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Research article

Can Jane Get a Mortgage Loan? Depends on When and Where

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Abstract: By analyzing data from 102 million mortgage loan applications in the US between 2004–2012 (about 90% of all applications) across 3,141 counties and 8,000 financial institutions, we investigate whether applicants' gender matters in the bank's lending decision. We find evidence that female applicants face a higher rejection rate than males, holding all else constant. Similar results are obtained for Hispanic applicants compared to non-Hispanics, and minorities compared to non-minorities. Moreover, we document that this discrimination is pro-cyclical (i.e. peaks in recessions) and that it varies substantially across states. Most importantly, we show that non-economic factors help explain the variation in discrimination across states while economic factors do not. Specifically, we find that gender discrimination in lending is higher in states with (i) high level of conservatism, (ii) low support for gay rights, and (iii) low female representation in the state legislature (JEL E32, G21, J16).

Keywords: lending; discrimination; HMDA

1. Introduction

Access to credit is crucial for the sustainable growth and development of both low-income and high-income countries. At the micro-level, access to credit significantly lowers households' income variability and improves their welfare (Quach and Mullineux, 2007; Karlan and Zinman, 2010;

Dehejia and Gatti, 2002), as well as enhances firms' level of productivity (Gatti and Love, 2008). At the macro-level, the development of credit markets improves countries' level of economic growth and reduces their output volatility (Coricelli and Masten, 2004).

Due to the importance of access to credit, discrimination in lending poses a serious issue as it inhibits growth, productivity, and development. Not only do discriminatory firms suffer from lower efficiency, productivity, market share, and higher production costs (Gwartney and Haworth, 1974), but society as a whole pays a severe cost as well. Historically, both developing and developed countries have suffered from the consequences of lending discrimination against certain groups. In African countries, for example, discrimination against females caused greater poverty, lower growth and lower living standards, which provided impetus for the microfinance movement in the 1970s to combat these implications (Cheston and Kuhn, 2002). Similarly, in countries as developed as the US, lending discrimination against minorities caused a severe urban decay and deterioration of neighborhoods during the 1970s (Werner et al., 1976).

In this paper, we examine how the probability of getting rejected for a mortgage loan varies across time, across states within the US, and across different borrower groups. Specifically, we examine rejection rate differences for females compared to males, minorities compared to non-minorities, and Hispanics compared to non-Hispanics.

To study rejection rate differences, we analyze data on lending behavior between 2004–2012 that is provided by the Home Mortgage Disclosure Act (HMDA). The data specifies information on relevant variables regarding *the loan applicant* (i.e. gender, ethnicity, race, income, geographic location), *the co-applicant* (i.e. gender, ethnicity, race), *the loan* (i.e. amount, type) and *the outcome* (i.e. rejected or approved).

Controlling for borrower, bank, and loan characteristics, we document higher rejection rates for female applicants compared to male applicants, holding all else equal. The results for racial groups are similar, as minorities and Hispanics also face a *ceteris paribus* higher likelihood of rejection compared to non-minorities and non-Hispanics. Higher rejection rates for all three groups still hold when conducting robustness tests that address endogeneity concerns regarding missing credit scores as well as bank-specific effects, further supporting the claim of discrimination in the mortgage market. More importantly, we find that gender and racial discrimination are pro-cyclical as they increase in recessions and peak during the 2008 financial crisis. At the peak of the crisis, the rejection rate female applicants face is about 3% points higher than that of males.

We also find evidence that gender differences in rejection rates vary significantly across states, as they range from 0% in Florida to 7% in Iowa in 2008. However, we show that these different levels of gender discrimination do not correlate with *economic* factors in each state but exhibit strong correlation with *noneconomic* factors. Specifically, we find that gender discrimination in lending is higher in states with (i) high level of conservatism, (ii) low support for gay rights, and (iii) low female representation in the state legislature.

The main contribution of this paper to the existing literature is threefold: First, we show that discrimination in mortgage lending still persists nowadays, decades after the enactment of HMDA legislation to address the issue. Second, we show that the relationship between discrimination and business cycles is pro-cyclical, documenting the peak of discrimination during times of recession. Third, we show the substantial variation in gender discrimination across states, and how this variation is strongly driven by noneconomic factors as opposed to economic factors. An understanding of the interplay of all these aspects of discrimination provides critical implications for policy-makers.

The paper proceeds as follows. Section 2 reviews existing literature on the topic, Section 3 describes the data, Section 4 discusses the methodology, Section 5 presents the results, and Section 6 concludes.

2. Literature Review

This paper relates to three main strands in the literature. The first strand examines economic theories regarding the sources of discrimination in the market. The second strand focuses on gender discrimination in the United States, especially within the context of the labor market. The third strand is the most relevant to my topic, and examines discrimination in US mortgage lending.

2.1. Discrimination Theories

The literature on discrimination cites two main classical theories regarding the source of discrimination in the market: *taste-based* (non-economic) discrimination and *statistical* (economic) discrimination.

The theory of taste-based discrimination, developed by Becker (1971), identifies the source of discrimination as preferences or personal tastes rooted in prejudice against a certain group. According to this theory, decision-makers do not base their decision solely on productivity, but incorporate an additional willingness-to-pay to satisfy their taste of interacting with certain groups and not others. In a market setting, taste-based discrimination undermines allocation efficiency and forces disadvantaged groups to “compensate” by exhibiting higher qualifications for the same level of return.

Therefore, applying this theory to the credit market suggests that a lender who discriminates against females acts as if he incurs additional costs by dealing with this group, thus forcing female applicants to “compensate” the lender by exhibiting either (i) a lower expected value of loss on the loan compared to males, (ii) a higher expected value of gain on the loan compared to males, or (iii) a lower probability of default on the loan compared to males (for more detail see Peterson, 1981).

In contrast, the theory of statistical discrimination, developed by Arrow (1971) and Phelps (1972), identifies discrimination as a product of *perception* not *taste*, and explains it in terms of rational behavior and limited information. As a result of uncertainty in the market, Arrow (1971) argues that observable characteristics such as sex or race are taken as proxies for relevant unavailable data about the qualifications of market participants. This process of attributing certain traits to certain groups stems from two sources: the discriminator's past experience with some groups or his/her exposure to common sociological beliefs. According to such theory, an employer (or creditor) statistically discriminates against women or minorities if he/she perceives their performance to be inferior due to his/her previous experience with such groups or due to the common belief that women and minorities grow up disadvantaged in society, and are therefore less capable of developing skills as high as their counterparts.

2.2. Gender Discrimination in the US

The literature on gender discrimination in the US focuses primarily on the *labor market*, and examines gender differences in market outcomes such as wage differentials between males and females. Even though the male/female wage gap remained relatively stable between the 1950s and 1970s, it later experienced a major decline during the 1980s (Altonji and Blank, 1999). Studies show that the principal factor behind this decline was the increase in female accumulation of education and experience during that period (O'Neill and Polachek, 1993; Ashraf, 1996; Blau and Kahn, 1997). Hence, such findings suggest that gender differences in socio-economic factors are the main drivers behind the male/female wage gap.

