Partisan Loan Officers and the Racial Gap in Mortgage Lending

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Abstract

Matching loan officers with their voter registration records, I find that Democratic loan officers originate more loans to minority borrowers than Republican loan officers. The results hold after controlling for demand-side factors. At the loan level, I find that Democratic loan officers are more likely to originate loans with higher debt-to-income ratios to minority borrowers than republican loan officers. Loans to minority borrowers originated by Democratic loan officers perform slightly better than those originated by Republican loan officers. These results suggest that Democratic loan officers collect and process more private information to help minority borrowers overcome deficiencies in hard information, and hence expand mortgage access for minority borrowers.

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

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1 Introduction

The boundaries of the political domain are blurring in an increasingly polarized society. Political ideology and identity now extend their influence far beyond elections and policy debates, shaping individual decisions in realms as diverse as beliefs about the economy (Cookson et al. 2020; Kempf and Tsoutsoura 2021; Dagostino et al. 2023), home buying and selling decisions (McCartney et al. 2023); portfolio choice (Meeuwis et al. 2022; Ke 2022), entrepreneurship (Engelberg et al. 2023), and even patenting activities (Engelberg et al. 2023b). This interconnectedness raises a critical question: how does political affiliation manifest in seemingly nonpolitical contexts, and what are its downstream consequences? In this paper, I study how the political ideology of loan officers affects mortgage lending to minorities.

The two major political parties in the US hold divergent perspectives on racial equity (Carmines and Stimson 2020). Therefore, it is interesting to study how the different views of individuals affiliated with different political parties impact their decisions on race-related issues. By exploring the intersection of political ideology and racial equity in mortgage lending, this paper aims to contribute to the understanding of the far-reaching impact of political affiliation on addressing racial disparities in financial opportunities.

Loan officers play an essential role in the mortgage lending process. They meet with prospective borrowers, evaluate their financial backgrounds, collect required documents and information, conduct interviews, and recommend mortgage plans tailored to each borrower's circumstances and needs. This process requires significant effort from loan officers, especially for marginal borrowers who may need more extensive documentation and support to overcome deficiencies in traditional credit metrics. Since a substantial component of loan officers' compensation is tied to originated loans, they assess the probability of each application's final approval when deciding how much effort to dedicate to a particular borrower.

If loan officers with certain political ideologies harbor conscious or unconscious biases against minority racial groups, they may provide substandard service or exert less effort on applications from minority borrowers. Such biases could manifest as negative preconceptions about the creditworthiness or risk profiles of minority borrowers. Consequently, loan officers may be less inclined to go the extra mile in collecting supporting documents or addressing deficiencies in these appli-

cations. This reduced effort could then decrease the likelihood of approval, reinforcing the initial biased beliefs and contributing to the perpetuation of racial disparities in mortgage lending.

I construct a novel testing sample by combining CoreLogic mortgage data, Nationwide Mortgage Licensing System (NMLS) loan officer data, the Home Mortgage Disclosure Act (HMDA) data, North Carolina voter registration data, and Fannie Mae and Freddie Mac loan level data. The CoreLogic mortgage data provide the unique NMLS ID number and name of loan officers, which I use to merge with the NMLS loan officer data. I use the North Carolina voter registration to identify the political affiliation of loan officers. Conducting a loan officer level analysis, I find that Democratic loan officers originate about 25% more loans to minority borrowers than Republican loan officers. The results are robust after controlling for lender-year and loan officer-year fixed effects.

To mitigate the concern that the results could be driven by demand-side factors, I construct a proxy for loan officer-county-level applications as the product of the total number of applications in the county and the loan officer's share of approved loans in the previous year. Constructing the pseudo-approval rate as the ratio between the number of approved loans and the proxy for the number of applications, 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-year-racial group fixed effects, further suggesting that the results are unlikely to be driven by demand-side factors.

To understand how loan officer political affiliation affects lending, I merge the CoreLogic mortgage data with the 2018-2022 HMDA mortgage data. Due to the lack of common identifiers, I rely on variables that are common in these two datasets for the matching. 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-year and city-year fixed effects, mitigating the concern that the results could be driven by demand-side factors. I also find similar results for other debt-to-income ratio thresholds.

In contrast, I do not find similar results for the loan-to-value ratio, another important under-

writing variable. I also examine whether the political affiliation of loan officers also affects the cost of mortgages to minority borrowers. In addition to the racial gap in mortgage access, the literature has also documented the racial gap in mortgage pricing (Black et al. 2003; Ghent et al. 2014; Bayer et al. 2018; Bartlett et al. 2022; Ambrose et al. 2021). It is therefore also important to understand the source of the pricing gaps and whether the political affiliation of loan officers contributes to the gap. In this regard, I find that the political affiliation of loan officers does not have an impact on the racial gap in mortgage interest rates, rate spreads, or mortgage origination costs.

Finally, I examine whether loan officer political affiliation affects ex post mortgage performance. If the results on mortgage origination are driven by taste-based discrimination, that is, Democratic loan officers favor minority borrowers, loans made by Democratic loan officers to minority borrowers are likely to perform worse. I merge the data with Fannie Mae and Freddie Mac loan-level datasets and use 60-day and 90-day delinquency as measures of mortgage performance. I find that loan officer political affiliation has very little impact on ex post mortgage performance. In fact, 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 taste-based discrimination. Rather, the results suggest that Democratic loan officers collect and process more soft information to help minority borrowers overcome deficiencies in hard information, such as the debt-to-income ratio.

To further confirm that the results are driven by Democratic loan officers collecting and processing soft information for minority borrowers, I split the sample based on whether the property is in loan officers' home counties. The literature suggests that soft information is more easily collected when the distance is short. Indeed, the effect of loan officer political affiliation on mortgage lending to minority borrowers is concentrated on borrowers in loan officers' home counties. Calculating the geographical distance between loan officers and the property, I also find that the effect is more pronounced when the distance is short. All these results are consistent with the fact that Democratic loan officers collect and process more soft information to help minorrity borrowers.

Finally, I also examine whether loan officer experience mitigates the bias. I argue that some loan officers could have biased beliefs about borrower credit risk and hence are unwilling to exert the effort to collect and process soft information although such effort could lead to loan origination

and, hence, more compensation for the loan officers. To the extent that experience could mitigate the biased belief, the pursuit of more compensation should reduce the gap in mortgage lending by 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.

This paper contributes to the literature on the racial gap in mortgage lending. The literature has well documented the racial gap 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. 2024). To understand the drives, the literature has examined the geographical and cross-lender variation of the racial gap (Holmes and Horvitz 1994; Tootell 1996; Bayer et al. 2018; Bartlett et al. 2022). However, until very recently, little has been done to understand the contribution of loan officers to the racial gap. In particular, Frame et al. (2022) and Jiang et al. (2022) find that the lack of minority loan officers is one source of the gap; Ambrose et al. (2021) find that broker race affects the cost of mortgages to minority borrowers. 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 impact of political affiliation. While the early literature mostly focuses on political outcomes (Campbell et al. 1980; Bartels 2002; Bullock et al. 2015), the recent literature has begun to explore the impact 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. 2023), fertility choices (Dahl et al. 2022), entrepreneurship and patenting activities (Engelberg et al. 2023; Engelberg et al. 2023b). This paper is the first to examine how the political ideology of economic agents interacts with racial equity in society.

The remainder of the paper is organized as follows. In Section 2, I describe the details of the data sources and the sample construction process. Section 3 presents the results of the loan officer level analysis. Section 4 presents the results of the loan level analysis. Section 5 presents the cross-sectional heterogeneities of the results. Section 5 concludes.

2 A Conceptual Framework

I first develop a simple model to understand the incentives of loan officers better and guide the empirical analysis. A loan officer helps a marginal borrower apply for a mortgage. After collecting all hard information, the loan officer finds that the loan application will only be approved if additional supporting material can be provided. However, collecting the additional information will require substantial effort on the loan officer's part. I assume that the total cost is $C = C_{i,j} + \epsilon_{i,j}$, where $C_{i,j}$ is a deterministic component $\epsilon_{i,j}$ is a random component, and i denotes loan application and j denotes loan officer. The deterministic component could depend on borrower, loan, or loan officer characteristics. The random component is bounded between $[0, C^{max}]$, with a cumulative distribution function of $F(\cdot)$. Given the nature of information collection, the deterministic component will capture most of the variation of the cost, and it is reasonable to assume that the random component is bounded.

