are near larger minority population, they would mechanically originate more loans to minority borrowers. With the branch-by-year-by-minority-group fixed effects, I compare loan officers in the same branch but with different political affiliations making loans to the same racial group (white or minority) in the same year. I use loan officer-by-year fixed effects to control for loan officer characteristics that could impact their loan origination decisions in general. With the loan-officer-by-year fixed effects, I compare lending to minority borrowers versus white borrowers by the same loan officer in the same year. I use county-by-year-by-minority-group fixed effects to control for racial-group-specific local demand side factors. Using the county-by-year-by-minority-group fixed effects, I compare loan officers with different political affiliations making loans in the same county to the same racial group in the same year. I find that Democratic loan offi-

cers originate about 30% more loans to minority borrowers than Republican loan officers. According to the estimates, the 2,461 Republican loan officers in the sample would have made 1,772 more loans to minority borrowers every year if they were to behave like their Democratic counterparts.

To further mitigate the concern that the results could be driven by demand-side factors, I construct a proxy for loan-officer-county-level applications. This is defined as the product of the total number of applications in the county (calculated using HMDA data) and the loan officer's share of approved loans (using CoreLogic data) in the previous year. I construct a pseudo-approval rate as the ratio of approved loans to the proxy for applications, and I find that Democratic loan officers have higher approval rates on minority loan applications than their Republican counterparts. The results hold even after controlling for the characteristics of loan application and county-by-year-by-minority-group fixed effects, further suggesting that the results are unlikely to be driven by demand-side factors.

I also examine how the percentages of active Republican and Democratic loan officers within a lender in a county affect the lender's loan origination in that county. I find that a higher percentage of Republican loan officers (and a lower percentage of Democratic loan officers) leads to a higher probability of minority loan applications being withdrawn or closed for incomplete information. In contrast, conditional on applications being submitted for underwriting, minority loan applications processed by Republican loan officers are slightly more likely to be approved than those processed by Democratic loan officers. Serving as an outcome test for loan officer screening, this result further confirms the presence of bias during the loan officer screening process. Furthermore, I find that Republican loan officers receive fewer loan applications from minority borrowers. These results are consistent with the fact that loan officers have more discretion during the pre-application stage but not during the underwriting process. These results suggest that biased loan officers may decide not to respond to the initial inquiries of minority borrowers, provide less information, or dissuade minority borrowers from submitting formal loan applications (Ross et al. 2008; Hanson et al. 2016).

To mitigate the concern that the results could be driven by politial selection, that is, driven by loan officer characteristics that are collelated with both political affiliation and lending decisions, I include the interaction terms between the minority dummy and loan officer characteristics variable, including gender, age, religion, education, language, and state of birth in the regressions. The results are robust to including these interaction terms, and more importantly, the magnitqude of partisan-racial gap does not decrease with the inclusion of these interactions terms, suggesting that the results are unlikely to be driven by political selection.

To identify the source of the bias, I examine whether loan officer experience mitigates the bias. Some loan officers may have biased beliefs about borrower credit risk and are thus unwilling to exert the effort to collect and process soft information, despite this effort potentially leading to loan originations and increased compensation. To the extent that experience mitigates biased beliefs, I expect that it should reduce the gap in mortgage lending between loan officers with different political ideologies. Using the number of loans a loan officer originated in the three years before the current year as a measure of experience, I find that the results are concentrated on less experienced loan officers, consistent with the predictions of inaccurate statistical discrimination (Bohren et al. 2019).

To further understand how loan officer political affiliation affects lending practices, I merge the CoreLogic mortgage data with the 2018-2021 HMDA data. Due to the absence of common identifiers, I match these datasets using variables that appear in both. The HMDA data provide a rich set of loan level characteristics, allowing me to conduct a loan level analysis. I first focus on the debt-to-income ratio, a critical underwriting variable. I find that loans to minority borrowers processed by Democratic loan officers are more likely to have a debt-to-income ratio greater than 36%, suggesting that Democratic loan officers relax the debt-to-income ratio requirement for minority borrowers. The results survive loan officer-by-year and city-by-year fixed effects, mitigating the concern that the results could be driven by demand-side factors.

I then examine whether loan officers' political affiliation also affects the cost of mortgages

to minority borrowers. Beyond mortgage access, the literature has documented racial gaps in mortgage pricing (Black et al. 2003; Ghent et al. 2014; Bayer et al. 2018; Bartlett et al. 2022; Ambrose et al. 2021). I examine whether loan officers' political affiliations contributes to these pricing disparities. I find that loan officers' political affiliation does not affect the racial gap in mortgage interest rates. However, loans to minority borrowers originated by Democratic loan officers carry lower rate spreads, a measure of overall mortgage cost that incorporates origination fees and points, part of which is paid to loan officers.

I examine whether loan officers' political affiliation affects ex post mortgage performance to address two alternative explanations for the mortgage origination results above. First, the results could be driven by Democratic loan officers favoring minority borrowers and relaxing lending standards for them. Under this explanation, loans made by Democratic loan officers to minority borrowers would perform worse. Second, Republican loan officers might be more risk-averse than Democratic loan officers, where race is correlated with risk. This explanation would also predict a worse performance for loans made by Democratic loan officers to minority borrowers. I merge the McDash loan data and use 60-day and 90-day delinquency as measures of mortgage performance. I find that loans to minority borrowers originated by Democratic loan officers have slightly lower delinquency rates than those originated by Republican loan officers. These results suggest that the differences in minority loan origination between Democratic and Republican loan officers are unlikely to be driven by Democratic loan officers favoring minority borrowers or by different risk preferences between Democratic and Republican loan officers.

Finally, I conduct an email correspondence experiment to provide direct evidence that a large part of the partisan-racial gap occurs at the pre-application stage. Specifically, I follow Hanson et al. (2016) and send email loan inquiries from African American-sounding and white-sounding names to real loan officers. I find that Republican loan officers are less likely to respond to loan inquiries from African American applicants than Democratic loan officers. Conditional on responding, Republican loan officers' responses to African American applicants are significantly shorter than those of Democratic loan officers.

This paper contributes to the literature on the racial gap in mortgage lending. Previous studies document racial gaps in mortgage access (e.g., Black et al. 1978; King 1980; Schafer and Ladd 1981; Maddala and Trost 1982; Munnell et al. (1996); Ross and Yinger 2002; Chu et al. 2025). To understand the drivers, the literature examines the geographical and cross-lender variation of the racial gap (Holmes and Horvitz 1994; Tootell 1996; Bayer et al. 2018; Bartlett et al. 2022). Bhutta and Hizmo (2021) and Bhutta et al. (2024) show that disparate treatment plays a limited role in generating the racial gap. However, until very recently, little has been done to understand the contribution of loan officers to the racial gap. Specifically, Frame et al. (2025) find that the lack of minority loan officers is one source of the gap; Ambrose et al. (2021) find that the race of the broker affects the cost of mortgages to minority borrowers. Using experimental methods, Ross et al. (2008) and Hanson et al. (2016) both find disparate treatment by loan officers during the pre-screening stage. This paper is the first to examine how the political ideology of loan officers could contribute to the racial gap in mortgage lending.

This paper also contributes to the literature on the broader impacts of political affiliation. While early studies mostly focus on political outcomes (Campbell et al. 1980; Bartels 2002; Bullock et al. 2015), the recent literature explores the impacts on social and economic outcomes, such as economic expectations and beliefs (Cookson et al. 2020; Kempf and Tsoutsoura 2021; Dagostino et al. 2023; Mian et al. 2023), hiring decisions (Gift and Gift 2015), responses to the COVID pandemic (Barrios and Hochberg 2021; Wallace et al. 2023), housing choices (Bernstein et al. 2022; McCartney et al. 2024), fertility choices (Dahl et al. 2022), entrepreneurship and patenting activities (Engelberg et al. 2025a; Engelberg et al. 2025b). This paper is the first to document that partisan ideology among financial intermediaries generates differential access to credit by race, with direct implications for minority households' wealth formation and intergenerational mobility.

The remainder of the paper proceeds as follows. Section 2 develops a simple analytical framework to guide my empirical analysis. Section 3 describes the data sources and sample construction process. Section 4 presents the loan officer-county-level analysis results. Section

5 presents the loan-level analysis results. Section 6 concludes.

2 A Conceptual Framework

I develop a simple model to understand loan officers' incentives and to guide the empirical analysis. There are two types of loan officers: unbiased (type U) and biased (type B). Each officer evaluates loan applications from two groups of borrowers: minority (M) and white (W).

After observing the information provided in the borrower's application, the loan officer forms an initial assessment of the borrower's creditworthiness, θ. I focus on marginal borrowers—those for whom $\theta < \bar{\theta}$, where $\bar{\theta}$ is the minimum threshold for automatic approval—because these are the applicants for whom additional information collection by the loan officer can change the lending outcome. For non-marginal borrowers (strong or clearly unqualified applicants), the political affiliation of the loan officer should have no differential impact, since no effort can improve or salvage the outcome.

If an officer exerts effort e at cost $c(e) = \frac{1}{2}\gamma e^2$ (where $\gamma > 0$ and $0 < e < 1$), they obtain additional information I with the following structure:

$$I = \begin{cases} I^{good} & \text{with probability } p \cdot e \\ I^{null} & \text{with probability } 1 - p \cdot e \end{cases}$$

Where I^{good} means favorable information that raises creditworthiness to $\theta + \Delta > \bar{\theta}$ and I^{null} means no additional useful information, creditworthiness remains θ.

Loan officers hold different beliefs about the information acquisition technology parameter *for minority applicants*: the unbiased officer believes $p = p_u$ (the correct belief), while the biased officer believes $p = p_b < p_u$, underestimating the likelihood that additional effort will uncover favorable information. For white applicants, both officer types share the same correct belief p_u. This asymmetry formalizes statistical discrimination: biased officers do not discriminate on the basis of taste, but rather hold systematically pessimistic beliefs about the

returns to effort when evaluating minority borrowers. The loan officer earns a commission proportional to the loan amount, αL, where L is the loan amount and $0 < \alpha < 1$, if the application is approved (Giacoletti et al. 2023).

Each officer type $j \in \{U, B\}$ solves:

$$\max_{e \in [0,1]} \quad \pi_j(e) = p_j \cdot e \cdot \alpha L - \frac{1}{2}\gamma e^2 \tag{1}$$

The first order condition is given by:

$$\frac{\partial \pi_j}{\partial e} = p_j \alpha L - \gamma e = 0 \tag{2}$$

Proposition 1. *The optimal effort levels are:*

$$e_u^* = \frac{p_u \alpha L}{\gamma} \quad \textit{and} \quad e_b^* = \frac{p_b \alpha L}{\gamma}$$

Since $p_b < p_u$, we have $e_b^* < e_u^*$, that is, the biased loan officer exerts less effort than the unbiased loan officer in collecting additional information.

The probability that officer type j approves the loan is:

$$P_j^{approve} = p_u \cdot e_j^* \tag{3}$$

The actual probability uses the true parameter $p = p_u$, not the officer's belief. We therefore have

Proposition 2. *The loan approval probability is higher for unbiased officers:*

$$P_u^{approve} = p_u \cdot e_u^* = \frac{p_u^2 \alpha L}{\gamma} > \frac{p_u p_b \alpha L}{\gamma} = p_u \cdot e_b^* = P_b^{approve}$$

, that is, loans processed by the unbiased officer are more likely to be approved than loans processed by the biased loan officer.

This framework generates a racial gap in lending: because biased officers underinvest in effort for minority applicants but not for white applicants, they approve fewer minority loans relative to white loans than unbiased officers do. Critically, the loans that biased officers do approve for minority applicants are no riskier than those approved by unbiased officers—the lower approval rate reflects suboptimal screening effort, not differential risk tolerance. This prediction is consistent with the finding that minority loans originated by Democratic officers exhibit lower, not higher, delinquency rates.

This bias captures statistical discrimination with inaccurate beliefs rather than taste-based discrimination. In this setting, the loan officer observes the outcome of her information collection effort and can therefore update her belief. As the biased loan officer accumulates experience, her belief p_b converges to the correct belief p_u, so the racial gap in lending should attenuate with experience. This prediction, unique to statistical discrimination with inaccurate beliefs, is borne out in the data.

I also want to point out that the bias in beliefs is not the only way to reach these theoretical predictions. For example, I can get equivalent results if I instead assume that the unbiased loan officers have a lower cost of collecting information, that is, $\gamma_u < \gamma_b$. I provide the alternative framework in Appendix A. In reality, this could happen if unbiased loan officers choose to invest in their information collection technology, but biased loan officers do not. On the surface, this channel is completely different from the above statistical discrimination story. However, at a deeper level, why the biased and unbiased loan officers make different decisions in investing in their information collection technology could still be driven by their differences in beliefs about the profitability of originating loans to minorities, that is, statistical discrimination underlies the differences in the information collection technology.