However, the convergence of wages for males and females later experienced a slowdown in the mid-1990s, despite the continuous progress of female educational attainment (Blau and Kahn, 2006). This trend undermined the role of socio-economic factors in explaining the wage gap, as more recent studies began emphasizing the influence of noneconomic factors instead. For example, Fortin (2009) demonstrates that changes in the perceptions of gender roles strongly accounted for the slowdown in wage convergence in the mid-1990s, as the HIV/AIDS crisis shifted attitudes towards conservative gender roles, which in turn negatively impacted female labor force participation and wages. Charles et al. (2009) also demonstrate a strong relationship between sexism in gender role attitudes and gender differences in labor market outcomes. Such studies suggest that noneconomic factors reflecting the population's conservative perception of gender roles play a stronger role than economic factors in driving the wage gap between males and females in the labor market. Hence, my paper relates to this literature by extending the same analysis to the *credit market* and examining the extent to which economic and noneconomic factors drive gender differences in rejection rates in mortgage lending.

2.3. Discrimination in US Mortgage Lending

The literature on discrimination in US mortgage lending focuses primarily on racial discrimination and examines three different dimensions of the issue. The first approach examines differences in *loan performance,* while the second approach examines differences in *loan pricing*, and the third approach examines differences in *rejection rates* between minorities and non-minorities.

By utilizing data provided by the Federal Housing Administration (FHA), Berkovec et al. (1998) examine the presence of racial discrimination by testing whether the *performance* of loans given out to minorities is better than their counterparts. While their approach lowers the potential for omitted variable bias, it only allows them to detect the presence of taste-based discrimination. Hence, even though their results suggest the lack of taste-based racial discrimination in the mortgage market, they do not rule out the presence of statistical racial discrimination. A further limitation of this approach is its failure to detect discrimination in cases where applicants that are unfairly denied credit eventually succeed in obtaining it from other nondiscriminatory lenders.

A more recent study by Bayer et al. (2014) examines racial discrimination in *loan pricing* by comparing interest rates received by whites and non-whites for the same loan amount. Their findings suggest evidence of racial discrimination by revealing a higher incidence of high cost loans for minorities and Hispanics compared to whites, even after accounting for important mortgage risk factors.

In terms of *rejection rate* differences, Black et al. (1978) examine the effect of demographic variables such as race on the probability of being rejected for a mortgage loan, *ceteris paribus*, and conclude the presence of racial discrimination in the US mortgage market. However, Munnell et al. (1996) argue that works prior to their study—including those by Black et al. (1978), King (1980) and Ladd et al. (1981) omit several important variables. Therefore, Munnell et al. (1996) utilize an augmented version of HMDA data for the city of Boston to account for previously unavailable variables regarding applicants' creditworthiness. Their findings show that even after controlling for variables such as credit history and credit scores, evidence of racial discrimination in mortgage lending still holds. The same method and findings are present in the study by Tootell (1996).

Since an analysis of either differences in loan performance or loan pricing focuses only on the sample of approved applicants, it fails to account for discrimination against unfairly rejected applicants. Hence, this paper studies discrimination through differences in rejection rates, as this approach detects discrimination in the initial stages of the application process. Furthermore, since most studies examining rejection rate differences were published in the 1970s–1990s, this paper contributes to the literature by exploring the relevance and persistence of discrimination nowadays, after decades of progress achieved by the US in addressing gender and racial inequality.

The study also contributes to past papers by not only examining the presence of discrimination, but also the variation in levels of discrimination across time and space. The temporal analysis examines how discrimination reacts to business cycles in the US. Even though an analysis of the relationship between discrimination and recessions has been done in the context of the *labor market*

(See Cummings, 1987), studies have yet to examine this relationship in the *credit market*. Furthermore, no study has yet examined whether levels of discrimination significantly differ across states within the US, hence the spatial analysis in this paper provides insight regarding the magnitude of this variation, as well as the type of factors driving it.

3. Data Description

3.1. HMDA

The data comes from the Home Mortgage Disclosure Act (HMDA), an act that requires financial institution to annually report details on each loan application they receive. This dataset provides micro-level data on approximately 90% of all loan applications in the United States. Specifically, the dataset offers financial information on the applicant in terms of the income level and loan amount requested, as well as demographic information such as gender, race, and ethnicity. If a co-applicant is present, the dataset provides information on the gender, ethnicity, and race of that person as well. In addition to reporting the size of the loan, the data also specifies the type of the loan requested as either home purchase, home improvement, or refinancing. Most importantly, it provides information on the application outcome by specifying if each loan is approved or rejected. Information on application location is also available, as the data specifies the state, county, and census tract of the financial institution where the application is submitted. A unique identifier for the bank processing the application is also included.

Overall, the dataset provides cross-section information on loans originating from all 50 states as well as the District of Columbia, 3,141 counties, approximately 8,000 financial institutions, and more than 19,000 census tracts for each year between 2004–2012.

Table 1 provides summary statistics for the dataset by year. The total number of loan applications varies significantly during the time period. In 2004, around 15 million loan applications were submitted. The number of loan applications increased in 2005, but experienced a decrease from 2006 onwards. The sharpest fall occurred in 2008, as loan applications fell to approximately 8 million, thus reflecting the severe decrease in demand for mortgage loans during the 2008 financial crisis. Despite the decline in demand from 2006–2008, the rejection rates continued to increase and experienced a peak of 32% during the financial crisis, suggesting the pro-cyclicality of rejection rates for mortgage loans in the US.

Of interest is to highlight two important characteristics of the rejection rates for men and women, as observed in the last two rows of Table 1. For each year in the sample, female applicants face a higher rejection rate than males, and the gap between these two rejection rates peaks in 2008 during the crisis. Granted, these two observations are based on aggregate data, but as we show in the following sections, even after controlling for many factors that could potentially explain the differences, these two stylized facts still survive.

Table 1. Summary statistics for HMDA data by year.

Year	*2004*	*2005*	*2006*	*2007*	*2008*	*2009*	*2010*	*2011*	*2012*
Loan Applications (million)	15	18	17	14	8	8	7	6	9
Loan Amount (thousand)	157	172	177	189	186	201	202	199	203
Income (thousand)	86	91	100	104	103	109	116	118	116
Loan to Income Ratio	2.16	2.18	2.07	2.18	2.21	2.25	2.13	2.05	2.14
Co-applicant	0.47	0.44	0.41	0.44	0.49	0.57	0.57	0.55	0.56
Female	0.31	0.32	0.34	0.33	0.31	0.27	0.27	0.27	0.27
Hispanic	0.11	0.13	0.15	0.13	0.09	0.05	0.05	0.05	0.06
Minority	0.17	0.18	0.19	0.18	0.15	0.11	0.12	0.12	0.12
Home Purchase	0.37	0.42	0.42	0.37	0.31	0.21	0.22	0.25	0.21
Home Improvement	0.09	0.09	0.10	0.12	0.12	0.07	0.07	0.07	0.06
Refinance	0.54	0.49	0.48	0.52	0.56	0.72	0.71	0.68	0.73
Rejection Rates									
Total	0.24	0.25	0.27	0.31	0.32	0.22	0.21	0.22	0.19
Female	0.27	0.29	0.31	0.35	0.37	0.26	0.25	0.26	0.23
Male	0.22	0.24	0.26	0.29	0.30	0.20	0.20	0.20	0.18

Because female applicants comprise about 30% of all applicants and their share is significantly higher than that of minorities and Hispanics in the sample, we focus my analysis more on gender discrimination than racial discrimination, as such an issue disadvantages a higher proportion of mortgage loan applicants in the US.

3.2. Call Reports

We obtain additional information regarding banks' financial information from the Consolidated Reports of Income and Condition (generally known as the Call Reports). These reports are submitted by banks to their respective regulator after every quarter, and contain detailed financial information on the banks' income statement and balance sheet. By relying on definitions of bank-specific factors outlined by Antoniades (2014), we construct relevant variables that reflect the banks' size, capital, funding stability, liquidity, and risk. Table 2 provides the definition for each of these variables.