The loan officer believes that, after exerting the effort and spending the cost C, the probablity of obtaining supporting material will either be p_m, for minority borrowers, or p_w, for white borrowers. p_m and p_w depend on the hard information that the loan officer has already obtained. The biased loan officer believes that $p_m < p_w$ even for borrowers with exactly the same hard information. The bias could be driven by taste-based discrimination or statistical discrimination (with accurate or inaccurate information). 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. The loan offocier's expected payoff is hence either $p_m \alpha L$ or $p_w \alpha L$.

Trading off the cost and beneift, the loan office will only try to collect additional (soft) information if $p_m \alpha L > C_{i,j} + \epsilon_{i,j}$ for minority borrower, or $p_w \alpha L > C_{i,j} + \epsilon_{i,j}$ for white borrowers. Therefore, the probablity of the loan officer trying to collect additional information will either be $F(\max(0, \min(C^{max}, p_m \alpha L - C_{i,j})))$ or $F(\max(0, \min(C^{max}, p_w \alpha L - C_{i,j})))$. Because the biased loan officer believes that $p_m < p_w$, I therefore have $F(\min(C^{max}, p_m \alpha L - C_{i,j})) \leq F(\min(C^{max}, p_m \alpha L - C_{i,j}))$, that is, the biased loan officer will be (weakly) less likely to collect additional information for minority borrowers than for white borrowers. Consequently, a marginal loan application from a minority borrower is less likely to be approved if it is processed by a biased loan officer, which is the first model prediction I take to the data.

Prediction 1. *A biased loan officer is less likely to collect additional (soft information) to help a minority borrower than an otherwise identical white borrower. As a result, a marginal loan application from a minority borrower is less likely to be approved if it is processed by a biased loan officer.*

Next, I will explore the cross-sectional implications of the model. First, for a given loan size L, if the deterministic component of collecting additional information is very high such that $\alpha L P_w C_{i,j} < C_{i,j}$, $F(\max(0, \min(C^{max}, p_m \alpha L - C_{i,j}))) = F(\max(0, \min(C^{max}, p_w \alpha L - C_{i,j}))) = F(0) = 0$. Intuitively, if the cost for collecting information is large enough, the loan officer will not even try to collect additional (soft) information for white borrowers. As the literature shows that distance often is the biggest obstacle for collecting soft information, I have the third prediction.

Prediction 2. *The different treatment of minority and white borrowers by a biased loan officer disappears when the distance between the borrower and the loan officer is sufficiently long.*

Next, if the loan size is very small such that $\alpha L p_w < C_{i,j}$, then $F(\max(0, \min(C^{max}, p_m \alpha L - C_{i,j}))) = F(\max(0, \min(C^{max}, p_w \alpha L - C_{i,j}))) = F(0) = 0$. This result implies that the biased loan officer's different treatment on minority and white borrowers will disappear if the loan size is small enough. Intuitively, when the loan size is large enough, the expected compensation the loan officer could receive is always greater than the cost, and hence the loan office will always try to collect the additional information, regardless of whether the borrower is a minority. This is the second model prediction that I will test empirically.

Prediction 3. *The different treatment of minority and white borrowers by a biased loan officer disappears if the loan size is sufficiently small.*

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 CoreLogic mortgage data provide loan officers' NMLSID since 2014. 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 the NMLSID to 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 the deed documents.

I start the sample in 2018 because our 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.

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. The names of the loan officers are used to match the CoreLogic loan officers to the voter registration data. I require exact matches of first name, middle name, and last name. I exclude matches in which the distance between the address recorded in the voter registration data and the location of the loan officers' 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 could help identify unique matches. I exclude any remaining non-unique matches. I am able to find voter registration records for 1,011 loan officers out of a total of 55,525 loan officers who made loans in North Carolina. These loan officers originated a total of 55,508 loans. 300 of these loan officers were always registered as Democrats, 416 were always registered as Republicans, 4 were always registered as Libertarians, and 288 were always registered as unaffiliated. The remaining three loan officers changed their party affiliations during the sample period. I also exclude Libertarian loan

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

officers from the final sample.

I use two approaches to determine the race and ethnicity of the borrowers. First, I use the names and addresses of the borrowers to match with the voter registration data. Among the 55,508 loans, I am able to match the borrowers with voter registration data for 19,277 loans. For the remaining 36,231 loans, I identify borrower race for 13,470 loans using the matched HMDA loan application data.[2] I then categorize African-American and Hispanic borrowers as minority borrowers. For the voter registration sample, 11.5% (or 4,068) of the borrowers are minorities. For the combined voter registration and HMDA sample, 13.5% of the borrowers are minorities. For our loan officer-level analysis, I calculate the number (value) of minority and non-minority loans made by each loan officer in each year, first based on the 19,277 loans in the voter registration sample, and then also the combined voter registration and HMDA sample.

I calculate the percentage of minority loans originated by each loan officer in each year, as in Table 1. In the voter registration sample, 11.90% of the loans originated by Democratic loan officers are from minority borrowers, higher than the 10.67% originated by unaffiliated loan officers. In contrast, only 8. 92% of the loans originated by Republican loan officers are from minority borrowers, less than those originated by unaffiliated loan officers. I also show that the difference in the percentage of minority loans between Democratic and Republican loan officers is statistically significant at the 1% level. The percentages calculated based on mortgage dollar values are similar. Furthermore, the pattern for the voter registration and HMDA combined sample is also similar.

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-mnority 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.

[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, only 85% (83%) of the cases are correctly identified by BIFSG. To avoid introducing too much noise, I only rely on voter registration and HMDA to identify borrower races and ethnicities.

3.3 Constructing the loan-level sample

Although CoreLogic mortgage data provide a rich set of information about the mortgages, it does 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 the CoreLogic loans with HMDA. Unfortunately, the two datasets 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. I then match these two datasets based on variables that are common in these two datasets. These variables are: 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 27,781 mortgages from 2018 to 2021.

I present the summary statistics of the main variable used in the analysis in Panel A of Table 3. The average property value is $ 332,358, and the average loan amount is $233,423. The average combined loan-to-value (CLTV) ratio is 74.79% and 35.6% of the loans have a debt-to-income ratio greater than 36%. About 51% of the loans are originated by Republican loan officers, 21.6% are by Democratic loan officers, and the remainder are by unaffiliated loan officers. The average mortgage interest rate is 3.55% and the average rate spread, the difference between the annual percentage rate (APR) and the survey-based average prime offer rates, is 41.5 basis points.

Finally, to assess the impact of loan officer political affiliation on loan performance, I match the loan-level sample with Fannie Mae and Freddie Mac loan-level datasets. There is no common identifier between CoreLogic or HMDA and the Fannie Mae-Freddie Mac data sets. I also match based on variables common in these data sets, 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. I again retain unique matches. This procedure produces a sample of 8,886 loans, among which 6,155 are Fannie Mae loans and 2,731 are Freddie Mac loans. Using the Fannie Mae and Freddie Mac monthly performance files, I identify loans that have ever experienced delinquencies of more than 60 days (*Delinq* 60) or 90 days (*Delinq* 90). In addition to the information available in CoreLogic and HMDA data, Fannie Mae and Freddie Mac also provide 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 2.6% (1.8%) of the loans ever experience a delinquency of more than 60 (90) days.