3 Data and Sample Construction

3.1 Data

I start the sample construction with all mortgages in the state of North Carolina in the CoreLogic mortgage database from 2018 to 2021. The Secure and Fair Enforcement for Mortgage Licensing Act (the SAFE Act) requires that all residential mortgage loan officers be federally registered or state licensed. The SAFE Act also mandates the establishment of a unique identifier, known as the NMLSID, and requires that this identifier be included in loan documents. As a result, most mortgage deed documents include the NMLSID of loan officers since 2014. CoreLogic collects this information from deed documents.

I start the sample in 2018 because my later analysis requires variables that are only available in the post-2018 Home Mortgage Disclosure Act (HMDA) data. I focus on mortgages in North Carolina because voter registration data for North Carolina are easily available. The CoreLogic mortgage data provide, among other things, the following information: exact location of the underlying property, the year the property was built, loan amount, mortgage term, mortgage origination date, mortgage maturity date, mortgage type (FHA, VA, Conventional, fixed-rate, adjustable-rate), property type (single-family, multifamily, manufactured home), mortgage purpose (purchase or refinance), lien status (first lien, second lien, etc.), borrower name, lender name, loan officer NMLSID. From the CoreLogic mortgage data, I retain only single-family, fixed-rate, first-lien mortgages. This yields a sample of 944,442 loans, originated by 52,288 loan officers, of which 10,677 are based in North Carolina.

I match the NMLSID of the loan officers with the NMLS B2B data to obtain the loan officers' names and locations. I exclude loan officers who are not based in North Carolina. I obtain North Carolina voter registration data from the North Carolina State Board of Elections website.[1] The voter registration data provide information on voters' names, party affiliations, races, ethnicities, home addresses, registration dates, age at the time of registration, and places of birth. I use loan officers' names to match the CoreLogic loan officers to the

[1] https://www.ncsbe.gov/results-data/voter-registration-data

voter registration data. I require exact matches of first, middle, and last names. I exclude matches in which the distance between the address recorded in the voter registration data and the location of the loan officer's branch is greater than 200 miles. I check the LinkedIn pages of the loan officers, if they exist, and determine their approximate birth years based on their years in college, which helps to identify unique matches. I exclude any remaining non-unique matches.

I find voter registration records for 6,415 loan officers out of the total of 10,677 North Carolina based loan officers who made loans in North Carolina during the sample period. These loan officers originated a total of 361,254 single-family, fixed-rate, first-lien mortgages, out of a total of 944,442 such mortgages. 1,407 of these loan officers were always registered as Democrats, 2,461 were always registered as Republicans, 54 were always registered as Libertarians, and 2,098 were always registered as unaffiliated. The remaining three loan officers changed their party affiliations during the sample period. I exclude loan officers affiliated with the Libertarian and Constitution Parties from the final sample.

I plot the branch locations of the loan officers who originated loans during 2018-2021 in Figure 1. Not surprisingly, most loan officers are in one of the three metro areas in North Carolina, that is, the Charlotte, Greensboro, and Raleigh metro areas. Rural areas have fewer loan officers. Most areas, especially large metro areas, have a mix of loan officers affiliated with different political parties, which allows us to compare mortgage lending by loan officers in the same branch but with different political affiliations.

I use two approaches to determine borrowers' race and ethnicity. First, I use the names and addresses of the borrowers to match with the voter registration data. Among the 361,254 loans, I am able to match the borrowers with voter registration data for 209,300 loans. For the remaining 152,873 loans, I identify borrower race in 64,498 cases using the matched HMDA loan application data.[2] I categorize African American and Hispanic borrowers as minority borrowers. In the matched sample of 273,798 loans, minority borrowers account for

[2]I provide the details of the match below. I also tried to use Bayesian Improved First Name Surname Geocoding (BIFSG) to infer the races and ethnicities of the borrowers. However, compared with voter registration (HMDA) data, BIFSG correctly identified only 84% (83%) of the cases. To avoid introducing too much noise, I only rely on voter registration and HMDA to identify borrower races and ethnicities.

16.1% of the sample.

I calculate the percentage of minority loans originated by each loan officer in each year, and then calculate the average percent of minority loans for Democratic, Republican, and unaffiliated loan officers, as in Table 1. 26.41% of loans originated by Democratic loan officers go to minority borrowers, higher than the 19.74% originated by unaffiliated loan officers. In contrast, only 15.84% of loans originated by Republican loan officers go to minority borrowers, less than those originated by unaffiliated loan officers. The difference in the percentage of minority loans between Democratic and Republican loan officers is statistically significant at the 1% level.

3.2 Constructing the loan-officer-county-year sample

I aggregate the sample at the loan officer-county-year level. Specifically, I calculate the number (value) of total mortgages to minority or non-minority borrowers originated by each loan officer in each county in each year. There are two observations for each loan officer-county-year triple. I exclude observations in which the loan officer did not originate any loan in the county in that year. I present the summary statistics in Table 2. An average loan officer originates 1.2 loans to minority loans and 6.2 loans to non-minority borrowers in each county each year.

3.3 Constructing the loan-level sample

Although the CoreLogic mortgage data provide a rich set of information on mortgages, they do not provide critical information associated with underwriting criteria, such as the debt-to-income ratio, the loan-to-value ratio, or the credit score. To analyze the lending standards at the loan level, I merge CoreLogic loans with HMDA. Unfortunately, the two data sets do not have a common identifier. I first match mortgage lenders with HMDA lenders on the Avery lender list based on lender names and lender addresses. Then, I match these two datasets based on variables that are common in these two datasets. These variables include year of origination, lender, census tract, loan amount, mortgage term, loan type, loan

purpose, and whether the loan has a co-applicant. I exclude loans with more than one match. The loan-level sample consists of 158,767 mortgages from 2018 to 2021.

I present the summary statistics of the main variables used in the loan-level analysis in Table 3. The average property value is $ 338,669, and the average loan amount is $246,895. The average combined loan-to-value (CLTV) ratio is 78.17% and 37.6% of the loans have a debt-to-income ratio greater than 36%. About 49.6% of the loans are originated by Republican loan officers, 17.5% are by Democratic loan officers, and the remainder are by unaffiliated loan officers. The average mortgage interest rate is 3.505% and the average rate spread, that is, the difference between the annual percentage rate (APR) and the survey-based average prime offer rates, is 39.5 basis points.

Finally, to assess the impact of loan officer political affiliation on loan performance, I match the loan-level sample with McDash loan-level datasets. There is no common identifier between CoreLogic or HMDA and the McDash data. I also match these data sets based on common variables, including the origination year and month, maturity year and month, loan amount, the first three digits of the zip code, mortgage interest rate, mortgage term, combined loan-to-value ratio, debt-to-income ratio, loan purpose, and whether the loan has a co-borrower. Again, I retain unique matches. This procedure produces a sample of 42,563 loans. Using McDash performance files, I identify loans that have ever experienced delinquencies of more than 60 days (*Delinq* 60) and 90 days (*Delinq* 90). In addition to the information available in CoreLogic and HMDA data, McDash also provides information on mortgage insurance, whether the borrower is a first-time home buyer, and the borrower's credit score. I present the summary statistics of the matched sample in Table 4. About 4.5% (3.5%) of the loans ever experience a delinquency of more than 60 (90) days.

4 Main results

4.1 Empirical strategy and identification

I examine how loan officers' political affiliation affects lending to minorities at the loan officer-county-year level with the fixed effects Poisson model,

$$E[Number\ of\ Loans_{ijct}] = \exp(\beta_1 Rep\ LO_{it} \times Minority_j + \beta_2 Dem\ LO_{it} \times Minority_j + \beta_3 Minority\ LO_i \times Minority_j + \beta_4 Minority_j + \gamma X_{icj} + \alpha_{i,c,t} + \alpha_{c,j,t} + \alpha_{b,j,t}), \quad (4)$$

where $E[\ ]$ is the expectation operator, $Number\ (Value)\ of\ Loans_{ijt}$ is the total number or value of loans loan officer i made to borrower type j (minority or non-minority) in county c in year t, $Rep\ LO_{it}$ is a dummy variable equal to one if loan officer i is registered as Republican in year t, $Dem\ LO_{it}$ is a dummy variable equal to one if loan officer i is registered as Democratic in year t, $Minority$ is a dummy variable equal to one if the borrower type is minority, $Minority\ LO_i$ is a dummy variable equal to one if loan officer i is African American or Hispanic. X_{icjt} is a set of average characteristics of loan applications by racial group j in county c in year t, including the natural logarithm of average income ($Log\ Average\ Income$), the natural logarithm of the average loan amount ($Log\ Average\ Loan\ Amount$), the natural logarithm of average property price ($Log\ Average\ Property\ Value$), the average combined loan-to-value ratio ($Mean\ CLTV$), the percentage of female applicants ($Percent\ Female$), the percentage with a co-applicant ($Percent\ Co-Applicant$), the percentage of applicants over the age of 62 ($Percent\ Age > 62$), and the percentage of debt-to-income ratio below 20% ($Percent\ DTI < 20$), between 20% and 30% ($Percent\ DTI20-30$), between 30% and 36% ($Percent\ DTI30-36$), between 36% and 40% ($Percent\ DTI36-40$), between 40% and 45% ($Percent\ DTI40-45$), between 45% and 50% ($Percent\ DTI45-50$), between 50% and 60% ($Percent\ DTI50-60$), and above 60% ($Percent\ DTI > 60$).

$\alpha_{i,c,t}$ is the loan officer-county-year fixed effect, $\alpha_{c,j,t}$ is the county-year-minority group fixed effects, and $\alpha_{b,j,t}$ is the branch-year-minority group fixed effects. Under this specifi-

cation, the omitted category is unaffiliated loan officers. β_1 and β_2 capture the mortgage lending to minority borrowers by Republican and Democratic loan officers, relative to unaffiliated loan officers.

The identifying assumption is that loan officers with different political affiliations face similar applicant pools. Unconditionally, this assumption could easily be violated if Democratic loan officers live or work near a larger minority population. To mitigate this concern, I include branch-by-year-by-minority group fixed effects, $\alpha_{m,j,t}$ in the model. As shown in Figure 1, most branches have a mix of loan officers affiliated with different political parties, which makes it possible to include the branch-by-year-by-minority group fixed effects. With the fixed effects, the identifying assumption becomes that loan officers working in the same branch but with different political affiliation face similar application pools in the same year, which is more plausible.

To further ensure that loan officers face similar applicant pools, I also include loan officer-by-county-by-year fixed effects $\alpha_{i,c,t}$ in the model. With that, I compare loans originated to minority and non-minority loan borrowers by the same loan officer in the same year in the same county. Finally, I include the county-by-year-by-minority group fixed effects, $\alpha_{c,j,t}$, controls for all county-level race specific demand side factors at the annual frequency to further ensure that loan officers face similar applicant pools in each race group.

I use the Poisson fixed effect model for estimation because (1) the dependent variable (the number or value of loans) is skewed; (2) the dependent variable could take the value of zero; and (3) Cohn et al. (2022) and Chen and Roth (2023) show that taking the natural logarithm of the dependent variable or one plus the dependent variable could lead to severe bias, and they both recommend using the Poisson fixed effect model to mitigate the bias. I include the term $Minority\ LO_i \times Minority_j$ in the model because Frame et al. (2025) show that minority loan officers are more likely to approve mortgage applications by minority borrowers, and whether the loan officer is a minority could also be correlated with her political affiliation. I cluster the standard error by loan officer.

4.2 Loan officer political affiliation and mortgage lending

I present the results of estimating Equation (4) in Table 5. The coefficient estimates on *Rep LO* × *Minority* are all negative and statistically significant. In contrast, the coefficient estimates on *Dem LO* × *Minority* are all positive and statistically significant. More importantly, the differences between the two estimates are large (about 30%) and statistically significant.

These results suggest that Democratic loan officers, relative to Republican loan officers, originate approximately 30% more loans to minority borrowers than to white borrowers. Evaluating this effect at the average number of minority loans originated by a loan officer in a county (1.178), Republican loan officers originate 0.36 fewer minority loans every year. The 2,461 Republican loan officers in the sample would have made 1,772 ($0.36 \times 2461 \times 2$, where 2 is the median number of counties that a loan officer makes loans to) more loans to minority borrowers in North Carolina each year if they behaved like their Democratic counterparts. It is also worth noting that the coefficient estimates on *Minority LO* × *Minority* are all positive and statistically significant, suggesting that minority loan officers originate much more minority loans than white loan officers.

I also replace the number of mortgages with the total value of the mortgages as the dependent variable and present the results in Table 6. The results are similar to those of Table 5, qualitatively and quantitatively.