The HMDA dataset for each year is then merged with the Call Report data from the fourth quarter of the previous year. The unique bank identification numbers are not identical in both datasets and are matched using the agency code of each bank's regulator in the HMDA data. The Call Reports contain data on 4,136 out of the 7,878 financial institutions that reported HMDA information in 2008, and the merged dataset retains more than 40% of the original dataset, as the number of loan applications falls from 8 million to 3.3 million after merging. Table 3 provides the summary statistics for both datasets in 2008.

Table 2. Call report bank variable definitions.

Variable	*Definition*
Assets	Total Assets (thousand)
Size	ln(Asset)
Capital	Total Equity Capital / Assets
Funding Stability	Deposits / Assets
Liquidity	(Cash + Federal Funds Sold + Securities Purchased under agreement to resell + Available for sale securities + Held to maturity securities) / Assets
Risk	(Total Risk weighted assets) / Assets

Note: These variables are based on definitions outlined in Antoniades (2014).

Table 3. Summary statistics of 2008 HMDA data & merged HMDA/Call reports data.

	Original Data (HMDA)	*Merged Data (HMDA + Call)*
States	51	51
Counties	3,141	3,138
Census Tracts	19,015	18,962
Financial Institutions	7,878	4,136
Loan Applications	8,013,827	3,345,780
Rejection Rate	0.32	0.26
Loan Amount (thousand)	186	173
Applicant Income (thousand)	103	109
Loan to Income Ratio	2.21	1.95
Female	0.31	0.29
Hispanic	0.09	0.09
Minority	0.15	0.13
Home Purchase	0.31	0.34
Home Improvement	0.12	0.16
Refinance	0.56	0.50
Co-applicant	0.49	0.50
Size	/	17.78
Capital	/	0.10
Funding Stability	/	0.68
Liquidity	/	0.23
Risk	/	0.77

4. Methodology

To examine whether gender and race play an independent role on a bank's lending decision, we regress whether the loan is rejected or not on the loan-specific and applicant-specific variables outlined in Table 1, as well as county fixed effects. The model takes the following form:

$$\begin{aligned} Rej_{icbt} = {} & \beta_0 + \beta_1 * Female_{icbt} + \beta_2 * Minority_{icbt} + \beta_3 * Hispanic_{icbt} + \beta_4 * ln(Loan)_{icbt} \\ & + \beta_5 * ln(Income)_{icbt} + \beta_6 * Co\text{-}applicant_{icbt} + \beta_7 * Home\_Improvement_{icbt} \\ & + \beta_8 * Refinance_{icbt} + \Gamma * County\_Fixed\_Effects_{ct} + \varepsilon_{icbt} \end{aligned} \quad (1)$$

where Rej_{icbt} is a dummy variable that takes the value of 1 if the loan application by applicant i in bank b and county c at time t is rejected, 0 otherwise.

Since the dependent variable equals 1 if the loan is rejected and 0 if it is approved, we expect β_4 to be positive, while β_5 and β_6 to be negative. That is, an increase in the loan amount requested should increase the probability of rejection as it reflects a higher probability of default, while an increase in the income level or the presence of a co-applicant should lower the probability of rejection as it reflects a higher capability to pay back the loan, *ceteris paribus*.

In cases of dichotomous dependent variables, the use of binary response models such as Probit or Logit models is recommended to overcome certain drawbacks of OLS models[1]. However, because we estimate a large number of fixed effects in my model, OLS provides more consistent estimates for the coefficients of these fixed effects compared to Probit or Logit models (Woolridge, 2010). Therefore, we use OLS as my method of estimation to overcome this issue, which is known as the "Incidental Parameters Problem". Furthermore, standard errors are clustered at the county-level as county-specific effects could generate correlations among the applicant-level error terms.

5. Results

5.1. Gender and Racial Discrimination

The baseline regression results for 2008 are reported in Table 4. We report OLS estimates (Column 1), and Probit estimates (Column 2) for comparison purposes, but only use OLS estimates for the subsequent analysis to overcome the incidental parameters problem suffered by Probit, as explained above.

[1] Drawbacks include fitted probabilities that can be less than zero or greater than one, as well as constant partial effects for each explanatory variable (Woolridge, 2012).

Table 4. Determinants of probability of mortgage loan application denial for 2008.

Variables	*(1) OLS*	*(2) Probit*
Female	**0.0279*****, (0.0010)	**0.0263*****, (0.0010)
Minority	**0.1560*****, (0.0056)	**0.1440*****, (0.0047)
Hispanic	**0.1330*****, (0.0034)	**0.1220*****, (0.0030)
ln(Loan)	0.0249***, (0.0012)	0.0233***, (0.0011)
ln(Income)	-0.0731***, (0.0024)	-0.0733***, (0.0026)
Co-applicant	-0.0325***, (0.0015)	-0.0339***, (0.0015)
Home Improve.	0.2810***, (0.0038)	0.2770***, (0.0035)
Refinance	0.1780***, (0.0040)	0.1870***, (0.0041)
Constant	0.3530***, (0.0100)	
Observations	8,013,827	8,013,781
R-squared	0.102	

Note: the dependent variable $Rej = 1$ if the loan is rejected and 0 if it is approved; County Effects are controlled for, but not reported; Robust standard errors are reported in parentheses and clustered on the county level; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The results indicate all regressors are statistically significant at the 1% and display the expected sign outlined in Section 3. Specifically, Table 4 shows that a higher loan amount requested increases the probability of being rejected, while a higher income or a presence of a co-applicant lowers such probability, *ceteris paribus.* More importantly, being either a female, minority, or Hispanic increases the probability of rejection in 2008 by 3%, 16%, and 13% respectively, thus suggesting the potential presence of discrimination against these groups.

Even though evidence of higher rejection rates for these groups is not a relatively new finding (See Black et al., 1978; Ladd and Shafer, 1981; Munnell et al., 1996; and Tootell et al., 1996), it is perhaps surprising to observe that this issue still persists two to three decades later, especially given how much progress the US has made in addressing gender and racial inequality. This finding is especially concerning given that the Home Mortgage Disclosure Act (HMDA) was enacted by Congress in 1975 mainly as a remedial measure against discriminatory lending behavior in the US (Guy et al., 1982), yet we cannot rule out the presence of discrimination more than 30 years after its enactment. Thus, the relevance and persistence of discrimination in mortgage lending highlights the necessity of continuously monitoring this issue and scrutinizing the effectiveness of current legislation aimed to address it.

A major issue with claiming the presence of discrimination based on this model includes endogeneity concerns regarding the omitted variable bias. For example, unavailable information on factors such as each applicant’s credit score or credit history could undermine the claim of discrimination. If the females, minorities, and Hispanics in the sample have worse credit scores than their counterparts, then the higher rejection rates they experience could likely be a result of this variable and not discrimination. Even though studies in the past have shown that including variables such as credit scores and credit history does not influence findings on the presence of discrimination

(See Munnell et al., 1996; Tootell, 1996), we nonetheless provide further evidence using the available data to show why such missing variables do not bias my results.