4 Loan Officer-County-Year Level Analysis

4.1 Origination volume

I examine how the political affiliation of loan officers affects lending to minorities at the loan officer-county-year level with the following specification,

$$E[Number\ (Value)\ of\ Loans_{ijct}] = \exp(\beta_1 Rep\ LO_{it} \times Minority_j + \beta_2 Dem\ LO_{it} \times Minority_j + \beta_3 Minority\ LO_i \times Minority_j + \beta_4 Minority_j + \gamma X_{icj} + \alpha_{i,c,t} + \alpha_{c,j,t}\alpha_{m,j,t}), \quad (1)$$

where $E[\ ]$ is the expectation sign, $Number\ (Value)\ of\ Loans_{ijt}$ is the total number or value of the loans loan officer i made to borrower tye 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 is African American or Hispanic. X_{icj} 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 $\alpha_{m,j,t}$ is the loan officer city-year-minority group fixed

effects. Under this specification, 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. With the loan officer-county-year fixed effects $\alpha_{i,t}$, I compare loans originated to minority and non-minority loan officers by the same loan officer in the same year in the same county. The county-year-minority group fixed effects, $\alpha_{c,j,t}$, controls for all county-level demand side factors at the annual frequency. With the loan officer city-year-minority group fixed effects, $\alpha_{m,j,t}$, I compare two loan officers in the same city, one Democratic and one Republican, make loans to the same racial group in the same year. Importantly, including loan officer city-year-minority group fixed effects mitigates the concern that Democratic loan officers live in areas with more minority populations and hence originate more minority loans.

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 logarithm of the dependent variable or one plus the dependent variable could lead to severe bias and 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. (2022) and Jiang et al. (2022) 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.

I present the results of estimating Equation (1) in Table 7, with panel A for the number of loans and panel B for the value of loans. In columns(1)-(3) of panel A, for the voter registration sample, the coefficient estimates on $Rep\ Lo \times Minority$ are all negative and mostly statistically significant. In contrast, the coefficient estimates on $Dem\ Lo \times Minority$ are all positive, although not statistically significant. More importantly, the differences between the two estimates are large (at least 30%) and statistically significant. These results suggest that Democratic loan officers, relative to Republican loan officers, originate 30% more loans to minority borrowers. Evaluating at the average number of minority loans originated by a loan officer (4.3), Democratic loan officers originate 1.3 fewer minority loans every year. The 300 Democratic loan officers in our sample would have made 390 more loans to minority borrowers in North Carolina each year. If I assume that unmatched loan officers have the same percentage of Democratic loan officers (29.6%), there will

be 17,581 Democratic among the 59,250 loan officers who made loans in North Carolina during the sample period, which would then translate to 21,097 more minority loans every year. It is also worth noting that the coefficient estimates on $MinorityLO \times Minority$ are all positive and statistically significant, suggesting that minority loan officers originate much more minority loans than non-minority loan officers. In columns (4)-(6), for the voter registration and HMDA combined sample, the results are similar. Furthermore, the results in panel B for the value of mortgages are also similar.

The results that Democratic loan officers make more minority loans than Republican loan officers could be driven by (1) Democratic loan officers matching with more minority loan applicants, or (2) Democratic loan officers approving more minority loan applications. Including the loan officer city-year-minority group fixed effects mitigates the concern that Democratic loan officers live in areas with more minority populations and hence originate more minority loans. Furthermore, loan applicants are unlikely to know the political affiliation of loan officers, and hence it is unlikely that loan applicants would deliberately choose loan officers based on their political affiliation. However, given that 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.

To mitigate this concern, 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,

$$s_{i,c,t-1} = \frac{n_{i,c,t-1}}{\Sigma_{i=1}^{I} n_{i,c,t-1}}, \tag{2}$$

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 a share specific to each racial group because differences in approval rates between racial groups could bias our 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.

To examine how the political affiliation of loan officers affects mortgage lending, I then estimate the following specification:

$$R_{i,c,t,j} = \beta_1 Rep\ LO_{it} \times Minority_j + \beta_2 Dem\ LO_{it} \times Minority_j + \beta_3 Minority\ LO_i \times Minority_j + \beta_4 Minority_j + \gamma X_{icj} + \alpha_{i,t} + \alpha_{c,j,t} + \alpha_{m,j,t} + \varepsilon_{ictj}, \quad (3)$$

where In addition to loan officer-year fixed effects, I can also include county-year fixed effects. Under this specification, replacing the number (value) of loans with the pseudo-approval rate, including the county-year-minority group fixed fixed effects, and including the set of controls could all mitigate the concern of demand side factors driving the results.

I present the results in Table 6, with panel A for the number based pseudo-approval rate and panel B for the value based pseudo-approval rate. Focusing on columns (1)-(3) in panel A for the voter registration sample, 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. The results in columns (4)-(6) for the combined voter registration and HMDA sample are similar. Additionally, the results for value-based pseudo-approval rates in panel B are also similar.

5 Loan-Level Analysis

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 the 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. In particular, I estimate the following specification,

$$DTI36_{ijkt} = \beta_1 Rep\ LO_{it} \times Minority_j + \beta_2 Dem\ LO_{it} \times Minority_j$$
$$+ \beta_3 Minority\ LO_i \times Minority_j + \beta_4 Rep\ LO_{it} + \beta_5 Dem\ LO_{it} + \beta_6 X_{ijkt} + \alpha_{i,t} + \varepsilon_{ijkt}, \quad (4)$$

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 borrower is above 62 ($Age¿62$), 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 (1). In particular, 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 7. In all regressions, I include year fixed effects to control for the impact of macroeconomic conditions, lender fixed effects to control for lender-specific underwriting standards, and census tract fixed effects to control location-specific demand and supply. Furthermore, I also include loan type (FHA, VA, and Conventional), loan purpose (purchase and refinance), applicant race, ethnicity, and gender fixed effects. In column (1), I additionally include loan officer fixed effects to control for loan officer specific differences. The coefficient estimate on $Rep\ LO \times Minority$ is negative, while the coefficient estimate on $Dem\ LO \times Minority$ is positive and statistically significant. Furthermore, the difference between the two coefficient estimates is statistically significant at the 5% level. In column (2), I further include lender-year fixed effects to control for time-varying lender-specific underwriting standards. The coefficient estimates on $Rep\ LO \times Minority$ and $Dem\ LO \times Minority$ are similar to those in column (1), and the difference between the two estimates remains statistically significant.

In column (3), I instead control for loan officer-year fixed effects to further control for time-varying loan officer specific lending standards. The coefficient estimate on $Rep\ LO \times Minority$ remains negative and statistically insignificant. The positive coefficient estimate on $Dem\ LO \times Minority$ remain statistically significant at the 5% level. To further control for time-varying location-specific factors, I include city-year fixed effects in the specification for column (4). I also

include loan characteristics in column (5). In all columns, the differences between the coefficient estimates on $Rep\ LO \times Minority$ and $Dem\ LO \times Minority$ are statistically significant at the 5% level. Democratic loan officers, relative to Republican loan officers, are at least 5% more likely to approve minority loans with a debt-to-income ratio greater than 36%. These results explain why Democratic loan officers make more loans to minority borrowers, as shown in Table 7.

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 8. 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 $DTI38$, $DTI40$, and $DTI42$. However, the differences become much smaller and statistically insignificant for $DT > 44$, and $DTI46$. It is well known that lenders are often reluctant to make loans with a debt-to-income ratio greater than 43%, and therefore loan officers have less discretion in approving such loans.

5.2 Loan-to-value ratio

I then examine the other underwriting criteria, the loan-to-value ratio. I construct dummy variables of whether the combined loan-to-value ratio is greater than 80% ($LTV80$), 90% ($LTV90$), and 95% ($LTV95$), and replace the dependent variable in Equation (4) with these dummy variables. The results are presented in columns (1)-(3) of Table 9. In column (1), the coefficient estimates on $Rep\ LO \times Minority$ and $Dem\ LO \times Minority$ are both small and statistically significant. The differences between the coefficient estimates are also small and statistically insignificant. In column (2), the coefficient estimates $Rep\ LO \times Minority$ and $Dem\ LO \times Minority$ are both positive, and the coefficient estimate on $Rep\ LO \times Minority$ is statistically significant. However, the difference is small and statistically insignificant. The same pattern holds in column (3). These results suggest that Republican and Democratic loan officers do not differ significantly in underwriting higher loan-to-value loans to minority borrowers.