4.3 Controlling for Demand-Side Factors and Endogenous Matching

Two potential mechanisms could explain the higher minority lending by Democratic loan officers: (1) Democratic loan officers matching with more minority loan applicants, or (2) Democratic loan officers approving more minority loan applications. The branch-by-year-by-minority group fixed effects mitigates the concern that Democratic loan officers live in areas with larger minority populations, and hence originate more minority loans. The limited

observability of loan officer political affiliation restricts opportunities for strategic matching by borrowers on the basis of political affiliation. Nevertheless, minority borrowers may engage in referral networks, directing co-ethnic contacts toward officers with whom they have had favorable experiences, thereby generating differential applicant pools. Importantly, because the initial positive experiences that generate referrals stem from differential treatment by loan officers, such referral-driven sorting patterns would themselves reflect underlying officer biases in treatment, which is part of the biases I seek to identify.

Loan officers could also try to differentiate themselves to attract clients with different characteristics that are correlated with race, also resulting in endogenous matching. I still consider this part of the bias I try to identify because loan officers' choice of specialization itself could be biased.

Nonetheless, there could be other sources of endogenous matching between borrowers and loan officers that could bias the results. Because I do not have loan application data for each loan officer, it is challenging to empirically assess how much of the effect is driven by endogenous matching. In this section, I use two different methods to mitigate this concern. In the first method, I combine the HMDA and Corelogic data to construct a proxy for the number of applications each loan officer receives. In the second method, I match individual loan applications in HMDA with the percent of Republican and Democratic loan officers at the lender-county-year level to control for demand.

First, I construct a proxy for demand at the loan officer-county level. First, I calculate the total number (value) of loan applications for racial group j in county c in year t, $N_{c,t,j}$, using the HMDA data. Second, I calculate the shares of loans originated by loan officer i in county c in year $t-1$, $s_{i,c,t-1}$, using CoreLogic data,

$$s_{i,c,t-1} = \frac{n_{i,c,t-1}}{\Sigma_{i=1}^{I} n_{i,c,t-1}}, \tag{5}$$

where $n_{i,c,t-1}$ is the number (value) of mortgages originated by loan officer i in county c in year $t-1$, and I is the total number of loan officers who originated loans in county c in

year $t-1$. I do not calculate the share specific to each racial group because differences in approval rates between racial groups could bias the measure. I calculate the share based on loans originated in $t-1$ to further mitigate bias. Third, I calculate $D_{i,c,t,j} = N_{c,t,j} \times s_{i,c,t-1}$ as a proxy for the number of applications loan officer i receives in county c in year t from racial group j. Finally, I calculate the pseudo-approval rate as $R_{i,c,t,j} = n_{i,c,t,j}/D_{i,c,t,j}$, where $n_{i,c,t,j}$ is the number of loans to racial group j made by loan officer i in county c in year t.

I then estimate the following specification:

$$R_{i,c,t,j} = \beta_1 Rep\ LO_{it} \times Minority_j + \beta_2 Dem\ LO_{it} \times Minority_j + \beta_3 Minority\ LO_i \times Minority_j + \beta_4 Minority_j + \gamma X_{icj} + \alpha_{i,t} + \alpha_{c,j,t} + \alpha_{b,j,t} + \varepsilon_{i,c,t,j}, \quad (6)$$

where $R_{i,c,t,j}$ is the pseudo-approval rate. I present the results in Table 7. The coefficient estimates on $Rep\ LO \times Minority$ are all negative and statistically significant. In contrast, the coefficient estimates on $Dem\ LO \times Minority$ are all positive, although not statistically significant. The differences between the two coefficient estimates are all negative and statistically significant at the 1% level. These results suggest that Democratic loan officers approve more loans to minority applicants than Republican loan officers, even after controlling for demand side factors, in particular, county-year fixed effects.

I then use an alternative method to control for demand side factors using the HMDA loan origination data. While the public HMDA data do not identify loan officers at the loan level, I use the Corelogic data to identify loan officers that are active in a county. I calculate $Percent_Dem_lct$ ($Percent_Rep_lct$) as the percentage of active Democratic (Republican) loan officers for lender l in county c in year t. These measures are more noisy than the political affiliations of the individual loan officers who actually processed the loans. However, they can still provide valuable insight, given that (1) most lenders have a limited number of loan officers in any given county and (2) most loan officers focus on certain geographical areas (Huang et al. 2024; Gao et al. 2025). I then examine whether these measures affect loan origination at the individual loan application level.

From the HMDA data, I only retain applications that are withdrawn (action type=4), closed for incomplete information (action type=5), rejected (action type=3), or approved and originated (action type=1). Examining withdrawn and incomplete applications provides a more complete picture of the mortgage origination process. I examine how loan officer political affiliation affects the percentage of withdrawn or incomplete applications with the following specification:

$$\begin{aligned} D_{i,c,t,l} &= \beta_1 Percent_Rep_{lct} \times Minority_i + \beta_2 Percent_Dem_{lct} \times Minority_i \\ &+ \beta_3 Percent_Minority_{lct} \times Minority_i + \beta_4 Minority_i + \gamma X_{ictl} \\ &+ \alpha_{l,c,t} + \alpha_{c,j,t} + \alpha_{l,t,j} + \varepsilon_{i,c,t,l}, \end{aligned} \tag{7}$$

where $D_{i,c,t,l}$ is a dummy variable of whether loan application i in county c by lender l in year t is withdrawn or closed for incomplete information, or approved. I include lender-by-county-by-year fixed effects to control lender and county level factors, lender-by-year-by-minority group fixed effects to control for time varying lender level race specific origination policy, and county-by-year-by-minority group fixed effects to control for time varying county level race specific demand side factors.

The estimation results for withdrawn or incomplete applications are presented in column (1) of Table 8. The coefficient estimate on $Percent_Rep \times Minority$ is positive and statistically significant and that on $Percent_Dem \times Minority$ is negative but insignificant. More importantly, the difference between the two estimates is statistically significant, suggesting that minority loan applications received by Republican loan officers are more likely to be withdrawn or closed for incomplete information.

In column (2), I exclude applications that are withdrawn or closed for incomplete information to focus on loans that are submitted to underwriters. I then replace the dependent variable with the dummy variable of whether the application is approved. The coefficient estimate on $Percent_Rep \times Minority$ is positive and that on $Percent_Dem \times Minority$ is

negative; but neither is statistically significant. Although the difference between the two coefficient estimates is also not statistically significant, the p-value is 14.4%. If anything, the result suggests that minority loan applications processed by Republican loan officers are more likely to be approved by underwriters. Taking this as the outcome test for loan officer screening (Becker 1971), these results further suggest the existence of loan officer biases in the pre-screening stage. Although the outcome test could be biased by the inframarginality problem (Ayres 2002; Siskin and Cupingood 1996), the result here is less likely to suffer from this problem. The inframarginality problem arises from potentially very different distributions of risk profiles of different groups. In this context, however, the inframarginality problem could only arise if the risk distributions of minority applications processed by Republican and Democratic loan officers are very different, which is unlikely.

The results in columns (1) and (2) confirm the bias after the mortgage applications are initiated. Ross et al. (2008) and Hanson et al. (2016) suggest that disparate treatment in mortgage lending could happen even before loan applications are submitted. A biased officer may choose not to respond to initial inquiries from minority borrowers, provide less information, or dissuade minority borrowers from even submitting formal loan applications. This bias could result in fewer minority applications for biased loan officers. To examine this possibility, I aggregate the applications at the lender-county-year-racial group level, and then examine whether the percent of Republican and Democratic loan officers affect the number of minority loan applications relative to white applications. I again use the Poisson fixed effects for estimation, and the results are presented in column (3). The results suggest that Republican loan officers receive about 15% fewer minority loan applications, relative to white loan applications, than Democratic loan officers.

4.3.1 Political Selection or Political Influence?

The results above suggest that the political affiliation of loan officers is associated with the number of loans to minority borrowers. However, the results do not necessarily suggest that political ideology causes the difference in mortgage lending. It is possible that loan officers

with different political affiliations have characteristics that are correlated with mortgage lending to minority borrowers. For example, political affiliation may be correlated with gender, age, religion, educational background, or other characteristics that affect lending behavior. To mitigate this concern, I further include the interaction terms between *Minority* with a rich set of loan officer characteristics in the regression, including age, gender, religion, education, and the state of birth. The results are presented in Table 9, in which I gradually saturate the model with these interaction fixed effects. The coefficient estimates on $Rep\ LO \times Minority$ and $Dem\ LO \times Minority$ remain similar in magnitude and statistical significance after controlling for these characteristics. Although it is impossible to control for all loan officer characteristics, the fact that the results survive these characteristics suggests that the differences in mortgage lending to minority borrowers by Republican and Democratic loan officers are unlikely to be driven by other characteristics correlated with political affiliation, or political selection.

4.4 The source of bias and loan officer experience

These results suggest that Republican loan officers are less willing than Democratic loan officers to collect and use soft information to help minority borrowers. Such behavior may not be optimal for Republican loan officers because loan officers are mostly compensated by commissions on the loan they originate. If so, more experienced loan officers are less likely to exhibit bias, as discussed in section 2. I use the number of loans originated by the loan officer during the last three years as the measure of loan officer experience and then split the sample based on whether the loan officer experience is above or below the sample median.

I then re-estimate Equation (4) for less experienced and more experienced loan officers separately. The results are presented in Table 10. In column (1), for less experienced loan officers, the difference between the coefficient estimates on $Rep\ LO \times Minority$ and $Dem\ LO \times Minority$ is negative and statistically significant. In contrast, in column (2), for more experienced loan officers, the difference between the coefficient estimates is much smaller with reduced statistical significance. These results in Table 10 suggest that loan

officer experience mitigates some of the bias in mortgage lending induced by political affiliation. The results also suggest that the differences in mortgage origination by Republican and Democratic loan officers are unlikely to be driven by taste-based discrimination because biased perference is unlikely to change with experience. Instead, the results are more consistent with inaccurate statistical discrimination, in which loan officers' beliefs are biased initially but converge to correct beliefs when they gain more experience. Consistent with this interpretation, in Table **??** in the appendix, I find that the partisan-racial gap is significantly larger in counties with higher political polarization, suggesting that ideology plays a direct role in shaping the gap rather than merely proxying for other loan officer characteristics.

5 Loan officer political affiliation, loan contracting, and loan performance

5.1 Debt-to-income ratio

To assess whether the difference in the number of minority loans between Republican and Democratic loan officers is driven by different lending standards, I examine the debt-to-income ratio of the loans. The debt-to-income ratio is one of the most important criteria lenders look at when approving a mortgage. In particular, most lenders prefer a debt-to-income ratio below 36%. I therefore use whether the loan has a debt-to-income ratio greater than 36% to assess differences in underwriting standards between loan officers. Specifically, I estimate the following specification,

$$DTI36_{ijkt} = \beta_1 Rep\ LO_{it} \times Minority_j + \beta_2 Dem\ LO_{it} \times Minority_j$$
$$+ \beta_3 Minority\ LO_i \times Minority_j + \beta_4 Rep\ LO_{it} + \beta_5 Dem\ LO_{it} + \beta_6 X_{ijkt} + \alpha_{i,t} + \varepsilon_{ijkt}, \quad (8)$$

where $DTI36_{ijkt}$ is a dummy variable that equals one if the debt-to-income ratio of loan k made by loan officer i to borrower j in year t is greater than 36%, and zero otherwise; X_{ijkt}

is a set of loan and borrower characteristics, including the age of the property ($House\ Age$), whether the loan is sold to Government Sponsored Enterprises (GSE), the natural logarithm of the amount of the loan ($Log\ Loan\ Amount$), and the natural logarithm of the term of the loan ($Log\ Term$). The other variables are the same as those in Equation (4). In addition to loan officer×county×year, county×year×minority, and branch×minority×year fixed effects, I also include borrower race and ethnicity, borrower gender, borrower age bracket, loan type, loan purpose, and census tract fixed effects in the regressions. β_1 and β_2 capture the differences in the lending standards of Republican and Democratic loan officers toward minority borrowers, relative to unaffiliated loan officers.

I present the results in Table 11. In column (1), I present the results for all HMDA matched loans. The coefficient estimate on $Rep\ LO \times Minority$ is negative and statistically significant at the 5% level. The coefficient estimate on $Dem\ LO \times Minority$ is positive, but statistically insignificant. Importantly, the difference between the two coefficient estimates is statistically significant at the 1% level. Democratic loan officers are 5.8% more likely to originate loans to minority borrowers with debt-to-income ratio greater than 36%.

I then split the sample according to loan officer experience. In columns (2), I present the results for loan officers with experience below the sample median. The coefficient estimate on $Rep\ LO \times Minority$ is negative; while the coefficient estimate on $Dem\ LO \times Minority$ is positive and statistically significant. More importantly, the difference between the two coefficient estimates almost double that in column (1), and statistically significant. In contrast, in column (3) for more experienced loan officers, the difference between the coefficient estimates is small and statistically insignificant. These results again suggest that the political bias in mortgage lending decreases with experience.