To address this issue, we run the baseline regression for 2008 on a sub-sample of individuals applying for jumbo loans only. Jumbo, or non-conforming, loans are mortgage loans that exceed conforming loan limits set annually by the Office of Federal Housing Enterprise Oversight (OFHEO), making them ineligible for repurchase by Government-Sponsored Enterprises (GSEs) such as Fannie Mae and Freddie Mac (Calem et al., 2013). The 2008 conforming loan limit was established at $417,000 in all states except Alaska and Hawaii, where it was 50% higher (Comeau, 2009). Because of the severe illiquidity of these loans, and banks' inability to resell them to GSEs, most financial institutions have set strict requirements for jumbo loan applicants in terms of minimum required credit scores and down payments, as many would barely consider applicants with a score lower than 720 (Martin, 2014).

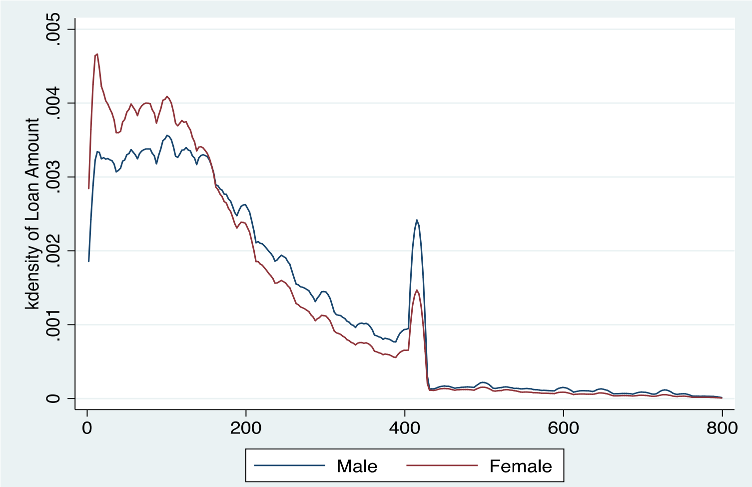


Figure 1. Data distribution for loan amounts requested in 2008 by gender.

Figure 1 demonstrates the 2008 data distribution for loan amounts by gender. Even though the proportion of males and females applying drops as the loan size gets bigger, there is nonetheless a spike at the conforming loan limit of $417,000. This suggests that applicants who want big loans apply for the maximum amount possible without qualifying for jumbo loans, due to the illiquidity, higher risk of rejection, and higher qualifications required for these loans.

Considering only the sub-sample of jumbo loan applicants reduces endogeneity concerns because it ensures a more homogenous sample of applicants along potential unobserved characteristics (especially credit history), regardless of their gender, race, or ethnicity. To see why, suppose that higher rejection rates for females are the outcome of an omitted variable bias and not that of discrimination. That would be the case, for example, if female applicants in the full sample had worse credit scores than males. Because, however, these credit scores for males and females are expected to converge for applicants of jumbo loan due to strict bank requirements, we would expect the omitted variable bias to be reduced substantially in the sub-sample of jumbo loans, and therefore the coefficient β_1 of *FEMALE* to drop to 0. To test this hypothesis, we run the same regression as in specification (1) for the 2008 full sample, as well as the sub-sample of jumbo loan applications only[2]. The results for these two specifications are reported in Column 1 and Column 2 of Table 5, respectively.

Table 5. Robustness check: determinants of probability of mortgage loan application denial for 2008 (All loans vs. Jumbo loans).

Variables	*(1) All Loans*	*(2) Jumbo Loans*
Female	**0.0279*****, (0.0010)	**0.0521*****, (0.0047)
Minority	**0.1560*****, (0.0056)	**0.0806*****, (0.0137)
Hispanic	**0.1330*****, (0.0034)	**0.1580*****, (0.0104)
ln(Loan)	0.0249***, (0.0012)	0.1200***, (0.0067)
ln(Income)	-0.0731***, (0.0024)	-0.1530***, (0.0046)
Co-applicant	-0.0325***, (0.0015)	-0.0779***, (0.0045)
Home Improve.	0.2810***, (0.0038)	0.2710***, (0.0128)
Refinance	0.1780***, (0.0040)	0.1980***, (0.0078)
Constant	0.3530***, (0.0100)	0.3180***, (0.0284)
Observations	8,013,827	381,439
R-squared	0.102	0.165

Note: the dependent variable *Rej* = 1 if the loan is rejected and 0 if it is approved; County Effects are controlled for, but not reported; Robust standard errors are reported in parentheses and clustered on the county level; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The results are consistent, if not stronger, when considering only jumbo loan applications. The lending rejection probability that women face on jumbo loans is 5 percentage points higher than that faced by men. Similarly, minorities and Hispanics face higher rejection rates compared to their counterparts. Therefore, these results suggest that it is highly unlikely that my findings are driven by unaccounted factors such as credit scores.

However, because banks may have different lending practices due to idiosyncratic factors such as their size and liquidity, if a disproportionately higher proportion of females, minorities, and Hispanics apply to certain banks, then the higher rejection rates we observe could be driven by bank-specific factors and not by discrimination.

To address this issue we incorporate bank-specific factors into the regression[3]. Specifically, we obtain financial data for each bank from the Consolidated Reports of Condition and Income (Call Reports). As outlined in Section 3, we then construct variables that influence a bank's propensity to

[2] We define jumbo loans as those exceeding the Conforming Loan Limits (CLL) for each county within the US, data on which is publically provided by the Federal Housing Finance Agency (FHFA).

[3] Simply adding bank fixed effects would mask potential discrimination because these fixed effects would capture how each banks differs in its propensity to lend, but would not reflect whether such variation is due to economic factors regarding the bank's balance sheet, or due to discrimination against applicants by the bank's lending officers.

lend, such as the bank's size, capital, funding stability, liquidity, and risk, and merge this bank-specific data from the Call reports to the HMDA dataset. The merged dataset represents more than 40% of the original dataset. Column 1 of Table 6 reports the baseline regression results for the full HMDA sample in 2008, Column 2 reports the results for the same baseline regression but for the merged sample, and Column 3 reports the results after incorporating the bank-specific variables to the regression in Column 2[4].

Table 6. Robustness check: the effects of application denial determinants for 2008 with and without bank controls.

Variables	*(1) Original Sample (Baseline)*	*(2) Merged Sample (Baseline)*	*(3) Merged Sample (Baseline + Banks Variables)*
Female	**0.0279*****, (0.0010)	**0.0186*****, (0.0011)	**0.0117*****, (0.0009)
Minority	**0.1560*****, (0.0056)	**0.1270*****, (0.0056)	**0.1160*****, (0.0055)
Hispanic	**0.1330*****, (0.0034)	**0.1350*****, (0.0047)	**0.1230*****, (0.0048)
Size			0.0136***, (0.0004)
Capital			0.2740***, (0.0298)
Funding Stability			-0.4380***, (0.0071)
Liquidity			0.1180***, (0.0169)
Risk			0.0772***, (0.0151)
Other Variables [a]	Yes	Yes	Yes
Constant	0.3530***, (0.0100)	0.4290***, (0.0061)	0.3990***, (0.0199)
Observations	8,013,827	3,345,780	3,345,780
R-squared	0.102	0.100	0.126

Note: [a] include ln(Loan), ln(Income), Co-applicant, Home Improvement, Refinance; Column 1 reports results for the HMDA dataset alone (identical to Table 4 Column 1); Columns 2 reports results for the same regression in Column 1, but for the smaller merged dataset; Column 3 reports results when bank variables are added to the regression in Column 2. The fact that the female, minority, and Hispanic coefficients remain positive and significant after adding bank controls supports the robustness of the original results; The dependent variable *Rej* =1 if the loan is rejected and 0 if it is approved; County Effects are controlled for, but not reported; Robust standard errors are reported in parentheses and clustered on the county level; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

As the comparison between Column 2 and Column 3 shows, even after adding bank-specific factors to the 2008 baseline regression, the coefficients for females, minorities, and Hispanics remain positive and highly significant, thus indicating the robustness of the initial results.