5.3 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

(4) with the mortgage interest rate and present the estimation results in column (1) of Table 10. The coefficient estimates on $Rep\ LO \times Minority$ and $Dem\ LO \times Minority$ are small and statistically insignificant. Furthermore, the difference between the two estimates is very close to zero and statistically insignificant. I then replace the dependent variable with the rate spread, the difference between APR and the average prime offering rate, and present the result in column (2) of Table 10. The coefficient estimates on $Rep\ LO \times Minority$ and $Dem\ LO \times Minority$ are again small and statistically insignificant, and the difference between the estimates is also statistically insignificant. Finally, I calculate the loan cost as the total loan origination cost scaled by loan amount and present the result in column (3). Again, the political affiliation of loan officers does not have an impact on the origination cost of loans to minority borrowers.

5.4 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. However, it is unclear whether the results are driven by bias, that is, Democratic loan officers favoring minority loan borrowers. One implication of the bias explanation is that minority loans originated by Democratic loan officers will be of lower quality. To examine whether this is the case, I use the Fannie Mae and Freddie Mac 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 4 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 ($Interest\ Rate$), which are available in the Fannie Mae and Freddie Mac data.

The results are presented in Table 11, with panel A for over 60-day delinquency and panel B for over 90-day delinquency. In panel A, the coefficient estimates on $Rep\ LO \times Minority$ are all negative and statistically insignificant. The coefficient estimates on $Dem\ LO \times Minority$ are also all negative and one of the estimates is statistically significant at the 10% level. Furthermore, the absolute values of the coefficient estimates on $Dem\ LO \times Minority$ are greater than those on $Rep\ LO \times Minority$, suggesting that the quality of minority loans originated by Democratic loan officers is at least as good as, if not better than, those originated by Republican loan officers. The

results in panel B for over-90 day delinquency show a similar pattern.

Overall, the results suggest that Democratic loan officers lower lending standards and make more loans to minority borrowers, but these loans are not of lower quality. The results are therefore unlikely to be driven by Democratic loan officers' biased preference toward minority borrowers. Instead, the results are consistent with Democratic loan officers more willing to collect more soft information for marginal minority borrowers (based on hard information, such as the debt-to-income ratio).

6 Cross-sectional Heterogeneity

6.1 Distance and soft information

The literature suggests that a shorter distance facilitates soft information collection (Liberti and Petersen 2019; Petersen and Rajan 2002; and Agarwal and Hauswald 2010). If the results above are driven by Democratic loan officers collecting and processing more soft information for minority borrowers, the effect should therefore be stronger if the distance between the loan officer and the borrower (property) is shorter, as in Prediction 2. I first examine whether the effect of political affiliation is stronger if the loan officer is in the same county as the property.

I separately calculate the pseudo-approval rates of a loan officer in his own county and not in his own county and reestimate Equation (3). The results are presented in columns (1) and (2) of Table 12. In column (1), for the number-based pseudo-approval rate in loan offiers' counties, the difference between the coefficient estimates on $Rep\ LO \times Minority$ and $Dem\ LO \times Minority$ remains negative and statistically significant. In column (2), although the difference between the coefficient estimates is also negative and statistically insignificant, the magnitude is much smaller.

I then re-estimate Equation (4) for loans that are in and not in loan officers' home counties sperately and present the results in columns (3) and (4) of Table 12. For loans in the same county, the difference between the two coefficient estimates is negative and statistically significant. For loans not in the same county, the difference is still nagetive but is much smaller and statistically insignificant.

Finally, I geocode the addresses of the branch locations of the loan officers and the property addresses to calculate the distance. I then split the sample based on whether the distance is below

or above the sample median, reestimate Equation (4). I present the results in columns (5) and (6) of Table 12. In column (5) for loans in which the distance is below the sample median, the difference between the coefficient estimates on $Rep\ LO \times Minority$ and $Dem\ LO \times Minority$ is greater than those reported in Table 7, and it is statistically significant at the 1% level. In contrast, in column (6) in which the distance is above the sample median, the difference between the coefficient estimates is much smaller and statistically insignificant. These results are consistent with shorter distances allowing Democratic loan officers to collect and process soft information for minority borrowers.

6.2 Loan size

The conceptual framework also predicts that the the different treatment of minority and white borroers by a biased loan officer disappears when the loan size is sufficiently small. To test this prediction, I define a loan is small if the loan amount is less than $135,000, which is the 25th percentile of loan amount in the sample. I then calculate the pseudo-approval rate for small and large loans separately and re-estimate Equation (3). The results are presented in columns (1) and (2) of Table 13. While the differences between the two coefficient estimates are both negative, it is only significant for larger loans. I then re-estimate Equation (4) and the difference between the two coefficient is again only ignificant for large loans. These results are consistent with Prediction 3.

6.3 Loan officer experience

The results above suggest that Republican loan officers are less willing to collect and use soft information to help minority borrowers than Democratic loan officers. Such behavior may not be optimal for Republican loan officers because loan officers are mostly compensated by commissions on the loan they originate. If that is the case, more experienced loan officers will be less likely to be subject to bias. 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 study whether loan officer experience also changes the effect of political affiliation on pseudo-approval rates by estimating Equation (3) on the two voter registration matched subsamples. The results are presented in columns (1) and (2) of Table 14. In column (1), for less experienced loan

officers, the difference between the coefficient estimates is negative and statistically significant. In contrast, in column (2), for more experienced loan officers, the difference between the coefficient estimates is positive, but statistically insignificant.

Finally, I also re-estimate Equation (4) on subsamples partitioned based on loan officer experience. In column (3), for less experienced loan officers, the difference between the coefficient estimates is negative and statistically significant. In column (4), for more experienced loan officers, the difference is close to zero and statistically insignificant. Overall, the results in Table 14 suggest that loan officer experience mitigates the bias in mortgage lending induced by political affiliation.

7 Conclusion

I construct a novel sample by combining CoreLogic, HMDA, Fannie Mae, and Freddie Mac mortgage data with the North Carolina voter registration data. I find that Democratic loan officers originate more loans to minority borrowers than Republican loan officers. The results hold after controlling for demand-side factors. At the loan level, I find that Democratic loan officers are more likely to originate loans with higher debt-to-income ratios to minority borrowers than Republican loan officers. Examining loan delinquency, I find that loans to minority borrowers originated by Democratic loan officers perform slightly better than those originated by Republican loan officers. These results suggest that Democratic loan officers collect and process more private information to help minority borrowers overcome deficiencies in hard information, and hence expand mortgage access for minority borrowers.

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Table 1: Loan officer political affiliation and the percent of minority loans

This table presents the percentage of minority loans originated by loan officers with different political affiliations.

Panel A: Voter Registration Matched Sample		
	Percent of Minority Loans	
Loan Officer Political Affiliation	Number	Value
Democratic	11.90%	11.57%
Republican	8.92%	8.42%
Unaffiliated	10.67%	10.44%
Democratic-Republican	2.98%***	3.14%***
	(0.85%)	(0.86%)
Panel B: Voter registration and HMDA combined sample		
Democratic	13.33%	12.51%
Republican	9.54%	8.84%
Unaffiliated	12.72%	12.19%
Democratic-Republican	3.79%***	3.68%***
	(0.83%)	(0.83%)

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

Panel A: Minority Loans

	N	Mean	SD	25th Perc.	Median	75th Perc.
Number_Loans (Voter Registration Sample)	12,708	0.169	0.561	0.000	0.000	0.000
Value_Loans (Voter Registration Sample)	12,708	34,352	190,890	0	0	0
Number_Loans (Voter Registration and HMDA Sample	12,708	0.265	0.799	0.000	0.000	0.000
Value_Loans (Voter Registration and HMDA Sample)	12,708	52,409	226,408	0	0	0

Panel B: Non-Minority Loans

	N	Mean	SD	25th Perc.	Median	75th Perc.
Number_Loans (Voter Registration Sample)	12,708	1.336	2.735	.000	1.000	1.000
Value_Loans (Voter Registration Sample)	12,708	307,710	769,732	0	91,073	300,000
Number_Loans (Voter Registration and HMDA Sample	12,708	2.297	5.121	.000	1.000	2.000
Value_Loans (Voter Registration and HMDA Sample)	12,708	540,722	1,415,373	0	187,000	442,000

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 age 62 or above.