To assess the robustness of the results, I also try other debt-to-income ratio cutoffs, including 38%, 40%, 42%, 44%, and 46%. The results are presented in Table 12. Control variables are included in the regressions, but are omitted from the table. The differences between the estimates on $Rep\ LO \times Minority$ and $Dem\ LO \times Minority$ remain negative and statistically significant for $DTI38$, and $DTI40$. However, the differences become much

smaller and statistically insignificant for $DTI42$, $DTI44$, and $DTI46$. These results are consistent with the idea that loan officers have less discretion when the debt-to-income ratio is very high.

5.2 Mortgage cost

In addition to underwriting standards, I also examine whether the political affiliation of loan officers affects their pricing of minority loans. First, replace the dependent variable in Equation (8) with the mortgage interest rate. I also additionally include the LTV grid×year and debt-to-income grid fixed effects in the regressions. I present the estimation results in column (1) of Table 7. The coefficient estimates on $Rep\ LO \times Minority$ and $Dem\ LO \times Minority$ are both negative, and the difference is small and statistically insignificant. I then again split the sample based on loan officer experience, and present the results in columns (2) and (3). In both columns, the coefficient estimates on $Rep\ LO \times Minority$ and $Dem\ LO \times Minority$ are all small and statistically insignificant. Furthermore, the differences between the two coefficient estimates are also small and statistically insignificant. These results suggest that the political affiliation of the loan officers does not affect the mortgage interest rate. The results are not surprising, because most mortgages in the US are priced against the credit score and loan-to-value grid (Bartlett et al. 2022).

I then replace the dependent variable with the rate spread, the difference between APR and the average prime offering rate. The rate spread incorporates origination fees and points, capturing the non-interest mortgage cost. In particular, the rate spread could also capture the fees charged by loan officers. The results for the full sample are presented in column (4) of Table 7. The coefficient estimates on $Rep\ LO \times Minority$ and $Dem\ LO \times Minority$ are both negative. The coefficient estimate on $Dem\ LO \times Minority$ is larger and statistically significant at the 10% level; while the coefficient estimate on $Rep\ LO \times Minority$ is smaller and statistically insignificant. However, the difference between the estimates is statistically insignificant.

I then also split the sample based on loan officer experience. In column (2) for less experi-

enced loan officers, the negative coefficient estimate on $Dem\ LO \times Minority$ is much larger and statistically significant. More importantly, the difference between the two coefficient estimates is larger and statistically significant at the 5% level. In contrast, in column (3) for more experienced loan officers, the coefficient estimates on both $Dem\ LO \times Minority$ and $Rep\ LO \times Minority$ are close to zero and statistically insignificant. The difference between the two is also close to zero and statistically insignificant. These results again suggest that political bias in mortgage lending decreases with experience, consistent with statistical discrimination with inaccurate belief.

5.3 Mortgage performance

The results so far suggest that Democratic loan officers originate more loans to minority borrowers and are more likely to approve loans with higher debt-to-income ratios from minority borrowers. The results are driven by Democratic loan officers favoring minority loan borrowers. However, if that is the case, it would imply that loans originated by Democratic loan officers will be of lower quality. To examine whether this is the case, I use the McDash matched sample to identify ex post loan performance. In particular, I use whether the loan ever experiences delinquencies of more than 60 days ($Delinq$ 60 or more than 90 days ($Delinq$ 90) to measure loan performance and then replace the dependent variable in Equation 8 with these loan performance measures. In addition, I also control for the debt-to-income ratio (DTI), credit score ($Credit\ Score$), loan-to-value ratio (LTV), and mortgage interest rate ($Interest\ Rate$).

The results are presented in Table 14. In column (1) for 60-day delinquency, the coefficient estimates on $Rep\ LO \times Minority$ is positive and that on $Dem\ LO \times Minority$ is negative. Furthermore, the difference between the two coefficient estimates is statistically significant at the 10% level. These results suggest that the quality of minority loans originated by Democratic loan officers is slightly better than those originated by Republican loan officers. I then also split the sample based on loan officer experience. The results in columns (2) and (3) again suggest that the difference is only present for less experienced loan officers.

The results in columns (4)-(6) for over-90 day delinquency show a similar pattern. These results suggest that Democratic loan officers do not favor minority borrowers. The results are consistent with the insights in Conklin (2017), who shows that loan officers could help borrowers with lower levels of financial literacy to make better financial decisions and hence lower mortgage default. These results therefore suggest that Democratic loan officers are more effective in helping minority borrowers in this regard.

6 Experimental Evidence

The empirical results suggest that the the majority of the partisan-racial gap in mortgage underwriting happens before mortgage applications are even submitted. However, to directly identify the pre-application gap is empirically challenging because pre-application data are not available. I therefore follow Ross et al. (2008) and Hanson et al. (2016) to conduct an experimental study to identify the pre-application partisan-racial gap in mortgage lending.

Specifically, I use a method similar to Hanson et al. (2016) and send email loan inquiries to real loan officers using obvious African American and white names. In addition to loan officer information collected by Hanson et al. (2016), I also use voter registration data to identify loan officers' political affiliation.

The full details of the experimental design are in Appendix B. In the following, I provide a brief description of the experimental design. I first collect names, emails, and working addresses of 500 loan officers who work in North Carolina from mortgage lender's websites. I then use a similar method as in the empirical analysis to match the loan officers with voter registration. This procedure produces a sample of 286 loan officers with matched voter registration records. Demographic information of these loan officers is in the appendix.

I create multiple email addresses with distinctively African American and white names to send loan inquiries to the 286 loan officers. Each loan officer receives two email loan inquiries, one with an African American name and the other with a white name. The email inquiries all provide the credit score and ask two of the three basic questions about loan types, mortgage

interest rate, and fees. The credit scores are either around the 25^{th} percentile (677-679) or the 75^{th} percentile (777-779) of the credit score distribution of North Carolina mortgage borrowers in 2023. The two emails to the same loan officers have different formats, different questions, but similar credit scores.[3]. The two emails are sent exactly a week apart. Then I record whether the loan officers responded to the email inquiries and if they did, the contents of their reply emails.

I present the regression results based on the experiment below. Additional results are in the appendix. Specifically, I first run the following regression:

$$Response_{ij} = \alpha_i + \alpha_j + \beta_1 Rep\ LO_i \times Minority_j + \beta_2 Dem\ LO_i \times Minority_j + \beta_3 Minority\ LO_i \times Minority_j + \varepsilon_{ij}, \quad (9)$$

where $Response_{ij}$ equals one if the loan officer i responded to the email inquiry from applicant j, and zero otherwise; α_i is the loan officer fixed effects and α_j is the applicant fixed effects. With these fixed effects, I compare the responses of the same loan officer to two email inquiries, one with an African American name and the other a white name. I cluster the standard error by loan officer.

The results are presented in Panel A of Table 15. In column (1) for the full sample, the coefficient estimate on $RepLo \times Minority$ is negative and that on $DemLo \times Minority$ is positive. However, the difference between the two estimates is statistically insignificant. In column (2) for email inquiries with low credit scores, the coefficient estimate on $RepLo \times Minority$ remains negative and that on $DemLo \times Minority$ also remains positive. However, the difference is much greater and statistically significant at the 5% level. The magnitude is large. Democratic loan officers are 27% more likely to respond to loan inquiries from minories than Republican loan officers when their credit score is low. In column (3) for high credit scores, the difference between the coefficient estimates on $RepLo \times Minority$ and

[3]The credit scores of African American emails are 1 point higher than those of white emails

$DemLo \times Minority$ turns positive, although statistically insignificant. These results suggest that Democratic loan officers are more likely to respond to emails from marginal minority applicants than Republican loan officers.

Then I then examine whether the contents of the response emails also differ, conditional on the loan officers' responding. Specifically, I measure the length the emails and estimate the Poisson fixed effect model with a similar specification as in Equation (9). The results are presented in Panel B of Table 15. In column (1) for all responses, the coefficient estimates on $RepLo \times Minority$ is negative and statistically significant, and the coefficient estimates on $DemLo \times Minority$ is much smaller and statistically insignificant. While the magnitude of the difference between the two estimates (-0.354) is big, it is statistically insignificant. In column (2) for responses to email inquiries with low credit scores, the coefficient estimates on $RepLo \times Minority$ remains negative and statistically significant, while the coefficient estimates on $DemLo \times Minority$ becomes positive, although statistically insignificant. More importantly, the difference between the two estimates is statistically significant at the 10% level. Conditional on responding to the email inquiries, the length of email responses to low credit minority applicants by Democratic loan officers are more than 50% longer than those by Republican loan officers. In contrast, in column (3) for applicants with high credit scores, The difference between the two coefficient estimates has the opposite sign, albeit statistically insignificant. These results suggest that Democratic loan officer are more likely to spend more effort in responding to inquiries from marginal minority applicants than Republican loan officers, another potential source of pre-application partisan-racial gap in mortgage origination.

Overall, these experimental results suggest that loan officers' political affiliation shapes both their willingness and the effort they invest in responding to marginal minority borrowers. This differential engagement at the pre-application stage provides a direct mechanism for the 30 percent partisan-racial gap in loan originations documented in the observational analysis: minority borrowers approaching Republican officers are less likely to receive the information and guidance needed to submit viable applications in the first place.

7 Conclusion

This paper provides new evidence that loan officers' political ideology is an important determinant of racial disparities in mortgage lending. Using a novel dataset that links voter registration records with mortgage origination data from CoreLogic, HMDA, and McDash, I document that Democratic loan officers originate approximately 30 percent more loans to minority borrowers than their Republican counterparts after controlling for branch location, applicant pool composition, and loan officer fixed effects. This gap reflects differences in lending decisions rather than differential access to minority applicants: an email correspondence experiment confirms that Republican loan officers are significantly less willing to engage with marginal minority applicants even before a formal application is submitted.

The evidence collectively points to statistical discrimination with inaccurate beliefs as the primary mechanism. Democratic loan officers are more likely to approve high-debt-to-income-ratio loans for minority applicants, yet these loans exhibit equal or better ex post performance, indicating that the partisan gap reflects underinvestment in information acquisition by Republican officers rather than excess risk-taking by Democratic ones. Consistent with this interpretation, the partisan gap attenuates substantially among experienced loan officers, who have had greater opportunity to update their priors through direct lending experience.

These findings carry meaningful economic implications. The 2,461 Republican loan officers in the sample collectively denied approximately 1,772 minority households per year access to mortgage credit in North Carolina alone. Given the central role of homeownership in household wealth accumulation and intergenerational mobility, such systematic exclusion may have consequences that compound over time. The results suggest that regulatory interventions targeting the information environment of loan officers—such as structured guidelines for handling marginal applications, or paired-testing monitoring programs—could help mitigate the partisan-racial gap without requiring costly oversight of individual lending decisions. More broadly, the findings highlight that the ideological composition of financial sector employees is a potentially important and underappreciated determinant of credit

market inequality.

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Appendix A: An Alternative Framework with Differential Information Acquisition Costs

The main model formalizes statistical discrimination through differences in loan officers' *beliefs* about the returns to effort for minority borrowers. This appendix develops an alternative framework that reaches the same predictions through a different channel: differences in the *cost* of acquiring information about minority borrowers. The two frameworks are observationally equivalent in cross-section but differ in their prediction about the role of experience, a distinction the empirical analysis exploits.

As in the main model, there are two types of loan officers—unbiased (type U) and biased (type B)—each evaluating applications from minority (M) and white (W) borrowers. I again focus on marginal minority borrowers, those for whom the initial creditworthiness assessment $\theta < \bar{\theta}$, as these are the applicants whose outcome depends on the officer's information collection effort.

If an officer exerts effort e at cost $c_j(e) = \frac{1}{2}\gamma_j e^2$ (where $\gamma_j > 0$, $0 < e < 1$, and $j \in \{U, B\}$), they obtain additional information I with the following structure:

$$I = \begin{cases} I^{good} & \text{with probability } p \cdot e \\ I^{null} & \text{with probability } 1 - p \cdot e \end{cases}$$

where I^{good} means favorable information that raises creditworthiness to $\theta + \Delta > \bar{\theta}$, and I^{null} means no additional useful information is uncovered. In this framework, *both officer types share the same correct belief* p about the returns to effort—the bias enters exclusively through the cost parameter. Specifically, I assume $\gamma_u < \gamma_b$: it is more costly for the biased officer to acquire information about minority borrowers, for example because of less developed referral networks, fewer co-ethnic contacts, or lower willingness to invest in minority-specific knowledge. For white applicants, I assume $\gamma_u = \gamma_b = \gamma$, so no cost differential exists and the two officer types behave identically.