Hence, my results suggest the presence of discrimination against females, minorities, and Hispanics, a finding the remains robust to missing credit score information and bank-specific factors. The next two sub-sections explore how discrimination behaves across time and space.

[4] We report the results of specification (1) but for the sub-sample of merged data between HMDA and Call reports (Column 2) in order to ensure that any differences in the estimates are not driven by changes in the sample size.

5.2. Discrimination Across Time

The US experienced substantial macro variation between 2004–2012 as the economy shifted from a boom (2004–2007) to a bust during the Great Recession (2007–2010) and to a boom again during the recovery years (2010–2012).

In this section, we examine how discrimination changes over the business cycle by studying how my measures of lending discrimination change over time. We do so by running specification (1) for each year between 2004–2012 (Results are reported in Table A1 in the Appendix). The coefficients β_1, β_2 and β_3 for females, minorities, and Hispanics respectively, are plotted by year in Figure 2.

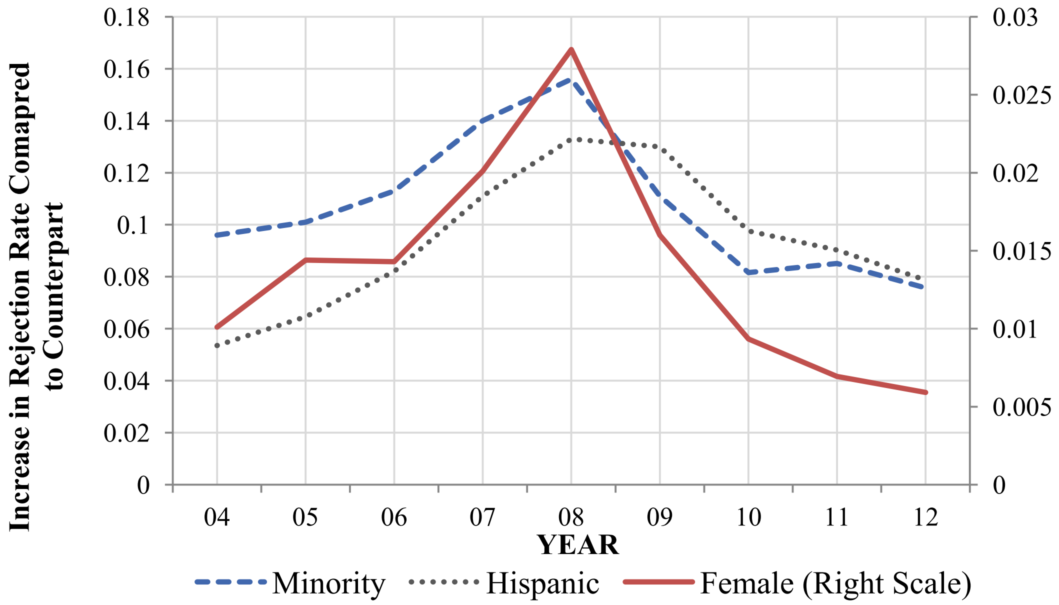


Figure 2. Gender and racial discrimination across time (2004–2012).

Note: probability of rejection for females, minorities, and Hispanics compared to males, non-minorities, and non-Hispanics peaks in 2008, coinciding with the financial crisis; Due to magnitude differences, the coefficient for females was rescaled to correspond to the right scale. The coefficients for minorities and Hispanics correspond to the left scale; Table A1 in the Appendix reports the detailed regression results for each year; Table A2 in the Appendix reports regression results for an appended 10% sample of each year, and confirms the statistical significance of this time trend.

Even though the *demand* for mortgage loans in the US declined during the financial crisis, the *supply* of these loans contracted by even more (Antoniades, 2014), causing banks to face heightened liquidity constraints. This resulted in higher rejection rates in general during the crisis, but especially for females, minorities, and Hispanics, as demonstrated by the 2008 peak of all three curves in Figure 2. This suggests that both gender and racial discrimination in mortgage lending are pro-cyclical[5].

5.3. Discrimination Across Space

Above we provided evidence suggesting lending discrimination against female, minority, and Hispanic applicants. Here, we document that the magnitude of lending discrimination varies across states, and then discuss factors that can potentially explain the variation. Surprisingly, we will argue that the variation is driven more strongly by cultural and social factors than economic factors.

To examine variation in lending practices across US states, we interact *Female* with State fixed effects. That is, we estimate the following model for 2008:

$$\begin{aligned} Rej_{isbt} = \beta_0 + \beta_1 * Female_{isbt} + \beta_2 * Minority_{isbt} + \beta_3 * Hispanic_{isbt} + \beta_4 * \ln(Loan)_{isbt} \\ + \beta_5 * \ln(Income)_{isbt} + \beta_6 * Co\text{-}applicant_{isbt} + \beta_7 * Home\_Improvement_{isbt} \\ + \beta_8 * Refinance_{isbt} + \Gamma * (State\_Fixed\_Effects_{st} \bullet Female_{isbt}) + \varepsilon_{isbt} \end{aligned} \tag{2}$$

where Rej_{isbt} is a dummy variable that takes the value of 1 if the loan application by applicant i in bank b and state s at time t is rejected, 0 otherwise. The vectors of estimated coefficients Γ capture lending discrimination for each US state relative to that of the omitted state.

The process is repeated for minorities and Hispanics as well. Table A3 in the Appendix reports the coefficients for all three groups by state and confirms their statistical significance. After computing the level of gender and racial discrimination in each state, the maps in Figure 3 demonstrate these effects, with darker shades of color reflecting higher levels of discrimination.

A relatively similar trend appears for the three groups, with higher levels of discrimination in states located at the center, such as Minnesota, Missouri, and Nebraska, and very low level of discrimination against these groups in states located in the far east and far west, such as Maine and California respectively. Such findings provide impetus to explore the type of factors contributing to stronger discrimination in some states compared to others.

[5] To examine the statistical significance of the time trend in Figure 2, WE append a 10% representative sample of each year and run the baseline regression with an added interaction term between the real GDP growth rate for each year & the female dummy. Similar interaction terms are included for minorities and Hispanics as well. Results are reported in Table A2 in the Appendix. The sign and statistical significance of the interaction terms further reinforce the pro-cyclicality of gender and racial discrimination.

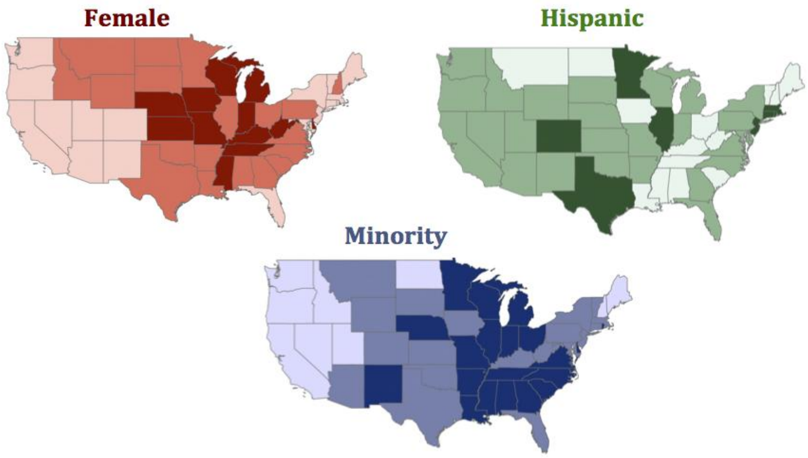


Figure 3. Gender and racial discrimination in 2008 by state.