	N	Mean	SD	25th Perc.	Median	75th Perc.
DTI36	27,781	0.356	0.479	0.000	0.000	1.000
DTI38	27,781	0.293	0.455	0.000	0.000	1.000
DTI40	27,781	0.231	0.421	0.000	0.000	0.000
DTI42	27,781	0.164	0.370	0.000	0.000	0.000
DTI44	27,781	0.108	0.310	0.000	0.000	0.000
DTI46	27,781	0.071	0.257	0.000	0.000	0.000
CLTV	27,654	74.787	19.210	62.100	79.679	90.000
Interest Rate	27,776	3.551	0.774	2.950	3.375	4.125
Rate Spread	27,346	0.415	0.534	0.067	0.329	0.690
Loan Cost	27,627	1.811	1.158	1.001	1.590	2.319
FHA	27,781	0.056	0.229	0.000	0.000	0.000
GSE	27,781	0.908	0.289	1.000	1.000	1.000
VA	27,781	0.049	0.216	0.000	0.000	0.000
Rep LO	27,781	0.510	0.500	0.000	1.000	1.000
Dem LO	27,781	0.216	0.411	0.000	0.000	0.000
Minority LO	27,781	0.094	0.292	0.000	0.000	0.000
Co Applicant	27,781	0.634	0.482	0.000	1.000	1.000
Minority	27,781	0.113	0.317	0.000	0.000	0.000
Loan Amount	27,781	233,423	161,288	135,000	197,000	284,747
Income	26,804	115.279	137.851	55.000	87.000	134.000
Property Value	27,639	332,358	245,390	185,000	275,000	395,000
House Age	27,036	34.134	23.738	16.000	27.000	48.000
Age>62	27,781	0.182	0.386	0.000	0.000	0.000

Table 4: Summary statistics of the CoreLogic-HMDA-Fannie-Freddie matched sample

This table presents the summary statistics of the CoreLogic-HMDA-Fannie-Freddie 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; $DTI36$ 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 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	7,681	0.026	0.159	0.000	0.000	0.000
Delinq 90	7,681	0.018	0.135	0.000	0.000	0.000
DTI36	7,681	0.395	0.489	0.000	0.000	1.000
DTI38	7,681	0.308	0.462	0.000	0.000	1.000
DTI40	7,681	0.240	0.427	0.000	0.000	0.000
DTI42	7,681	0.174	0.379	0.000	0.000	0.000
DTI44	7,681	0.106	0.308	0.000	0.000	0.000
DTI46	7,681	0.062	0.242	0.000	0.000	0.000
CLTV	7,675	77.323	17.446	68.000	80.000	93.860
Interest Rate	7,681	3.560	0.793	2.875	3.375	4.125
Rate Spread	7,447	0.339	0.435	0.077	0.279	0.538
Loan Cost	7,644	1.895	1.093	1.161	1.684	2.402
Rep LO	7,681	0.571	0.495	0.000	1.000	1.000
Dem LO	7,681	0.189	0.391	0.000	0.000	0.000
Minority LO	7,681	0.070	0.256	0.000	0.000	0.000
Co Applicant	7,681	0.576	0.494	0.000	1.000	1.000
Minority	7,681	0.074	0.262	0.000	0.000	0.000
Loan Amount	7,681	213,476	105,546	135,000	192,685	267,750
Income	7,490	101.994	106.061	51.000	80.000	122.000
Property Value	7,653	293,411	165,905	185,000	255,000	355,000
House Age	7,168	40.883	25.144	21.000	37.000	57.000
Age>62	7,681	0.151	0.358	0.000	0.000	0.000
Credit Score	7,670	758.422	114.160	729.000	766.000	793.000
First Time Home Buyer	7,681	0.279	0.449	0.000	0.000	1.000
Mortgage Insurance	7,681	0.388	0.487	0.000	0.000	1.000

Table 5: Loan officer political affiliation and mortgage lending to minority borrowers
This table presents the results of estimating Equation (1). The sample is at the loan officer-racial group-year level. The dependent variable in panel A is $Number\ of\ Loans$, the total number of loans a loan officer originates to minority or non-minority borrowers in a given year; 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.

Panel A: Number of loans

	Voter Registration			Voter Registration and HMDA		
	(1)	(2)	(3)	(4)	(5)	(6)
Rep LO×Minority	-0.179	-0.275**	-0.274*	-0.151	-0.272*	-0.282*
	(0.119)	(0.139)	(0.142)	(0.123)	(0.145)	(0.148)
Dem LO×Minority	0.139	0.142	0.102	0.202	0.156	0.121
	(0.127)	(0.145)	(0.147)	(0.141)	(0.152)	(0.154)
Minority	-3.925***			-4.264***		
	(0.239)			(0.219)		
Minority LO×Minority	1.027***	1.053***	1.107***	1.160***	1.228***	1.268***
	(0.147)	(0.168)	(0.171)	(0.164)	(0.174)	(0.178)
Percent DTI<20	-3.518			-5.324***		
	(2.165)			(1.885)		
Percent DTI 20-30	-0.686			0.013		
	(1.659)			(1.491)		
Percent DTI 30-36	7.680***			7.351***		
	(1.800)			(1.737)		
Percent DTI 36-40	4.068**			4.035**		
	(1.829)			(1.660)		
Percent DTI 41-45	2.208			2.411		
	(1.741)			(1.549)		
Percent DTI 46-50	0.611			-1.557		
	(2.162)			(2.269)		
Percent DTI 50-60	8.095***			7.469***		
	(2.781)			(2.306)		
Percent DTI>60	-5.047*			-4.307*		
	(2.837)			(2.396)		
Log Average Income	-0.027			-0.110		
	(0.069)			(0.068)		
Percent Female	7.618***			8.013***		
	(0.752)			(0.672)		
Percent with Co-Applicant	-2.814***			-3.431***		
	(1.048)			(0.956)		
Pecent Age>62	4.467***			5.062***		
	(0.762)			(0.716)		
Average LTV	-0.750			0.047		
	(1.264)			(1.211)		
Log Average Loan Amount	-0.428			-0.631**		
	(0.328)			(0.279)		
Log Average Property Value	1.178***			1.455***		
	(0.434)			(0.391)		
Rep LO×Minority	-0.318**	-0.417**	-0.376***	-0.353***	-0.428***	-0.403***
-Dem LO×Minority	(0.126)	(0.138)	(0.139)	(0.125)	(0.141)	(0.141)
Observations	18,226	13,071	11,796	21,510	17,179	15,871
Loan Officer×Year	Yes			Yes		
Loan Officer×County	Yes			Yes		
County×Year	Yes			Yes		
Loan Officer×County×Year		Yes	Yes		Yes	Yes
Loan Officer City×Minority		Yes			Yes	
County×Year×Minority		Yes	Yes		Yes	Yes
Loan Officer City×Year×Minority			Yes			Yes

Panel B: Value of loans

	Voter Registration			Voter Registration and HMDA		
	(1)	(2)	(3)	(4)	(5)	(6)
Rep LO×Minority	-0.216*	-0.294*	-0.301*	-0.212	-0.337**	-0.339**
	(0.123)	(0.155)	(0.159)	(0.132)	(0.158)	(0.160)
Dem LO×Minority	0.144	0.187	0.138	0.199	0.174	0.144
	(0.144)	(0.162)	(0.164)	(0.159)	(0.167)	(0.169)
Minority	-3.762***			-4.096***		
	(0.266)			(0.252)		
Minority LO×Minority	1.057***	1.104***	1.150***	1.193***	1.335***	1.366***
	(0.168)	(0.193)	(0.197)	(0.189)	(0.196)	(0.200)
Percent DTI<20	-2.253			-5.458***		
	(2.356)			(2.070)		
Percent DTI 20-30	-2.793			-2.689		
	(1.941)			(1.843)		
Percent DTI 30-36	8.174***			7.902***		
	(2.097)			(1.932)		
Percent DTI 36-40	3.503			2.911		
	(2.291)			(2.158)		
Percent DTI 41-45	1.384			1.351		
	(2.061)			(1.913)		
Percent DTI 46-50	-1.595			-4.552		
	(3.268)			(3.600)		
Percent DTI 50-60	8.208***			7.894***		
	(3.073)			(2.477)		
Percent DTI>60	-5.932*			-4.594*		
	(3.047)			(2.506)		
Log Average Income	-0.061			-0.133		
	(0.106)			(0.113)		
Percent Female	8.937***			9.247***		
	(0.975)			(0.972)		
Percent with Co-Applicant	-1.959			-2.769**		
	(1.245)			(1.088)		
Pecent Age>62	3.220***			3.546***		
	(0.928)			(0.919)		
Average LTV	-1.844			-1.764		
	(1.680)			(1.685)		
Log Average Loan Amount	-0.151			-0.792**		
	(0.385)			(0.321)		
Log Average Property Value	1.932***			2.603***		
	(0.522)			(0.486)		
Rep LO×Minority	-0.360***	-0.481***	-0.439***	-0.411***	-0.511***	-0.483***
-Dem LO×Minority	(0.130)	(0.148)	(0.150)	(0.131)	(0.148)	(0.148)
Observations	18,226	13,071	11,796	21,510	17,179	15,871
Loan Officer×Year	Yes			Yes		
Loan Officer×County	Yes			Yes		
County×Year Fixed Effects	Yes			Yes		
Loan Officer×County×Year		Yes	Yes		Yes	Yes
Loan Officer City×Minority		Yes			Yes	
County×Year×Minority Fixed Effects		Yes	Yes		Yes	Yes
Loan Officer City×Year×Minority			Yes			Yes