The loan officer earns a commission proportional to the loan amount, αL, where L is the

loan amount and $0 < \alpha < 1$, if the application is approved (Giacoletti et al., 2023). Each officer type $j \in \{U, B\}$ solves:

$$\max_{e \in [0,1]} \quad \pi_j(e) = p \cdot e \cdot \alpha L - \frac{1}{2}\gamma_j e^2 \tag{10}$$

The first-order condition is:

$$\frac{\partial \pi_j}{\partial e} = p\alpha L - \gamma_j e = 0 \tag{11}$$

Proposition 3. *The optimal effort levels for minority applicants are:*

$$e_u^* = \frac{p\alpha L}{\gamma_u} \quad \textit{and} \quad e_b^* = \frac{p\alpha L}{\gamma_b}$$

Since $\gamma_u < \gamma_b$, we have $e_b^* < e_u^*$: the biased loan officer exerts less effort than the unbiased loan officer when evaluating minority applicants.

The probability that officer type j approves a minority loan is:

$$P_j^{approve} = p \cdot e_j^* \tag{12}$$

Proposition 4. *The minority loan approval probability is higher for unbiased officers:*

$$P_u^{approve} = p \cdot e_u^* = \frac{p^2 \alpha L}{\gamma_u} > \frac{p^2 \alpha L}{\gamma_b} = p \cdot e_b^* = P_b^{approve}$$

That is, minority loans processed by unbiased officers are more likely to be approved than those processed by biased officers.

Since both officer types behave identically for white applicants (same p and same cost γ), the differential in approval rates applies only to the minority group. This generates a racial gap in lending that is qualitatively identical to that in the main model: biased officers approve relatively fewer minority loans than unbiased officers, not because they take more

risk, but because they invest less in uncovering favorable information.

Loan quality prediction. As in the main model, the minority loans that biased officers do approve carry no more risk than those approved by unbiased officers, since the true approval probability $p \cdot e_j^*$ reflects the same underlying technology p. The lower approval rate therefore reflects underinvestment in screening effort, not differential risk tolerance—consistent with the finding that minority loans originated by Democratic officers exhibit lower ex post delinquency rates.

Relationship to experience. The key distinction between this framework and the main model lies in the experience channel. In the main model, the bias arises from inaccurate beliefs that are updated through experience, so the partisan-racial gap should attenuate as loan officers accumulate more loans. In this alternative framework, the higher cost γ_b is not directly connected to a belief that can be updated; if the cost reflects a fixed investment decision or structural disadvantage, the gap would *not* attenuate with experience. The empirical finding that the partisan-racial gap is significantly smaller among experienced loan officers is therefore more consistent with the main (inaccurate-beliefs) model. Nonetheless, as discussed in the main text, cost differences could themselves be rooted in prior beliefs about profitability: biased officers who underestimate the returns to effort for minority borrowers rationally underinvest in the technology for doing so, making the two frameworks complementary at a deeper level.

Appendix B: Experimental Design and Addtional Experimental Results

I first identify the top 10 mortgage lenders based on the number of mortgages they made in North Carolina in 2022 in HMDA. I calculate the weights of these 10 lenders also based on the number of mortgage they made in North Carolina in 2022. I gather the lists of all loan officers who are affiliated with these lenders and work in North Carolina. I randomly choose loan officers from these lists. For each lender, the number of loan officers sampled is 500 times the weights calculated above. For example, if the total number of mortgages made by these top 10 lenders is 10,000, and lender X made 1,000 loans, I will randomly choose 50 (500×10%) loan officers from lender X's list of loan officers.

Then I then match these 500 loan officers with North Carolina voter registration data using a procedure similar to the empirical analysis. Whenever possible, I also used the images of the loan officers on their websites to determine race and age range. resulting in 286 matched loan officers.

I register four gmail accounts, two using African American names and white names. I follow Hanson et al. (2016) to compile the top 10 first names of African Americans and white Americans using New York City Department of Health and Human Hygiene(DHHH) records for babies born in 1990. I then compile the top 10 last names of African American and white Americans using the Word et al. (2008)'s list of names from 2000 Census. I then randomly pick two African American first names and combine them with randomly picked African American last names to create the two African American names. I use the same method to create the two white names. The gmail accounts uses combinations of the first and last names as the email addresses.[4]

I create four different versions of the emails with greetings, the source of email information, the questions, and the credit score. Each email contains two of the three questions regarding the types of loans available, the interest rate, and the fees. The emails are sent in

[4]The IRB prohibits the disclosure of the exact names and email addresses used in the study.

two batches with exactly one week apart. The credit scores in the first batch are either 678 or 778, which are the 25^{th} and 75^{th} percentile of the credit scores of all mortgage borrowers in North Carolina in 2022 based on McDash data. Each loan officer receives one email from each batch, one from an eamil associated with an African American name and the other from an email associated with a white name. To minimize the propobability of exposing the study, credit scores in the second batch emails are either one point higher or one point below the credit scores in the first email to the same loan officer. In all cases, the credit scores associated with the African American names are always one point higher.

I waited two weeks to check the responses. I then remove the following loan officers (emails) from the sample: emils that did not go through, email responses saying the loan officer is no longer with the company, email responses saying the loan officer will be out of officer for a period of time, or email responses by a team. The final sample contains 263 loan officers, among which 49.8% are Republican and 16% are Democrats, which are similar to the sample of loan officers used in the empirical analysis, as shown in Tables 3 and 4. 9.1% of the loan officers are minority, higher than those in the empirical analysis, possibly due to the increasing share of minority loan officers over time.

I also present the descriptive statistics of the email responses in Table B.1, with Panel A for the dummy variable of whether the loan officers respond to the email inquiries and Panel B for the length of the email responses.

Table B.1: Descriptive experimental results

This table provides the descriptive experimental results regarding loan officers' responses to email inquiries (Panel A) and the length of the response emails (Panel B) for the whole sample, and subsamples partitioned based on loan officer political affiliation, whether the applicant is African American, and the credit score in the email inquiries.

Panel A: Email response

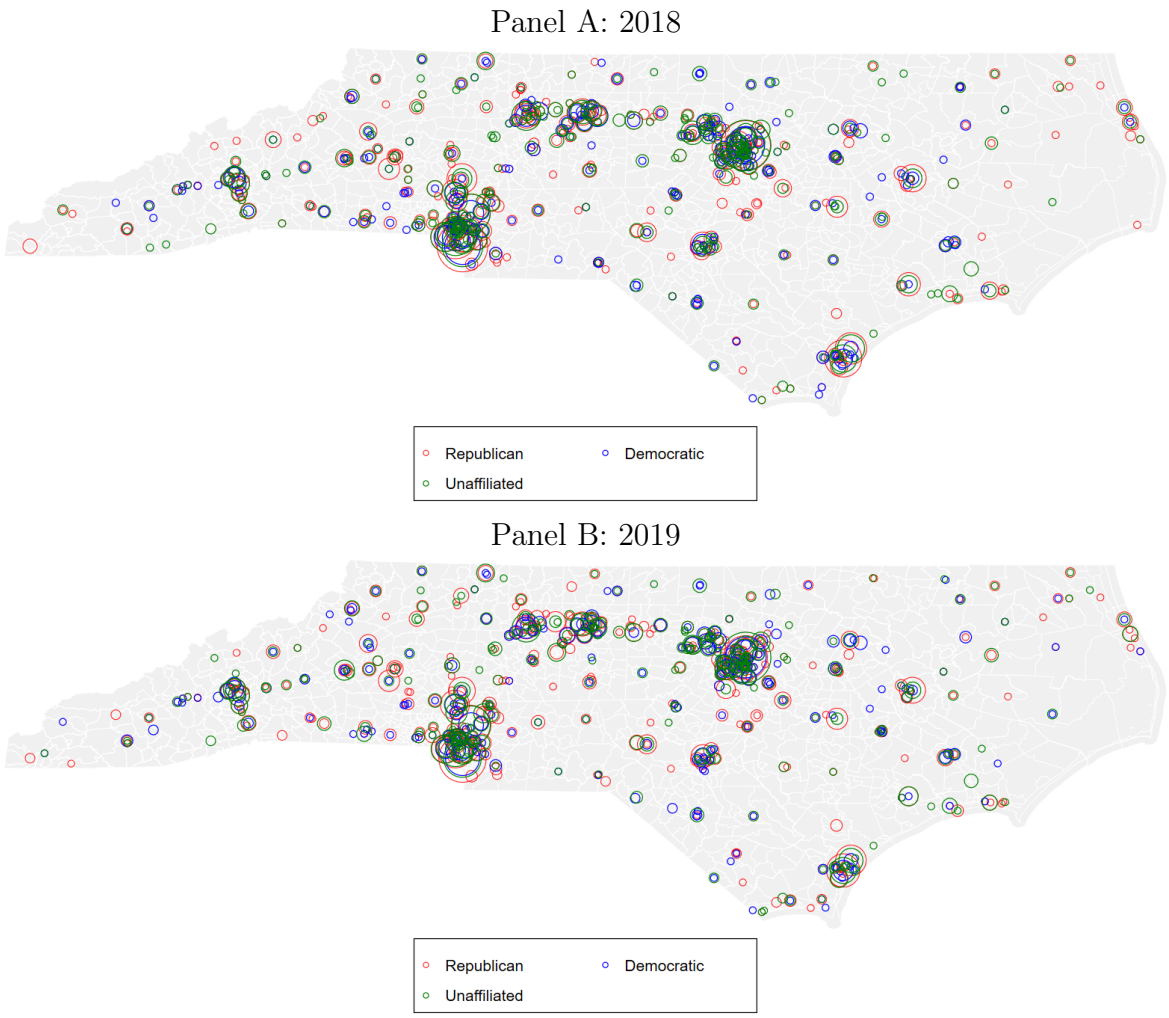
		All	Low Credit Score	High Credit Score
(1)	Full Sample	0.456	0.437	0.482
		(0.022)	(0.029)	(0.033)
(2)	Minority Applicant	0.405	0.348	0.478
		(0.030)	(0.039)	(0.046)
(3)	White Applicant	0.508	0.522	0.486
		(0.031)	(0.041)	(0.048)
(4)	(2)-(3)	-0.103**	-0.174***	-0.008
		(0.043)	(0.056)	(0.067)
(5)	Republican LO and Minority Applicant	0.409	0.347	0.483
		(0.043)	(0.057)	(0.062)
(6)	Republican LO and White Applicant	0.561	0.606	0.508
		(0.044)	(0.058)	(0.066)
(7)	(5)-(6)	-0.152**	-0.258***	-0.025
		(0.061)	(0.081)	(0.092)
(8)	Democratic LO and Minority Applicant	0.476	0.458	0.500
		(0.078)	(0.104)	(0.121)
(9)	Democratic LO and White Applicant	0.524	0.541	0.500
		(0.078)	(0.104)	(0.121)
(10)	(8)-(9)	-0.048	-0.083	0.000
		(0.110)	(0.147)	
(11)	(7)-(10)	-0.105	0.175	-0.025
		(0.125)	(0.164)	(0.193)

Panel B: Length of email response (characters)

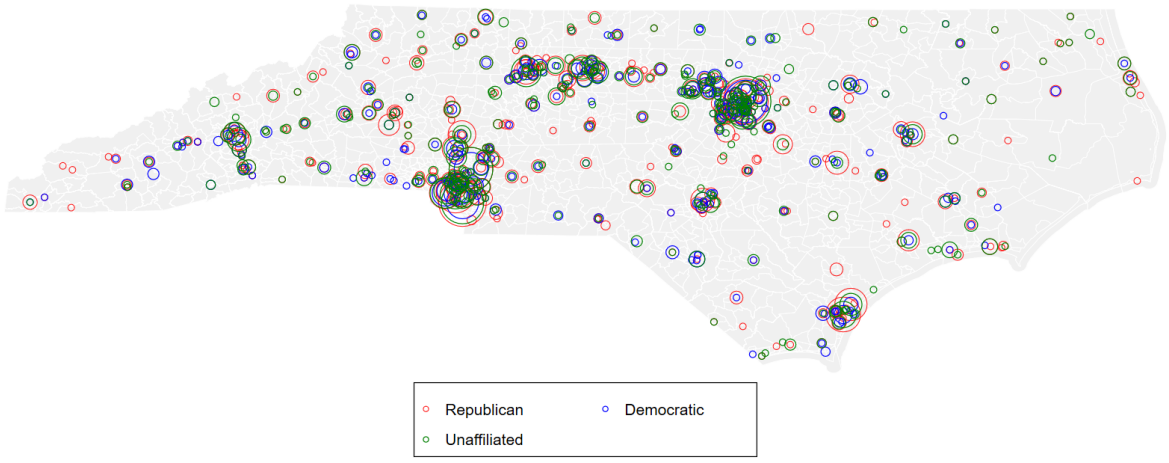
		All	Low Credit Score	High Credit Score
(1)	Full Sample	440.5	474.1	399.4
		(24.8)	(37.3)	(30.7)
(2)	Minority Applicant	410.7	410.7	410.7
		(30.1)	(43.8)	(41.7)
(3)	White Applicant	464.4	515.3	387.7
		(37.6)	(54.3)	(45.6)
(4)	(2)-(3)	-53.8	-104.6	22.9
		(49.9)	(76.1)	(61.7)
(5)	Republican LO and Minority Applicant	381.2	372.24	388.9
		(34.1)	(52.0)	(45.9)
(6)	Republican LO and White Applicant	478.7	571.7	345.5
		(57.7)	(90.4)	(45.9)
(7)	(5)-(6)	-97.6	-199.4*	43.3
		(73.3)	(124.3)	(64.9)
(8)	Democratic LO and Minority Applicant	511.4	480.9	548.7
		(102.3)	(132.5)	(167.5)
(9)	Democratic LO and White Applicant	568.4	505.8	650.9
		(91.0)	(91.0)	(182.9)
(10)	(8)-(9)	-57.0	-24.9	-110.2
		(136.4)	(156.7)	(248.0)
(11)	(7)-(10)	-40.1	-174.6	153.6
		(148.9)	(226.9)	(178.0)

Figure 1: Loan officer location

This figure shows the branch locations of the loan officers analyzed in the paper. The size of the circles are proportional to the number of loan officers at that location.