Note: darker shades reflect higher levels of discrimination; Figures were produced using ArcGIS; Table A3 in the Appendix reports the magnitude and statistical significance of discrimination faced by each group in each state.

To better depict the variation across states, Figure 4 plots the magnitude of discrimination faced by females in each state in 2008. Every column shows the gap in rejection rates between males and females, *ceteris paribus*. According to this figure, the difference in rejection rates between males and females in 2008 was 0% in Florida but reached a maximum of 7% in Iowa at the other end of the spectrum, thus highlighting the substantial degree of variation in levels of gender discrimination across the US.

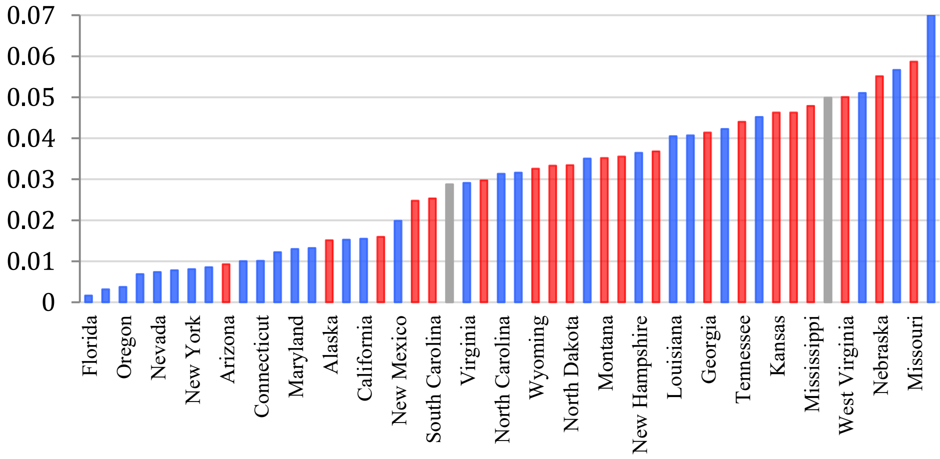
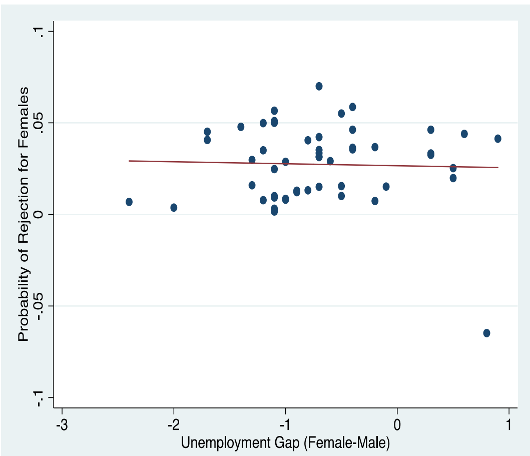


Figure 4. Gender discrimination by state in 2008.

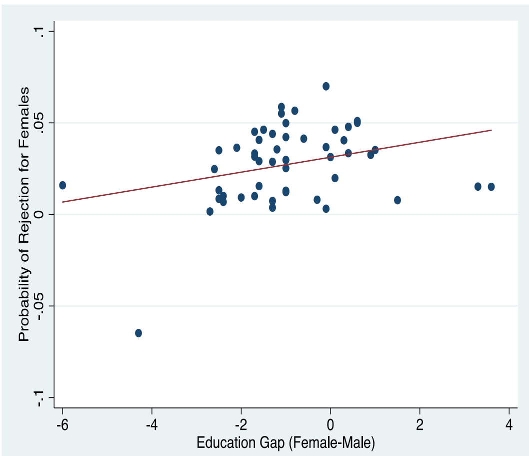
Note: each column shows the rejection gap (Female Rejection Rate–Male Rejection Rate), computed using estimates in Table A3 in the Appendix; Red columns reflect "Red States" and blue columns reflect "Blue States" in 2008.

One may suspect that the observed variation in female lending discrimination reflects differences in *economic* factors between males and females in each state. For example, in states where females face much higher unemployment rates or much lower education levels relative to males, such features might influence society's perceptions of all females as less qualified economic agents and consequently motivate higher discrimination against them.

To test this, we provide a scatter plot of gender discrimination in each state with gender differences in unemployment and education in 2008. Intuitively, one would expect that a higher female unemployment rate compared to male unemployment rate (i.e. a bigger unemployment gap[6]) would be correlated with a higher level of gender discrimination in that state, however Figure 5a demonstrates a lack of correlation between the two factors. Similarly, one would expect that states with higher female educational attainment relative to males (i.e. a higher educational gap[7]) would be correlated with lower levels of discrimination against females. However, instead of a negative relationship, Figure 5b reveals a positive relationship between these two variables. This may suggest that gender discrimination is not driven by perceptions of lower female educational attainment, but rather pushes females in highly discriminatory states to pursue education more strongly than males to overcome the higher barriers against them. Hence, the plots, reported in Figure 5, show that economic variables fail to adequately the explain variation in lending discrimination against females across states.



(a) Unemployment Gap



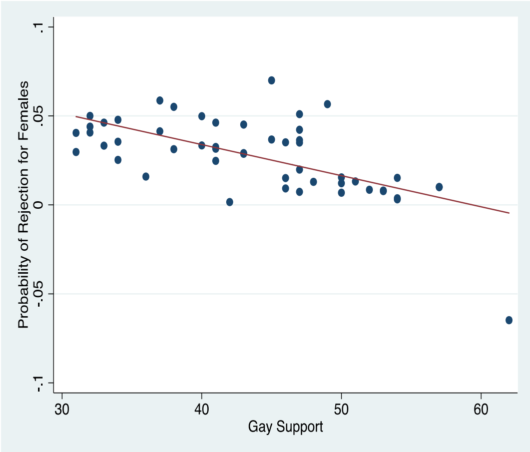
(b) Education Gap

Figure 5. Correlation between gender discrimination in each state and economic factors.

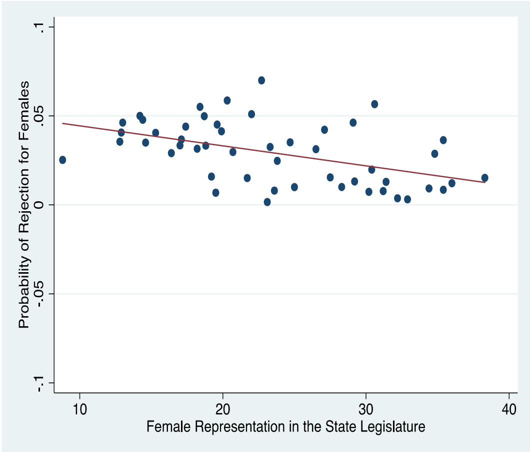
[6] Unemployment Gap = Female Unemployment Rate – Male Unemployment Rate. This data is provided by the American Community Survey (ACS), made available by the US Census Bureau.

[7] Education Gap = Proportion of Females with Bachelor's degrees - Proportion of Males with Bachelor's degrees. This data is also provided by the American Community Survey (ACS), made available by the US Census Bureau.