Table 6: Loan officer political affiliation and pseudo-approval rate

This table presents the results of estimating Equation (3). The sample is at the loan officer-county-racial group-year level. The dependent variable in panel A is the number-based 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; The dependent variable in panel B is the value-based pseudo-approval rate, which is the value of loans a loan officer originates to minority or non-minority borrowers in a county scaled by the total value 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; *Log Average Income* is the natural logarithm of average income, *Log Average Loan Amount* is the natural logarithm of the average loan amount , *Log Aveargе Property Value* is the natural logarithm of the average property price, $Average\ CLTV$ is the average combined loan-to-value ratio, $Percent\ Female$ is the percentage of female applicants, $Percent\ Co-Applicant$ is the percentage with a co-applicant, $Percent\ Age¿62$ the percentage of applicants over the age of 62, $Percent\ DTI < 20$ is the percentage of debt-to-income ratio below 20%, $Percent\ DTI20-30$ is the percentage of debt-to-income ratio between 20% and 30%, $Percent\ DTI30-36$ is the percentage of debt-to-income ratio between 30% and 36%, $Percent\ DTI36-40$ is the percentage of debt-to-income ratio between 36% and 40%, $Percent\ DTI40-45$ is the percentage of debt-to-income ratiobetween 40% and 45%, $Percent\ DTI45-50$ is the percentage of debt-to-income ratio between 45% and 50%, $Percent\ DTI50-60$ is the percentage of debt-to-income ratiobetween 50% and 60%, and $Percent\ DTI > 60$ is the percentage of debt-to-income ratio above 60%. 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: Pseudo-approval rate based on number of loans

	Voter Registration			Voter Registration and HMDA		
	(1)	(2)	(3)	(4)	(5)	(6)
Rep LO×Minority	-0.028	-0.064**	-0.063**	-0.036	-0.086**	-0.085*
	(0.021)	(0.027)	(0.029)	(0.032)	(0.043)	(0.045)
Dem LO×Minority	0.034	0.041	0.036	0.050	0.048	0.045
	(0.028)	(0.037)	(0.039)	(0.045)	(0.055)	(0.058)
Minority	-0.121***			-0.230***		
	(0.038)			(0.057)		
Minority LO×Minority	0.186***	0.185***	0.192***	0.318***	0.295***	0.305***
	(0.041)	(0.048)	(0.050)	(0.067)	(0.074)	(0.078)
Percent DTI<20	-0.905***			-1.186***		
	(0.309)			(0.405)		
Percent DTI 20-30	-0.503**			-0.842**		
	(0.256)			(0.375)		
Percent DTI 30-36	0.286			0.096		
	(0.292)			(0.393)		
Percent DTI 36-40	-0.228			-0.340		
	(0.274)			(0.416)		
Percent DTI 41-45	-0.160			-0.038		
	(0.293)			(0.417)		
Percent DTI 46-50	-0.683*			-1.548***		
	(0.403)			(0.585)		
Percent DTI 50-60	0.269			0.184		
	(0.403)			(0.530)		
Percent DTI>60	-0.721**			-0.654		
	(0.327)			(0.431)		
Log Average Income	-0.003			-0.016		
	(0.015)			(0.020)		
Percent Female	0.288**			0.521***		
	(0.133)			(0.179)		
Percent with Co-Applicant	0.119			0.045		
	(0.154)			(0.236)		
Pecent Age>62	0.019			0.074		
	(0.129)			(0.191)		
Average LTV	-0.034			-0.143		
	(0.218)			(0.311)		
Log Average Loan Amount	0.030			0.042		
	(0.092)			(0.111)		
Log Average Property Value	-0.057			-0.101		
	(0.096)			(0.122)		
Rep LO×Minority	-0.062***	-0.105***	-0.099***	-0.086**	-0.134***	-0.130**
-Dem LO×Minority	(0.023)	(0.033)	(0.034)	(0.037)	(0.050)	(0.053)
Observations	9,236	9,116	8,622	9,236	9,116	8,622
R-squared	0.484	0.611	0.638	0.540	0.658	0.675
Loan Officer×Year	Yes			Yes		
Loan Officer×County	Yes			Yes		
County×Year Fixed Effects	Yes			Yes		
Loan Officer×County×Year		Yes	Yes		Yes	Yes
Loan Officer City×Minority		Yes			Yes	
County×Year×Minority		Yes	Yes		Yes	Yes
Loan Officer City×Year×Minority			Yes			Yes

Panel B: Pseudo-approval rate based on value of loans

	Voter Registration			Voter Registration and HMDA		
	(1)	(2)	(3)	(4)	(5)	(6)
Rep LO×Minority	-0.036	-0.086**	-0.081**	-0.056	-0.132**	-0.128**
	(0.030)	(0.038)	(0.040)	(0.044)	(0.058)	(0.062)
Dem LO×Minority	0.016	0.022	0.018	0.027	0.009	0.002
	(0.040)	(0.049)	(0.052)	(0.063)	(0.075)	(0.080)
Minority	-0.182***			-0.343***		
	(0.059)			(0.089)		
Minority LO×Minority	0.235***	0.237***	0.248***	0.398***	0.356***	0.367***
	(0.054)	(0.064)	(0.066)	(0.089)	(0.099)	(0.103)
Percent DTI<20	-1.022**			-1.672***		
	(0.410)			(0.584)		
Percent DTI 20-30	-0.497			-1.031*		
	(0.415)			(0.590)		
Percent DTI 30-36	0.333			0.015		
	(0.425)			(0.608)		
Percent DTI 36-40	0.120			-0.028		
	(0.386)			(0.619)		
Percent DTI 41-45	0.126			0.549		
	(0.398)			(0.614)		
Percent DTI 46-50	-0.709			-1.946**		
	(0.556)			(0.859)		
Percent DTI 50-60	0.575			0.501		
	(0.595)			(0.772)		
Percent DTI>60	-1.047**			-1.186*		
	(0.513)			(0.708)		
Log Average Income	0.005			-0.013		
	(0.022)			(0.029)		
Percent Female	0.457**			0.899***		
	(0.193)			(0.273)		
Percent with Co-Applicant	0.028			-0.077		
	(0.236)			(0.364)		
Pecent Age>62	-0.231			-0.400		
	(0.194)			(0.293)		
Average LTV	-0.289			-0.444		
	(0.336)			(0.495)		
Log Average Loan Amount	-0.119			-0.229		
	(0.116)			(0.161)		
Log Average Property Value	-0.022			-0.012		
	(0.122)			(0.165)		
Rep LO×Minority	-0.052*	-0.108**	-0.099**	-0.083*	-0.141*	-0.130*
-Dem LO×Minority	(0.032)	(0.042)	(0.044)	(0.052)	(0.066)	(0.071)
Observations	9,236	9,116	8,622	9,236	9,116	8,622
R-squared	0.487	0.621	0.640	0.542	0.661	0.675
Loan Officer×Year	Yes			Yes		
Loan Officer×County	Yes			Yes		
County×Year Fixed Effects	Yes			Yes		
Loan Officer×County×Year		Yes	Yes		Yes	Yes
Loan Officer City×Minority		Yes			Yes	
County×Year×Minority		Yes	Yes		Yes	Yes
Loan Officer City×Year×Minority			Yes			Yes

Table 7: Loan officer political affiliation and loan debt-to-income ratio being greater than 36%
This table reports the results of estimating Equation (4). 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.