Panel C: 2020



Panel D: 2021

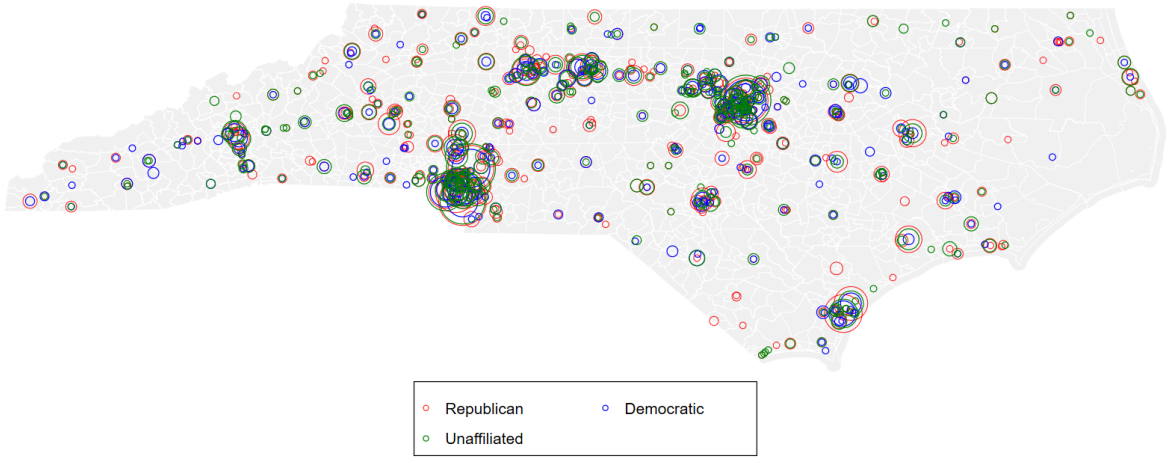


Table 1: Loan officer political affiliation and the percent of minority loans
This table presents the percentages of minority loans originated by loan officers with different political affiliations.

Loan Officer Political Affiliation	Percent of Minority Loans
Democratic	26.41%
Republican	15.84%
Unaffiliated	19.74%
Democratic-Republican	10.57%***
	(0.55%)

Table 2: Summary Statistics of the Loan Officer-County-Year Sample
This table presents the summary statistics of the number (value) of loans originated by each loan officer in each county in each year to minority and non-minority loans.

Panel A: Minority Loans						
	N	Mean	SD	25th Perc.	Median	75th Perc.
Number_Loans (Full Sample)	31,023	1.178	2.689	0.000	0.000	1.000
Value_Loans (Full Sample))	31,023	266,607.8	683,290.4	0.000	0.000	293,292.0
Number_Loans (Voter Registration Sample)	31,023	.930	2.180	0.000	0.000	1.000
Value_Loans (Voter Registration Sample)	31,023	217,083.7	592,193.8	0.000	0.000	243,399.0
Pseudo Approval Rate (Full Sample)	17,188	0.448	0.832	0.000	0.054	0.502
Pseudo Approval Rate (Voter Registration Sample)	17,188	0.346	0.690	0.000	0.000	0.358
Panel B: Non-Minority Loans						
Number_Loans (Full Sample)	31,023	6.207	11.501	2.000	3.000	6.000
Value_Loans (Full Sample)	31,023	1,627,342.6	3,774,849.8	349,597.0	659,708.0	1,443,192.0
Number_Loans (Voter Registration Sample)	31,023	4.753	9.033	1.000	2.000	5.000
Value_Loans (Voter Registration Sample)	31,023	1,265,571.7	3,102,284.7	235,400.0	515,831.0	1138550.0
Pseudo Approval Rate (Full Sample)	17,188	0.445	0.493	0.167	0.300	0.536
Pseudo Approval Rate (Voter Registration Sample)	17,188	0.341	0.405	0.112	0.222	0.420

Table 3: Summary statistics of the CoreLogic-HMDA matched sample

This table presents the summary statistics of the CoreLogic-HMDA matched sample. $DTI36$ is a dummy variable equal to one if the debt-to-income ratio is greater than 36%; $DTI38$ is a dummy variable equal to one if the debt-to-income ratio is greater than 36%; $DTI40$ is a dummy variable equal to one if the debt-to-income ratio is greater than 40%; $DTI42$ is a dummy variable equal to one if the debt-to-income ratio is greater than 42%; $DTI44$ is a dummy variable equal to one if the debt-to-income ratio is greater than 44%; $DTI46$ is a dummy variable equal to one if the debt-to-income ratio is greater than 46%; $CLTV$ is the combined loan-to-value ratio; *Interest Rate* is the mortgage interest rate (in percentage points); *Rate Spread* is the difference between mortgage APR and the average prime offering rate (in percentage points); *Origination Cost* is the total origination costs scaled by loan amount (in percentage points); FHA is a dummy variable equal to one if the loan is an FHA loan; VA is a dummy variable equal to one if the loan is an VA loan; GSE is a dummy variable equal to one if the loan is sold to a GSE; *Rep LO* is a dummy variable equal to one if the loan officer is Republican; *Dem LO* is a dummy variable equal to one if the loan officer is Democratic; *Minority LO* is a dummy variable equal to one if the loan officer is African American or Hispanic; $Co-Applicant$ is a dummy variable is a dummy variable if the loan has a co-applicant, *Loan Amount* is the mortgage loan amount; *Income* is the borrower annual income; *Property Value* is the value of the property; *House Age* is the age of the property; and $Age > 62$ is a dummy variable equal to one if the borrower is aged 62 or above.

	N	Mean	SD	25th Perc.	Median	75th Perc.
DTI36	158,767	0.376	0.484	0.000	0.000	1.000
DTI38	158,767	0.312	0.463	0.000	0.000	1.000
DTI40	158,767	0.249	0.432	0.000	0.000	0.000
DTI42	158,767	0.183	0.386	0.000	0.000	0.000
DTI44	158,767	0.125	0.330	0.000	0.000	0.000
CLTV	157,491	78.168	245.131	66.250	80.000	95.000
Interest Rate	158,757	3.505	0.792	2.875	3.250	4.000
Rate Spread	155,356	0.395	0.566	0.035	0.292	0.661
FHA	158,767	0.081	0.273	0.000	0.000	0.000
GSE	158,767	0.904	0.294	1.000	1.000	1.000
VA	158,767	0.080	0.271	0.000	0.000	0.000
Rep LO	158,767	0.496	0.500	0.000	0.000	1.000
Dem LO	158,767	0.175	0.380	0.000	0.000	0.000
Minority LO	158,767	0.048	0.215	0.000	0.000	0.000
Co Applicant	158,767	0.618	0.486	0.000	1.000	1.000
Minority	158,767	0.127	0.333	0.000	0.000	0.000
Loan Amount	158,767	246,895	147,308	152,000	218,400	305,000
Income	154,339	112.158	112.063	57.000	88.000	135.000
Property Value	157,831	338,669	233,843	205,000	285,000	405,000
House Age	153,230	32.283	23.878	15.000	25.000	46.000
Age>62	158,767	0.153	0.360	0.000	0.000	0.000

Table 4: Summary statistics of the CoreLogic-HMDA-McDash matched sample
This table presents the summary statistics of the CoreLogic-HMDA-McDash matched sample. *Delinq*60 is a dummy variable equal to one if the loan ever experiences a more than 60-day delinquency; *Delinq*90 is a dummy variable equal to one if the loan ever experiences a more than 90-day delinquency; *Delinq*120 is a dummy variable equal to one if the loan ever experiences a more than 120-day delinquency; $CLTV$ is the combined loan-to-value ratio; *Interest Rate* is the mortgage interest rate (in percentage points); *Rate Spread* is the difference between mortgage APR and the average prime offering rate (in percentage points); *Origination Cost* is the total origination costs scaled by loan amount (in percentage points); FHA is a dummy variable equal to one if the loan is an FHA loan; VA is a dummy variable equal to one if the loan is an VA loan; GSE is a dummy variable equal to one if the loan is sold to a GSE; *Rep LO* is a dummy variable equal to one if the loan officer is Republican; *Dem LO* is a dummy variable equal to one if the loan officer is Democratic; *Minority LO* is a dummy variable equal to one if the loan officer is African American or Hispanic; $Co-Applicant$ is a dummy variable is a dummy variable if the loan has a co-applicant, *Loan Amount* is the mortgage loan amount; *Income* is the borrower annual income; *Property Value* is the value of the property; *House Age* is the age of the property; and $Age > 62$ is a dummy variable equal to one if the borrower is age 62 or above. *Credit Score* is the borrower credit score; *First Time Home Buyer* is a dummy variable equal to one if the borrower is a first-time home buyer; *Mortgage Insurance* is a dummy variable equal to if the loan has private mortgage insurance.

	N	Mean	SD	25th Perc.	Median	75th Perc.
Delinq 60	42,563	0.045	0.208	0.000	0.000	0.000
Delinq 90	42,563	0.035	0.185	0.000	0.000	0.000
CLTV	42,160	84.692	472.635	73.565	85.000	96.500
Interest Rate	42,555	3.403	0.680	2.875	3.250	3.750
Rate Spread	41,563	0.322	0.591	-0.061	0.183	0.578
FHA	42,563	0.147	0.354	0.000	0.000	0.000
GSE	42,563	0.861	0.346	1.000	1.000	1.000
VA	42,563	0.140	0.347	0.000	0.000	0.000
Rep LO	42,563	0.526	0.499	0.000	1.000	1.000
Dem LO	42,563	0.157	0.364	0.000	0.000	0.000
Minority LO	42,563	0.048	0.214	0.000	0.000	0.000
Co Applicant	42,563	0.597	0.490	0.000	1.000	1.000
Minority	42,563	0.130	0.336	0.000	0.000	0.000
Loan Amount	42,563	248,348	142,873	162,011	220,800	296,073
Income	41,070	103.789	114.903	55.000	83.000	125.000
Property Value	42,467	316,581	218,895	195,000	265,000	375,000
House Age	41,217	31.489	23.564	15.000	25.000	45.000
Age>62	42,563	0.122	0.328	0.000	0.000	0.000
Credit Score	36,333	735.017	55.885	693.000	745.000	782.000

Table 5: Loan officer political affiliation and mortgage lending to minority borrowers
This table presents the results of estimating Equation (4). The sample is at the loan officer-county-racial group-year level. The dependent variable is *Number of Loans*, the total number of loans a loan officer originates to minority or non-minority borrowers in a year in a county; the dependent variable in panel B is *Value of Loans*, the total dollar value of all loans a loan officer originates to minority or non-minority borrowers in a given year; *Rep LO* is a dummy variable equal to one if the loan officer is Republican; *Dem LO* is a dummy variable equal to one if the loan officer is Democratic; *Minority LO* is a dummy variable equal to one if the loan officer is African American or Hispanic; *Minority* is a dummy variable equal to one if the borrower is African American or Hispanic. Standard errors clustered by loan officer are reported in parentheses below the coefficient estimates. The significance at the levels of 1%, 5%, and 10% is indicated by ***, **, and *, respectively.