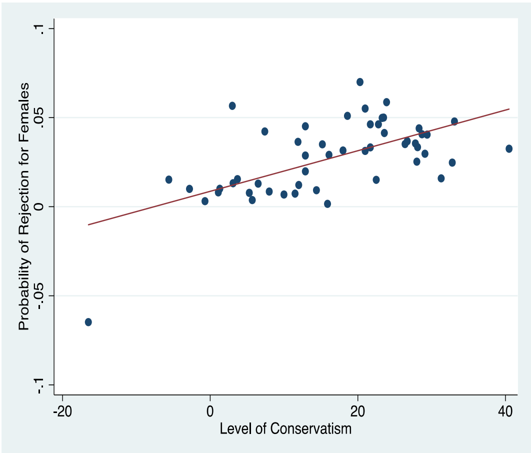
Next, we show that *non-economic* factors that reflect the population's attitudes and political beliefs do a better job at explaining the documented cross-state variation in lending discrimination against females. Specifically, we examine three main noneconomic factors: the level of gay support[8], female political representation[9], and conservatism[10] in each state.



(a) Gay Support



(b) Female Political Representation



(c) Conservatism

Figure 6. Correlation between gender discrimination in each state and noneconomic factors.

[8] Measures the level of support for gay rights in each state. Data is provided by Flores et al. (2013).

[9] Defined as the percentage of seats in the state legislature held by females in 2008. Data is provided by the Center for American Women and Politics (CAWP).

[10] Defined as the Conservative Advantage in each state, which equals the proportion of the population that is conservative minus the proportion of the population that is liberal. Levels of conservative advantage in 2013 for each state are publically provided by Gallup Analytics (State of the States).

The scatter plots in Figure 6 reveal that gender discrimination exhibits a negative correlation with gay support, as well as female political representation, and a positive correlation with the level of conservatism in each state. This suggests that states with a higher level of support for gay rights, a higher proportion of females in the state legislature, or a lower level of conservatism exhibit lower levels of discrimination against females in the mortgage market. However, even though these three noneconomic variables are themselves likely to be correlated, they nonetheless offer different channels of illustrating the intricate relationship between gender discrimination in mortgage lending and the surrounding social and political context, namely by illustrating that women in more conservative and traditional states are more prone to higher levels of discrimination.

Table 7. Effects of economic and social factors on mortgage rejection rates.

Variables	*(1)* *Gay Support*	*(2)* *Female Political Rep.*	*(3)* *Conservatism*	*(4)* *Unemployment Gap*	*(5)* *Education Gap*	*(6)* *All Except Gap Support*
Female	0.0857***	0.0584***	0.0113***	0.0292***	0.0347***	0.0344***
	(0.0126)	(0.0072)	(0.0036)	(0.0025)	(0.0037)	(0.0087)
Gay Support	-0.0007					
	(0.0007)					
Female*Gay Support	**-0.0013*** **					
	(0.0003)					
Women in Legislature		-0.0005				-0.0008
		(0.0006)				(0.0010)
Female*Women in Legislature		**-0.0013*** **				**-0.0006** **
		(0.0004)				(0.0002)
Conservative Adv.			0.0002			-0.0004
			(0.0005)			(0.0010)
Female*Conservative Adv.			**0.0011*** **			**0.0008*** **
			(0.0002)			(0.0002)
Unemployment Gap				-0.0007		0.0038
				(0.0086)		(0.0077)
Female*Unemployment Gap				**0.0027**		**-0.0016**
				(0.0034)		(0.0024)
Education Gap					-0.0120*	-0.0125*
					(0.0070)	(0.0070)
Female*Education Gap					**0.0055** **	**0.0041*** **
					(0.0025)	(0.0014)
Other Variables+	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.4100***	0.3950***	0.3870***	0.3930***	0.3840***	0.4040***
	(0.0373)	(0.0287)	(0.0279)	(0.0280)	(0.0261)	(0.0523)
Observations	8,013,827	7,999,090	8,013,827	8,013,827	8,013,827	7,999,090
R-squared	0.087	0.087	0.087	0.087	0.087	0.088

To check the statistical significance of these correlations, we interact both economic and noneconomic factors with the female dummy in specification (1) for 2008. The first 5 columns of Table 7 show the results of adding each variable separately, while the last column shows the results for all the variables in the same regression. The variable gay support is omitted from the last specification as it proved to be insignificant and highly correlated with the conservative advantage variable.

Column 6 of Table 7 confirms the direction and significance of the correlations in Figure 5 and Figure 6. In terms of *economic* factors, the interaction term between the female dummy and the unemployment gap displays a negative sign and is statistically insignificant, suggesting the unemployment gap's lack of influence on rejection rates for females. The interaction term between the female dummy and the education gap is highly significant and positive, suggesting that discrimination is not driven by low levels of female education, but perhaps pushes females in highly discriminatory states to pursue education more strongly than males in such states. In contrast, interaction terms between the female dummy and *noneconomic* factors are significant and display the expected signs, as having more females in the state legislature lowers the probability of rejection for females, while applying in a more conservative state increases the probability of rejection for females, *ceteris paribus*. These findings suggest that noneconomic factors that reflect the population's attitudes and political beliefs explain the variation in gender discrimination across states much better than economic factors.

6. Conclusion

We use a rich dataset on lending behavior in the United States to examine the presence of gender and racial discrimination in mortgage lending between 2004–2012. My findings suggest that discrimination against females, minorities, and Hispanics still persists nowadays, despite the efforts to address gender and racial inequality in the past decades. The temporal analysis suggests the pro-cyclicality of discrimination as its effects become more pronounced during recessions. The spatial analysis suggests that a wide variation in levels of gender discrimination exists across US states, and that this variation is driven more by noneconomic factors that reflect the population's attitudes and beliefs (e.g. level of gay support, female political representation, and conservatism), than economic factors that reflect females' qualifications as economic agents (e.g. unemployment, education).

Therefore, this paper contributes to the existing literature not only by showing that gender discrimination in mortgage lending still exists, but also by providing two new stylized facts: (1) discrimination against females, minorities, and Hispanics is pro-cyclical, (2) the variation in gender discrimination across states is better explained by noneconomic than economic factors.

An understanding of the interplay of all these aspect of discrimination provides critical policy implications. For example, the temporal trend highlights that vulnerable groups in society such as females, minorities, and Hispanics, become even more vulnerable and in need of protection relative to their counterparts in times of recession. The spatial trends highlight that efforts to ameliorate discrimination against females by improving their socio-economic status in terms of education or employment relative to males could prove to be ineffective, as gender discrimination is more strongly driven by noneconomic factors related to the attitudes and beliefs of the population. Thus, such findings highlight the importance of a deeper examination of the driving forces behind discrimination, in order to more effectively inform future policies aimed at addressing this persistent issue.

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Conflict of Interest

All authors declare no conflict of interest in this paper.

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Appendix

Table A1. Determinants of probability of mortgage loan application denial by year (2004–2012).