	(1)	(2)	(3)	(4)	(5)
Rep LO×Minority	-0.006	-0.002	-0.003	-0.001	-0.002
	(0.025)	(0.026)	(0.025)	(0.026)	(0.026)
Dem LO×Minority	0.059*	0.062**	0.063**	0.072**	0.078**
	(0.030)	(0.031)	(0.030)	(0.030)	(0.030)
Minority LO×Minority	0.038	0.036	0.040	0.037	0.037
	(0.029)	(0.030)	(0.028)	(0.029)	(0.029)
House Age	-0.000**	-0.000***	-0.000***	-0.000**	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age>62	0.107***	0.105***	0.107***	0.109***	0.135***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
GSE	0.015	0.019	0.015	0.019	0.020
	(0.013)	(0.013)	(0.013)	(0.014)	(0.014)
Log Loan Amount					0.063***
					(0.010)
Log Term					0.059***
					(0.012)
CLTV					0.002***
					(0.000)
Rep LO×Minority-Dem LO×Minority	-0.065**	-0.064**	-0.066**	-0.073**	-0.080***
	(0.029)	(0.030)	(0.029)	(0.029)	(0.030)
Observations	26,701	26,663	26,801	26,342	26,215
R-squared	0.187	0.196	0.183	0.233	0.243
Loan Officer Fixed Effects	Yes	Yes			
Year Fixed Effects	Yes				
Lender Fixed Effects	Yes				
Tract Fixed Effects	Yes	Yes	Yes	Yes	Yes
Loan Type Fixed Effects	Yes	Yes	Yes	Yes	Yes
Loan Purpose Fixed Effects	Yes	Yes	Yes	Yes	Yes
Borrower Race Fixed Effects	Yes	Yes	Yes	Yes	Yes
Borrower Ethnicity Fixed Effects	Yes	Yes	Yes	Yes	Yes
Lender-Year Fixed Effects		Yes			
Loan Officer-Year Fixed Effects			Yes	Yes	Yes
City-Year Fixed Effects				Yes	Yes

Table 8: Loan officer political affiliation and other debt-to-income ratio cutoffs

This table reports the results of estimating Equation (4). 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 equal to one if 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%; $DTI44$, a dummy variable equal to one if the debt-to-income ratio is greater than 44%; $DTI46$, a dummy variable equal to one if the debt-to-income ratio is greater than 46%; *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 if 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; *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.

	(1) DTI38	(2) DTI40	(3) DTI42	(4) DTI44	(5) DTI46
Rep LO×Minority	-0.012	-0.024	-0.016	-0.004	0.009
	(0.024)	(0.023)	(0.020)	(0.017)	(0.016)
Dem LO×Minority	0.059**	0.042	0.053**	0.026	0.038*
	(0.030)	(0.028)	(0.027)	(0.023)	(0.020)
Rep LO×Minority-Dem LO×Minority	-0.065**	-0.057**	-0.051*	-0.022	-0.028
	(0.027)	(0.028)	(0.026)	(0.022)	(0.019)
Observations	26,342	26,342	26,342	26,342	26,342
R-squared	0.227	0.223	0.225	0.221	0.220
Loan Officer-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Tract Fixed Effects	Yes	Yes	Yes	Yes	Yes
City-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Loan Type Fixed Effects	Yes	Yes	Yes	Yes	Yes
Loan Purpose Fixed Effects	Yes	Yes	Yes	Yes	Yes
Borrower Race Fixed Effects	Yes	Yes	Yes	Yes	Yes
Borrower Ethnicity Fixed Effects	Yes	Yes	Yes	Yes	Yes

Table 9: Loan officer political affiliation and combined loan-to-value ratios

This table reports the results of estimating the relationship between loan officer political affiliation and combined loan-to-value ratios. The dependent variables are $CLTV80$, a dummy variable equal to one if the combined loan-to-value ratio is greater than 80%; $CLTV90$, a dummy variable equal to one if the combined loan-to-value ratio is greater than 90%; $CLTV95$, a dummy variable equal to one if the combined loan-to-value ratio is greater than 95%; *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.

	CLTV80	CLTV90	CLTV95
	(1)	(2)	(3)
Rep LO×Minority	0.015	0.044**	0.028
	(0.021)	(0.018)	(0.019)
Dem LO×Minority	-0.002	0.031	0.006
	(0.025)	(0.020)	(0.021)
Rep LO×Minority-Dem LO×Minority	0.017	0.011	0.022
	(0.025)	(0.017)	(0.020)
Observations	26,263	26,263	26,263
R-squared	0.491	0.536	0.560
Loan Officer-Year Fixed Effects	Yes	Yes	Yes
Tract Fixed Effects	Yes	Yes	Yes
City-Year Fixed Effects	Yes	Yes	Yes
Loan Type Fixed Effects	Yes	Yes	Yes
Loan Purpose Fixed Effects	Yes	Yes	Yes
Borrower Race Fixed Effects	Yes	Yes	Yes
Borrower Ethnicity Fixed Effects	Yes	Yes	Yes

Table 10: 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; *Rate Spread*, the difference between the mortgage APR and the average prime offering rate; *Origination Cost*, the total origination cost scaled by mortgage amount; *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.

	(1) Interest Rate	(2) Rate Spread	(3) Origination Cost
Rep LO×Minority	0.007	-0.019	-0.014
	(0.026)	(0.027)	(0.044)
Dem LO×Minority	-0.000	-0.020	-0.053
	(0.032)	(0.032)	(0.055)
Rep LO×Minority-Dem LO×Minority	0.007	0.001	0.039
	(0.029)	(0.032)	(0.055)
Observations	26,136	25,700	25,990
R-squared	0.795	0.535	0.694
Loan Officer-Year Fixed Effects	Yes	Yes	Yes
Tract Fixed Effects	Yes	Yes	Yes
City-Year Fixed Effects	Yes	Yes	Yes
Loan Type Fixed Effects	Yes	Yes	Yes
Loan Purpose Fixed Effects	Yes	Yes	Yes
Borrower Race Fixed Effects	Yes	Yes	Yes
Borrower Ethnicity Fixed Effects	Yes	Yes	Yes
Debt-to-Income Ratio Fixed Effects	Yes	Yes	Yes

Table 11: 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 $Delinq60$, 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 $Delinq90$, 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; *CLTV* is the combined 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.

Panel A: 60-day delinquency

	(1)	(2)	(3)	(4)
Rep LO×Minority	-0.024	-0.032	-0.026	-0.025
	(0.030)	(0.030)	(0.029)	(0.027)
Dem LO×Minority	-0.045	-0.048	-0.052	-0.062*
	(0.039)	(0.038)	(0.038)	(0.035)
Minority LO×Minority	0.003	0.001	0.010	0.029
	(0.051)	(0.049)	(0.047)	(0.047)
House Age	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Age>62	-0.007	-0.008	-0.008	-0.008
	(0.006)	(0.006)	(0.006)	(0.007)
GSE	-0.003	-0.005	-0.004	-0.001
	(0.015)	(0.015)	(0.013)	(0.016)
Log Loan Amount	0.006	0.005	0.006	0.003
	(0.007)	(0.007)	(0.007)	(0.008)
Log Loan Term	0.016	0.014	0.016	0.007
	(0.011)	(0.011)	(0.010)	(0.012)
Credit Score	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
LTV	-0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
DTI	0.001**	0.001**	0.001***	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Interest Rate	0.010	0.010	0.010	0.010
	(0.009)	(0.009)	(0.008)	(0.010)
Rep LO×Minority-Dem LO×Minority	0.019	0.016	0.026	0.037
	(0.029)	(0.032)	(0.033)	(0.032)
Observations	6,324	6,260	6,365	5,902
R-squared	0.295	0.323	0.284	0.409
Loan Officer Fixed Effects	Yes	Yes		
Year Fixed Effects	Yes			
Lender Fixed Effects	Yes			
Tract Fixed Effects	Yes	Yes	Yes	Yes
Loan Type Fixed Effects	Yes	Yes	Yes	Yes
Loan Purpose Fixed Effects	Yes	Yes	Yes	Yes
Borrower Race Fixed Effects	Yes	Yes	Yes	Yes
Borrower Ethnicity Fixed Effects	Yes	Yes	Yes	Yes
Lender-Year Fixed Effects		Yes		
Loan Officer-Year Fixed Effects			Yes	Yes
City-Year Fixed Effects				Yes