	(1)	(2)	(3)
Rep LO×Minority	-0.110**	-0.164***	-0.168***
	(0.053)	(0.043)	(0.043)
Dem LO×Minority	0.212***	0.196***	0.185***
	(0.074)	(0.064)	(0.065)
Minority	-3.323***		
	(0.106)		
Minority LO×Minority	0.750***	0.691***	0.706***
	(0.117)	(0.110)	(0.112)
Percent DTI<20	-0.990		
	(0.834)		
Percent DTI 20-30	4.134***		
	(0.752)		
Percent DTI 30-36	6.491***		
	(0.820)		
Percent DTI 36-40	5.169***		
	(0.837)		
Percent DTI 41-45	1.345		
	(0.846)		
Percent DTI 46-50	1.395		
	(1.131)		
Percent DTI 50-60	8.950***		
	(1.104)		
Percent DTI>60	-7.746***		
	(1.389)		
Log Average Income	-0.063**		
	(0.029)		
Percent Female	7.866***		
	(0.419)		
Percent with Co-Applicant	-3.511***		
	(0.471)		
Pecent Age>62	3.644***		
	(0.377)		
Average LTV	-1.627**		
	(0.709)		
Log Average Loan Amount	-0.913***		
	(0.126)		
Log Average Property Value	1.432***		
	(0.171)		
Rep LO×Minority-Dem LO×Minority	-0.322***	-0.360***	-0.353***
	(0.063)	(0.067)	(0.068)
Observations	61,168	60,326	59,056
Loan Officer×Year FE	Yes		
Loan Officer×County FE	Yes		
County×Year FE	Yes		
Loan Officer×County×Year FE		Yes	Yes
Branch×Minority FE		Yes	
County×Year×Minority FE		Yes	Yes
Branch×Year×Minority FE			Yes

Table 6: Loan officer political affiliation and mortgage lending by value
This table presents the results of estimating Equation (4). The sample is at the loan officer-county-racial group-year level. The dependent variable is *Value of Loans*, the total value of loans a loan officer originates to minority or non-minority borrowers in a year in a county. *Rep LO* is a dummy variable equal to one if the loan officer is Republican; *Dem LO* is a dummy variable equal to one if the loan officer is Democratic; *Minority LO* is a dummy variable equal to one if the loan officer is African American or Hispanic; *Minority* is a dummy variable equal to one if the borrower is African American or Hispanic. Standard errors clustered by loan officer are reported in parentheses below the coefficient estimates. The significance at the levels of 1%, 5%, and 10% is indicated by ***, **, and *, respectively.

	(1)	(2)	(3)
Rep LO×Minority	-0.125**	-0.158***	-0.167***
	(0.055)	(0.044)	(0.044)
Dem LO×Minority	0.208***	0.212***	0.201***
	(0.077)	(0.068)	(0.069)
Minority	-3.266***		
	(0.119)		
Minority LO×Minority	0.739***	0.699***	0.713***
	(0.118)	(0.110)	(0.111)
Rep LO×Minority-Dem LO×Minority	-0.333***	-0.370***	-0.368***
	(0.074)	(0.072)	(0.073)
Observations	61,168	60,326	59,056
Controls	Yes		
Loan Officer×Year FE	Yes		
Loan Officer×County FE	Yes		
County×Year FE	Yes		
Loan Officer×County×Year FE		Yes	Yes
Branch×Minority FE		Yes	
County×Year×Minority FE		Yes	Yes
Branch×Year×Minority FE			Yes

Table 7: Loan officer political affiliation and pseudo-approval rate

This table presents the results of estimating Equation (6). The sample is at the loan officer-county-racial group-year level. The dependent variable is the pseudo-approval rate, which is the number of loans a loan officer originates to minority or non-minority borrowers in a county scaled by the number of expected applications; *Rep LO* is a dummy variable equal to one if the loan officer is Republican; *Dem LO* is a dummy variable equal to one if the loan officer is Democratic; *Minority LO* is a dummy variable equal to one if the loan officer is African American or Hispanic; *Minority* is a dummy variable equal to one if the borrower is African American or Hispanic. Standard errors clustered by loan officer are reported in parentheses below the coefficient estimates. The significance at the levels of 1%, 5%, and 10% is indicated by ***, **, and *, respectively.

	(1)	(2)	(3)
Rep LO×Minority	-0.053**	-0.062**	-0.061**
	(0.023)	(0.025)	(0.026)
Dem LO×Minority	0.134***	0.129***	0.133***
	(0.039)	(0.042)	(0.045)
Minority	0.024		
	(0.050)		
Minority LO×Minority	0.421***	0.415***	0.427***
	(0.075)	(0.075)	(0.080)
Rep LO×Minority-Dem LO×Minority	-0.187***	-0.191***	-0.194***
	(0.038)	(0.041)	(0.044)
Observations	33,890	33,692	33,124
R-squared	0.551	0.665	0.684
Loan Officer×Year FE	Yes		
Loan Officer×County FE	Yes		
County×Year FE	Yes		
Loan Officer×County×Year FE		Yes	Yes
Branch×Minority FE		Yes	
County×Year×Minority FE		Yes	Yes
Branch×Year×Minority FE			Yes

Table 8: Loan origination and local loan officer political affiliation

This table presents the results of estimating Equation (7). The sample is at the lender-county-racial group-year level. The dependent variables are: the dummy variable of whether the loan applications that are withdrawn or closed for incomplete information (column (1)), approved (column (2)), the total number of applications recieved by a lender in a county in a year. Columns (1)-(2) are estimated with OLS and column (3) is estimated with the Poisson model. *Percent Rep* (*Percent Dem*) is the percentage of Republican (Democratic) loan officers of the lender in the county in the year; *Minority* is a dummy variable equal to one if the borrower is African American or Hispanic. Standard errors double clustered by lender and county are reported in parentheses below the coefficient estimates. The significance at the levels of 1%, 5%, and 10% is indicated by ***, **, and *, respectively.

	(1) Withdrawn or Incomplete	(2) Approved	(3) Total Applications
Percent Rep×Minority	0.019**	0.014	-0.055
	(0.008)	(0.009)	(0.049)
Percent Dem×Minority	-0.005	0.002	0.092*
	(0.010)	(0.010)	(0.056)
Percent Minority×Minority	-0.011	0.010	0.252***
	(0.017)	(0.010)	(0.080)
Percent Rep×Minority	0.024**	-0.012	-0.147**
-Percent Dem×Minority	(0.010)	(0.008)	(0.075)
Observations	1,267,853	1,012,076	26,178
R-squared	0.108	0.277	
Controls	Yes	Yes	
Loan Type FE	Yes	Yes	
Loan Purpose FE	Yes	Yes	
Borrower Race FE	Yes	Yes	
Borrower Ethnicity FE	Yes	Yes	
Borrower Gender FE	Yes	Yes	
Borrower Age Bracket FE	Yes	Yes	
Company×County×Year FE	Yes	Yes	Yes
County×Year×Minority FE	Yes	Yes	Yes
Company×County×Year FE	Yes	Yes	Yes
Tract×Year FE	Yes	Yes	

Table 9: Political Selection?

This table presents the results of testing whether the partisan bias is driven by political selection. The sample is at the loan officer-county-racial group-year level. The dependent variable is $Value\ of\ Loans$, the total value of loans a loan officer originates to minority or non-minority borrowers in a year in a county. *Rep LO* is a dummy variable equal to one if the loan officer is Republican; *Dem LO* is a dummy variable equal to one if the loan officer is Democratic; $Minority\ LO$ is a dummy variable equal to one if the loan officer is African American or Hispanic; $Minority$ is a dummy variable equal to one if the borrower is African American or Hispanic. Standard errors clustered by loan officer are reported in parentheses below the coefficient estimates. The significance at the levels of 1%, 5%, and 10% is indicated by ***, **, and *, respectively.

	(1)	(2)	(3)	(4)
Rep LO×Minority	-0.072	-0.088	-0.078	-0.188**
	(0.050)	(0.081)	(0.083)	(0.094)
Dem LO×Minority	0.227***	0.288***	0.311***	0.233*
	(0.068)	(0.108)	(0.109)	(0.132)
Minority LO×Minority	0.532***	0.624***	0.545***	0.332
	(0.126)	(0.187)	(0.202)	(0.246)
LO Age × Minority	-0.007***	-0.011***	-0.011***	-0.011*
	(0.002)	(0.004)	(0.004)	(0.006)
Rep LO×Minority -Dem LO×Minority	-0.299***	-0.376***	-0.389***	-0.421***
	(0.070)	(0.111)	(0.113)	(0.124)
Loan Officer Gender × Minority	Yes	Yes	Yes	Yes
Loan Officer Religion × Minority		Yes	Yes	Yes
Loan Officer Language × Minority			Yes	Yes
Loan Officer Education × Minority				Yes
Loan Officer Birth State × Minority				Yes
Loan Officer×County×Year	Yes	Yes	Yes	Yes
Branch×Year×Minority	Yes	Yes	Yes	Yes
County×Year×Minority Fixed Effects	Yes	Yes	Yes	Yes

Table 10: Loan officer experience and the effect of loan officer political affiliation on mortgage lending

This table reports the results of how loan officer experience impacts the effect of political affiliation on mortgage lending. The sample is partitioned based on the number of loans the loan officer made during the three year period before the current year. The dependent variables is *Number of Loans*, the total number of loans a loan officer originates to minority or non-minority borrowers in a given year. *Rep LO* is a dummy variable equal to one if the loan officer is Republican; *Dem LO* is a dummy variable equal to one if the loan officer is Democratic; *Minority LO* is a dummy variable equal to one if the loan officer is African American or Hispanic; *Minority* is a dummy variable equal to one if the borrower is African American or Hispanic. Standard errors clustered by loan officer are reported in parentheses below the coefficient estimates. The significance at the levels of 1%, 5%, and 10% is indicated by ***, **, and *, respectively.

	Experience	
	Less	More
	(1)	(2)
Rep LO×Minority	-0.226***	-0.126**
	(0.048)	(0.062)
Dem LO×Minority	0.215***	0.136
	(0.059)	(0.121)
Minority LO×Minority	0.639***	0.827***
	(0.100)	(0.184)
Rep LO×Minority-Dem LO×Minority	-0.441***	-0.262**
	(0.063)	(0.118)
Observations	24,939	32,620
Loan Officer×County×Year FE	Yes	Yes
Branch×Year×Minority FE	Yes	Yes
County×Year×Minority FE	Yes	Yes

Table 11: Loan officer political affiliation and loan debt-to-income ratio being greater than 36%

This table reports the results of estimating Equation (8). The dependent variable $DTI36$ is a dummy variable equal to one if the debt-to-income ratio is greater than 36% and zero otherwise. *Rep LO* is a dummy variable equal to one if the loan officer is Republican; *Dem LO* is a dummy variable equal to one if the loan officer is Democratic; $Minority\ LO$ is a dummy variable equal to one if the loan officer is African American or Hispanic; $Minority$ is a dummy variable equal to one if the borrower is African American or Hispanic; $HouseAge$ is the age of the property; GSE is a dummy variable if the loan is GSE loan; *Log Loan Amount* is the natural logarithm of the loan amount; $Log\ Term$ is the natural logarithm of the loan term; $CLTV$ is the combined loan-to-value ratio. Standard errors clustered by loan officer are reported in parentheses below the coefficient estimates. The significance at the levels of 1%, 5%, and 10% is indicated by ***, **, and *, respectively.

	Full Sample	Less Experienced	More Experienced
	(1)	(2)	(3)
Rep LO×Minority	-0.044***	-0.018	-0.074***
	(0.015)	(0.023)	(0.022)
Dem LO×Minority	0.014	0.084***	-0.077**
	(0.020)	(0.028)	(0.032)
Minority LO×Minority	0.047*	0.012	0.076*
	(0.024)	(0.038)	(0.041)
House Age	-0.000***	-0.000**	-0.000**
	(0.000)	(0.000)	(0.000)
GSE	-0.002	-0.017	0.009
	(0.007)	(0.012)	(0.009)
Co Applicant	-0.060***	-0.065***	-0.055***
	(0.004)	(0.005)	(0.005)
Rep LO×Minority-Dem LO×Minority	-0.058***	-0.102***	0.003
	(0.018)	(0.027)	(0.030)
Observations	121,374	50,833	70,199
R-squared	0.269	0.350	0.239
Loan Officer×County×Year FE	Yes	Yes	Yes
Branch×Minority×Year FE	Yes	Yes	Yes
County×Year×Minority FE	Yes	Yes	Yes
Tract FE	Yes	Yes	Yes
Loan Type FE	Yes	Yes	Yes
Loan Purpose FE	Yes	Yes	Yes
Borrower Race FE	Yes	Yes	Yes
Borrower Ethnicity FE	Yes	Yes	Yes
Borrower Age Bracket FE	Yes	Yes	Yes
Borrower Gender FE	Yes	Yes	Yes

Table 12: Loan officer political affiliation and other debt-to-income ratio cutoffs
This table reports the results of estimating Equation (8). The dependent variables are $DTI38$, a dummy variable equal to one if the debt-to-income ratio is greater than 38%; $DTI40$, a dummy variable of the debt-to-income ratio is greater than 40%; $DTI42$, a dummy variable equal to one if the debt-to-income ratio is greater than 42%; and $DTI46$, a dummy variable equal to one if the debt-to-income ratio is greater than 44%. *Rep LO* is a dummy variable equal to one if the loan officer is Republican; *Dem LO* is a dummy variable equal to one if the loan officer is Democratic; *Minority LO* is a dummy variable equal to one if the loan officer is African American or Hispanic; *Minority* is a dummy variable equal to one if the borrower is African American or Hispanic; *HouseAge* is the age of the property; GSE is a dummy variable if the loan is GSE loan; and *Co Applicant* is a dummy variable of whether the application has a co-applicant. Standard errors clustered by loan officer are reported in parentheses below the coefficient estimates. The significance at the levels of 1%, 5%, and 10% is indicated by ***, **, and *, respectively.