Panel B: 90-day delinquency

	(1)	(2)	(3)	(4)
Rep LO×Minority	-0.006	-0.009	-0.006	-0.007
	(0.024)	(0.024)	(0.023)	(0.024)
Dem LO×Minority	-0.029	-0.029	-0.027	-0.035
	(0.031)	(0.030)	(0.028)	(0.030)
Minority LO×Minority	0.017	0.019	0.016	0.040
	(0.049)	(0.047)	(0.044)	(0.046)
House Age	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Age>62	-0.007	-0.008	-0.008	-0.007
	(0.005)	(0.005)	(0.005)	(0.006)
GSE	-0.005	-0.005	-0.008	-0.005
	(0.011)	(0.011)	(0.010)	(0.012)
Log Loan Amount	0.005	0.006	0.005	0.004
	(0.006)	(0.006)	(0.006)	(0.008)
Log Loan Term	0.004	0.002	0.004	-0.006
	(0.009)	(0.010)	(0.009)	(0.011)
Credit Score	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
LTV	-0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
DTI	0.000**	0.000**	0.000***	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Interest Rate	0.012	0.013	0.012	0.011
	(0.008)	(0.009)	(0.008)	(0.009)
Rep LO×Minority-Dem LO×Minority	0.023	0.020	0.021	0.028
	(0.019)	(0.017)	(0.016)	(0.027)
Observations	6,324	6,260	6,365	5,902
R-squared	0.295	0.317	0.283	0.390
Loan Officer Fixed Effects	Yes	Yes		
Year Fixed Effects	Yes			
Lender Fixed Effects	Yes			
Tract Fixed Effects	Yes	Yes	Yes	Yes
Loan Type Fixed Effects	Yes	Yes	Yes	Yes
Loan Purpose Fixed Effects	Yes	Yes	Yes	Yes
Borrower Race Fixed Effects	Yes	Yes	Yes	Yes
Borrower Ethnicity Fixed Effects	Yes	Yes	Yes	Yes
Lender-Year Fixed Effects		Yes		
Loan Officer-Year Fixed Effects			Yes	Yes
City-Year Fixed Effects				Yes

Table 12: Soft information and the effect of loan officer political affiliation

This table reportst the results on whether the effect is driven by soft information processing. The sample is partitioned according to whether the loan officer and the property are in the same county in columns (1)-(4) and whether the distance between the loan officer and the property is below or above the sample median in columns (5) and (6). Columns (1) and (2) present the results number-based pseudo-approval rate; and columns (3)-(6) present the results for $DTI36$. *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.

	(1)	(2)	(3)	(4)	(5)	(6)
	Pseudo Approval Rate		DTI36			
	Same County		Same County		Distance	
	Yes	No	Yes	No	Short	Long
Rep LO×Minority	-0.139*	-0.050*	-0.014	-0.039	-0.018	-0.001
	(0.074)	(0.030)	(0.046)	(0.036)	(0.041)	(0.044)
Dem LO×Minority	0.064	0.018	0.095	0.005	0.093*	0.012
	(0.096)	(0.037)	(0.058)	(0.040)	(0.048)	(0.051)
Rep LO×Minority-Dem LO×Minority	-0.203***	-0.068*	-0.109**	-0.044	-0.111**	-0.013
	(0.078)	(0.035)	(0.055)	(0.040)	(0.043)	(0.046)
Observations	1,860	7,052	9,357	15,642	12,537	12,288
R-squared	0.677	0.608	0.295	0.318	0.284	0.351
Loan Officer-County-Year Fixed Effects	Yes	Yes				
County-Year-Minority Fixed Effects	Yes	Yes				
Loan Officer-Year Fixed Effects			Yes	Yes	Yes	Yes
Tract Fixed Effects			Yes	Yes	Yes	Yes
City-Year Fixed Effects			Yes	Yes	Yes	Yes
Loan Type Fixed Effects			Yes	Yes	Yes	Yes
Loan Purpose Fixed Effects			Yes	Yes	Yes	Yes
Borrower Race Fixed Effects			Yes	Yes	Yes	Yes
Borrower Ethnicity Fixed Effects			Yes	Yes	Yes	Yes

Table 13: Loan size and the effect of loan officer political affiliation

This table reportst the results on whether the effect is varies by loan size. The sample is partitioned according to whether the loan amount is below $135,000. Columns (1) and (2) present the results number-bbased pseudo-approval rate; and columns (3)-(4) present the results for $DTI36$. *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.

	(1)	(2)	(3)	(4)
	Pseudo_Approval Rate		DTI36	
Loan Size	Small	Large	Small	Large
Rep LO×Minority	-0.067	-0.022	0.010	0.001
	(0.045)	(0.024)	(0.052)	(0.033)
Dem LO×Minority	-0.011	0.049	0.067	0.076**
	(0.053)	(0.032)	(0.068)	(0.038)
Rep LO×Minority-Dem LO×Minority	-0.056	-0.071**	-0.057	-0.75**
	(0.052)	(0.031)	(0.071)	(0.038)
Observations	3,862	7,656	5,530	19,113
R-squared	0.647	0.591	0.475	0.268
Loan Officer×County×Year	Yes	Yes		
Loan Officer City×Minority	Yes	Yes		
County×Year×Minority Fixed Effects	Yes	Yes		
Loan Officer-Year Fixed Effects			Yes	Yes
Tract Fixed Effects			Yes	Yes
City-Year Fixed Effects			Yes	Yes
Loan Type Fixed Effects			Yes	Yes
Loan Purpose Fixed Effects			Yes	Yes
Borrower Race Fixed Effects			Yes	Yes
Borrower Ethnicity Fixed Effects			Yes	Yes

Table 14: 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. Columns (1) and (2) present the results of estimating Equation (1); columns (3) and (4) present the results of estimating Equation (3); and columns (5) and (6) present the results of estimating Equation (4). The dependent variables are, *Number of Loans*, the total number of loans a loan officer originates to minority or non-minority borrowers in a given year, in columns (1) and (2); the number-based pseudo-approval rate, the number of loans a loan officer originates to minority or non-minority borrowers in a county scaled by the number of expected applications, in columns (3) and (4), and $DTI36$, a dummy variable equal to one if the debt-to-income ratio is greater than 36% and zero otherwise in columns (5) and (6). *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.

	(1)	(2)	(3)	(4)
	Pseudo Approval Rate		DTI36	
Loan Officer Experience	Low	High	Low	High
Rep LO×Minority	-0.163***	0.024	0.013	-0.026
	(0.051)	(0.024)	(0.040)	(0.037)
Dem LO×Minority	-0.030	0.086**	0.091**	-0.025
	(0.065)	(0.037)	(0.043)	(0.046)
Rep LO×Minority-Dem LO×Minority	-0.133**	-0.062*	-0.078*	-0.001
	(0.056)	(0.035)	(0.041)	(0.001)
Observations	4,476	4,482	12,600	12,867
R-squared	0.633	0.647	0.334	0.288
Loan Officer-County-Year Fixed Effects	Yes	Yes		
County-Year-Minority Fixed Effects	Yes	Yes		
Loan Officer-Year Fixed Effects			Yes	Yes
Tract Fixed Effects			Yes	Yes
City-Year Fixed Effects			Yes	Yes
Loan Type Fixed Effects			Yes	Yes
Loan Purpose Fixed Effects			Yes	Yes
Borrower Race Fixed Effects			Yes	Yes
Borrower Ethnicity Fixed Effects			Yes	Yes