	(1) DTI38	(2) DTI40	(3) DTI42	(4) DTI44	(5) DTI46
Rep LO×Minority	-0.034**	-0.039***	-0.025**	-0.018*	-0.006
	(0.014)	(0.013)	(0.012)	(0.010)	(0.009)
Dem LO×Minority	0.006	-0.003	-0.007	-0.010	0.001
	(0.018)	(0.017)	(0.015)	(0.013)	(0.011)
	(0.146)	(0.153)	(0.127)	(0.053)	(0.061)
Minority LO×Minority	0.065***	0.038**	0.002	0.011	0.011
	(0.023)	(0.019)	(0.016)	(0.017)	(0.014)
House Age	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GSE	-0.006	-0.007	-0.007	-0.001	-0.005
	(0.007)	(0.006)	(0.006)	(0.005)	(0.005)
Co Applicant	-0.053***	-0.043***	-0.029***	-0.018***	-0.012***
	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)
Rep LO×Minority-Dem LO×Minority	-0.040**	-0.035**	-0.018	-0.008	-0.005
	(0.017)	(0.015)	(0.014)	(0.013)	(0.007)
Observations	121,374	121,374	121,374	121,374	121,374
R-squared	0.265	0.263	0.257	0.260	0.257
Loan Officer×County×Year FE	Yes	Yes	Yes	Yes	Yes
Branch×Minority×Year FE	Yes	Yes	Yes	Yes	Yes
County×Year×Minority FE	Yes	Yes	Yes	Yes	Yes
Tract FE	Yes	Yes	Yes	Yes	Yes
Loan Type FE	Yes	Yes	Yes	Yes	Yes
Loan Purpose FE	Yes	Yes	Yes	Yes	Yes
Borrower Race FE	Yes	Yes	Yes	Yes	Yes
Borrower Ethnicity FE	Yes	Yes	Yes	Yes	Yes
Borrower Age Bracket FE	Yes	Yes	Yes	Yes	Yes
Borrower Gender FE	Yes	Yes	Yes	Yes	Yes

Table 13: Loan officer political affiliation and the cost of mortgages

This table reports the results of estimating the relationship between loan officer political affiliation and cost of mortgage. The dependent variables are *Interest Rate*, the mortgage interest rate; and *Rate Spread*, the difference between the mortgage APR and the average prime offering rate *Dem LO* is a dummy variable equal to one if the loan officer is Democratic; *Minority LO* is a dummy variable equal to one if the loan officer is African American or Hispanic; *Minority* is a dummy variable equal to one if the borrower is African American or Hispanic; $HouseAge$ is the age of the property; GSE is a dummy variable if the loan is GSE loan; *Log Loan Amount* is the natural logarithm of the loan amount; *Log Term* is the natural logarithm of the loan term; $CLTV$ is the combined loan-to-value ratio. Standard errors clustered by loan officer are reported in parentheses below the coefficient estimates. The significance at the levels of 1%, 5%, and 10% is indicated by ***, **, and *, respectively.

	Interest Rate				Rate Spread		
	Full Sample	Less Experienced	More Experienced		Full Sample	Less Experienced	More Experienced
	(1)	(2)	(3)		(4)	(5)	(6)
Rep LO×Minority	-0.001	0.010	0.000		-0.014	-0.002	-0.009
	(0.013)	(0.019)	(0.022)		(0.014)	(0.022)	(0.020)
Dem LO×Minority	-0.011	-0.030	0.022		-0.032*	-0.059**	-0.004
	(0.017)	(0.024)	(0.025)		(0.018)	(0.027)	(0.021)
Minority LO×Minority	0.015	0.030	-0.005		0.029	0.070	-0.032
	(0.024)	(0.039)	(0.030)		(0.023)	(0.046)	(0.025)
House Age	0.000***	0.000**	0.000***		0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
GSE	0.010	0.016	0.005		-0.019**	-0.017	-0.023**
	(0.008)	(0.011)	(0.011)		(0.008)	(0.012)	(0.011)
Co Applicant	0.030***	0.031***	0.028***		0.033***	0.031***	0.035***
	(0.003)	(0.005)	(0.004)		(0.003)	(0.005)	(0.004)
Log Loan Amount	-0.138***	-0.146***	-0.130***		-0.188***	-0.175***	-0.198***
	(0.005)	(0.007)	(0.008)		(0.006)	(0.009)	(0.008)
Log Term	0.649***	0.605***	0.687***		0.013	0.085***	-0.047***
	(0.006)	(0.008)	(0.009)		(0.009)	(0.012)	(0.012)
Rep LO×Minority	0.010	0.040	-0.022		0.018	0.057**	-0.004
-Dem LO×Minority	(0.016)	(0.024)	(0.024)		(0.016)	(0.027)	(0.015)
Observations	121,363	50,828	70,194		118,622	49,792	68,493
R-squared	0.816	0.834	0.813		0.649	0.653	0.665
Loan Officer×County×Year FE	Yes	Yes	Yes		Yes	Yes	Yes
Branch×Minority×Year FE	Yes	Yes	Yes		Yes	Yes	Yes
County×Minority×Year FE	Yes	Yes	Yes		Yes	Yes	Yes
Tract FE	Yes	Yes	Yes		Yes	Yes	Yes
Loan Type FE	Yes	Yes	Yes		Yes	Yes	Yes
Loan Purpose FE	Yes	Yes	Yes		Yes	Yes	Yes
Borrower Age Bracket FE	Yes	Yes		Yes	Yes	Yes	
Borrower Race FE	Yes	Yes	Yes		Yes	Yes	Yes
Borrower Ethnicity FE	Yes	Yes	Yes		Yes	Yes	Yes
DTI Grid FE	Yes	Yes	Yes		Yes	Yes	Yes
LTV Grid×Year FE	Yes	Yes	Yes		Yes	Yes	Yes

Table 14: Loan officer political affiliation and mortgage performance

This table reports the results of estimating the relationship between loan officer political affiliation and ex post mortgage performance. The dependent variable in panel A is *Delinq*60, a dummy variable equal to one if the loan ever experiences a delinquency of more than 60 days; and the dependent variable in panel B is *Delinq*90, a dummy variable equal to one if the loan ever experiences a delinquency of more than 90 days. *Rep LO* is a dummy variable equal to one if the loan officer is Republican; *Dem LO* is a dummy variable equal to one if the loan officer is Democratic; *Minority LO* is a dummy variable equal to one if the loan officer is African American or Hispanic; *Minority* is a dummy variable equal to one if the borrower is African American or Hispanic; *HouseAge* is the age of the property; $Age > 62$ is a dummy variable equal to one if the age of the borrower is greater than 62; *GSE* is a dummy variable if the loan is GSE loan; *Log Loan Amount* is the natural logarithm of the loan amount; *Log Term* is the natural logarithm of the loan term; *LTV* is the loan-to-value ratio; *Credit Score* is the credit score of the borrower; *DTI* is the debt-to-income ratio; *Interest Rate* is the mortgage interest rate. Standard errors clustered by loan officer are reported in parentheses below the coefficient estimates. The significance at the levels of 1%, 5%, and 10% is indicated by ***, **, and *, respectively.

	Delinq60			Delinq90		
	Full Sample	Less Experienced	More Experienced	Full Sample	Less Experienced	More Experienced
	(1)	(2)	(3)	(4)	(5)	(6)
Rep LO×Minority	0.012	0.059	0.028	-0.005	0.075	0.001
	(0.023)	(0.056)	(0.037)	(0.018)	(0.054)	(0.036)
Dem LO×Minority	-0.046	-0.159*	0.055	-0.063**	-0.124	0.021
	(0.035)	(0.081)	(0.054)	(0.031)	(0.079)	(0.053)
Minority LO×Minority	-0.002	0.114	-0.026	0.017	0.166**	-0.003
	(0.036)	(0.069)	(0.061)	(0.033)	(0.068)	(0.058)
House Age	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GSE	-0.010	0.004	-0.017	-0.008	-0.001	-0.014
	(0.008)	(0.014)	(0.011)	(0.007)	(0.012)	(0.009)
Log Loan Amount	0.006	0.014	-0.003	0.002	0.005	-0.008
	(0.006)	(0.009)	(0.009)	(0.005)	(0.008)	(0.008)
Log Term	-0.014*	-0.002	-0.012	-0.016**	0.002	-0.021**
	(0.007)	(0.012)	(0.011)	(0.007)	(0.011)	(0.009)
Credit Score	-0.001***	-0.001***	-0.001***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LTV	0.002	-0.019	0.012	0.025*	0.011	0.033
	(0.018)	(0.028)	(0.025)	(0.015)	(0.024)	(0.021)
Interest Rate	0.014**	-0.003	0.012	0.013**	-0.004	0.011
	(0.006)	(0.010)	(0.009)	(0.006)	(0.010)	(0.008)
Rep LO×Minority	0.058*	0.218***	-0.022	0.058*	0.20**	-0.020
-Dem LO×Minority	(0.032)	(0.081)	(0.040)	(0.030)	(0.079)	(0.038)
Observations	25,680	10,975	14,227	25,680	10,975	14,227
R-squared	0.399	0.511	0.388	0.405	0.518	0.396
Loan Officer×County×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Branch×Minority×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County×Year×Minority FE	Yes	Yes	Yes	Yes	Yes	Yes
Tract FE	Yes	Yes	Yes	Yes	Yes	Yes
Loan Type FE	Yes	Yes	Yes	Yes	Yes	Yes
Loan Purpose FE	Yes	Yes	Yes	Yes	Yes	Yes
Borrower Race FE	Yes	Yes	Yes	Yes	Yes	Yes
Borrower Age Bracket FE						
Borrower Ethnicity FE	Yes	Yes	Yes	Yes	Yes	Yes
Borrower Gender FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 15: Loan officer political affiliation and racial gap in the pre-application stage: Evidence from the experiment

This table presents the regression results of the email experiments. In Panel A, the dependent variable is the indicator variable of whether the loan officer responded to the email inquiry within two weeks or receiving the email. In Panel B, the dependent variable is the length of the response emails, and I use the Poisson fixed effect model for estimation. *Rep LO* is a dummy variable equal to one if the loan officer is Republican; *Dem LO* is a dummy variable equal to one if the loan officer is Democratic; *Minority LO* is a dummy variable equal to one if the loan officer is African American or Hispanic; *Minority* is a dummy variable equal to one if the email is from an African American name. Standard errors clustered by loan officer are reported in parentheses below the coefficient estimates. The significance at the levels of 1%, 5%, and 10% is indicated by ***, **, and *, respectively.

Panel A: Email response

	Full Sample	Low Credit Score	High Credit Score
	(1)	(2)	(3)
Rep LO×Minority	-0.110	-0.140	-0.079
	(0.077)	(0.092)	(0.134)
Dem LO×Minority	0.025	0.134	-0.111
	(0.097)	(0.130)	(0.161)
Minority LO×Minority	0.156	0.089	0.056
	(0.135)	(0.149)	(0.207)
Credit_Score	-0.002		
	(0.002)		
Rep LO×Minority-Dem LO×Minority	-0.135	-0.274**	0.033
	(0.095)	(0.121)	(0.165)
Observations	526	290	212
R-squared	0.703	0.759	0.644
Loan Officer Fixed Effects	Yes	Yes	Yes
Applicant Fixed Effects	Yes	Yes	Yes
Email Version Fixed Effects	Yes	Yes	Yes

Panel B: Email length

	Full Sample	Low Credit Score	High Credit Score
	(1)	(2)	(3)
Rep LO×Minority	-0.479***	-0.501**	-0.275
	(0.171)	(0.224)	(0.337)
Dem LO×Minority	-0.121	0.004	-0.347
	(0.267)	(0.297)	(0.433)
Minority LO×Minority	-0.691**	-1.633***	-1.218***
	(0.271)	(0.166)	(0.273)
Credit_Score	-0.007**		
	(0.003)		
Rep LO×Minority-Dem LO×Minority	-0.358	-0.505*	0.072
	(0.275)	(0.292)	(0.360)
Observations	154	82	64
Loan Officer Fixed Effects	Yes	Yes	Yes
Applicant Fixed Effects	Yes	Yes	Yes
Email Version Fixed Effects	Yes	Yes	Yes