Variables	*2004*	*2005*	*2006*	*2007*	*2008*	*2009*	*2010*	*2011*	*2012*
Female	**0.0101*** **	**0.0144*** **	**0.0143*** **	**0.0202*** **	**0.0279*** **	**0.0160*** **	**0.0093*** **	**0.0069*** **	**0.0059*** **
	(0.0009)	(0.0008)	(0.0008)	(0.0009)	(0.0010)	(0.0008)	(0.0008)	(0.0007)	(0.0006)
Minority	**0.0959*** **	**0.1010*** **	**0.1130*** **	**0.1400*** **	**0.1560*** **	**0.1110*** **	**0.0815*** **	**0.0849*** **	**0.0757*** **
	(0.0043)	(0.0037)	(0.0035)	(0.0040)	(0.0056)	(0.0066)	(0.0070)	(0.0066)	(0.0058)
Hispanic	**0.0536*** **	**0.0648*** **	**0.0823*** **	**0.1120*** **	**0.1330*** **	**0.1300*** **	**0.0976*** **	**0.0902*** **	**0.0786*** **
	(0.0034)	(0.0028)	(0.0027)	(0.0025)	(0.0034)	(0.0053)	(0.0050)	(0.0051)	(0.0040)
ln(Loan)	-0.0180***	-0.0039***	0.0106***	0.0170***	0.0249***	0.0070***	0.0009	-0.0004	-0.0133***
	(0.0009)	(0.0010)	(0.0010)	(0.0010)	(0.0012)	(0.0012)	(0.0011)	(0.0010)	(0.0012)
ln(Income)	-0.0588***	-0.0572***	-0.0572***	-0.0518***	-0.0731***	-0.0643***	-0.0673***	-0.0678***	-0.0549***
	(0.0028)	(0.0028)	(0.0029)	(0.0028)	(0.0024)	(0.0016)	(0.0019)	(0.0020)	(0.0017)
Co-applicant	-0.0361***	-0.0391***	-0.0428***	-0.0404***	-0.0325***	-0.0370***	-0.0354***	-0.0381***	-0.0320***
	(0.0014)	(0.0012)	(0.0015)	(0.0016)	(0.0015)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Home Improve.	0.1870***	0.1890***	0.1980***	0.2360***	0.2810***	0.2040***	0.1820***	0.2000***	0.1760***
	(0.0045)	(0.0047)	(0.0059)	(0.0053)	(0.0038)	(0.0048)	(0.0047)	(0.0046)	(0.0046)
Refinance	0.1180***	0.1240***	0.1310***	0.1790***	0.1780***	0.0821***	0.0653***	0.0783***	0.0517***
	(0.0053)	(0.0056)	(0.0061)	(0.0055)	(0.0040)	(0.0028)	(0.0020)	(0.0021)	(0.0020)
Constant	0.4810***	0.4220***	0.3680***	0.3070***	0.3530***	0.3890***	0.4500***	0.4580***	0.4600***
	(0.0064)	(0.0066)	(0.0062)	(0.0071)	(0.0100)	(0.0089)	(0.0094)	(0.0097)	(0.0086)
Observations	15,245,058	18,109,060	17,094,142	13,775,727	8,013,827	7,713,977	6,911,658	6,362,836	8,800,440
R-squared	0.076	0.069	0.064	0.083	0.102	0.068	0.060	0.065	0.058

Note: the dependent variable Rej =1 if the loan is rejected and 0 if it is approved; Coefficients for females, minorities, and Hispanics are plotted by year in Figure 2; County Effects are controlled for, but not reported; Robust standard errors are reported in parentheses and clustered on the county level; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A2. Robustness check: impact of business cycles on gender & racial discrimination for a 10% appended sample from 2004–2012.

Variables	*10% Sample*
Female	0.0207***
	(0.0009)
Minority	0.1310***
	(0.0055)
Hispanic	0.1220***
	(0.0020)
Female*Growth	**-0.0028*** **
	(0.0002)
Minority*Growth	**-0.0110*** **
	(0.0008)
Hispanic*Growth	**-0.0187*** **
	(0.0009)
Other Variables [a]	Yes
Constant	0.4240***
	(0.0082)
Observations	10,199,652
R-squared	0.069

Note: [a]include ln(Loan), ln(Income), Co-applicant, Home Improvement, Refinance, and Growth; County fixed effects and year fixed effects are controlled for, but not reported; Growth refers to the annual percentage change in US Real GDP, chained 2009 dollars (inflation-adjusted). Source: US Bureau of Economic Analysis; the dependent variable Rej =1 if the loan is rejected and 0 if it is approved; The significance of the interaction terms confirms the impact of business cycles on discrimination, as well as confirms the significance of the time trend in Figure 2; Robust standard errors are reported in parentheses and clustered on the county level; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A3. The effect of being female, minority, or hispanic on probability of rejection in each State.

State	*Female*	*Minority*	*Hispanic*
Coefficient	0.0407***	0.2130***	0.0659***
Interaction with:			
Alaska	-0.0256***	-0.0730***	-0.0133***
Arizona	-0.0314***	-0.0860***	0.0779***
Arkansas	-0.0110***	-0.0177***	0.0601***
California	-0.0252***	-0.1420***	0.0810***
Colorado	-0.0285***	-0.0822***	0.0989***
Connecticut	-0.0306***	-0.0364***	0.1490***
Delaware	0.0160***	-0.0005	0.0339***
District of Columbia	-0.1050***	-0.1010***	0.0272***
Florida	-0.0390***	-0.0548***	0.0564***
Georgia	0.0007	0.0163***	0.0518***
Hawaii	-0.0376***	-0.2290***	0.0531***
Idaho	-0.0159***	-0.1110***	0.0475***
Illinois	0.0016	-0.0212***	0.0964***
Indiana	0.0092***	0.0036**	0.0404***
Iowa	0.0293***	-0.0800***	0.0061**
Kansas	0.0056**	-0.0460***	0.0451***
Kentucky	0.0056***	-0.0539***	-0.0126***
Louisiana	-0.0002	-0.0196***	0.0227***
Maine	-0.0329***	-0.1420***	-0.0119***
Maryland	-0.0277***	-0.0364***	0.0856***
Massachusetts	-0.0307***	-0.0844***	0.1550***
Michigan	0.0045***	0.0242***	0.0426***
Minnesota	-0.0119***	-0.0191***	0.1140***
Mississippi	0.0072***	-0.0123***	0.0196***
Missouri	0.0180***	0.0322***	0.0368***
Montana	-0.0055**	-0.0731***	-0.0272***
Nebraska	0.0144***	-0.0347***	0.0536***
Nevada	-0.0333***	-0.1090***	0.0549***
New Hampshire	-0.0043	-0.1310***	-0.0007
New Jersey	-0.0275***	-0.0828***	0.1010***
New Mexico	-0.0208***	0.0115***	0.0663***
New York	-0.0326***	-0.0934***	0.0555***
North Carolina	-0.0096***	-0.0044***	0.0296***
North Dakota	-0.0072***	-0.1040***	0.0149***
Ohio	-0.0091***	-0.0169***	0.0218***
Oklahoma	-0.0052***	-0.0815***	0.0350***
Oregon	-0.0369***	-0.1370***	0.0481***
Pennsylvania	-0.0057***	-0.0407***	0.0552***
Rhode Island	-0.0338***	0.0034**	0.1780***
South Carolina	-0.0154***	0.0032***	0.0095***
South Dakota	-0.0039*	-0.0566***	0.0552***
Tennessee	0.0033***	0.0266***	0.0169***
Texas	-0.0074***	-0.0580***	0.0937***
Utah	-0.0247***	-0.1150***	0.0363***
Vermont	-0.0255***	-0.0918***	-0.0582***
Virginia	-0.0116***	-0.0319***	0.0472***
Washington	-0.0322***	-0.1200***	0.0705***
West Virginia	0.0094***	-0.0838***	0.0190***
Wisconsin	0.0103***	0.0131***	0.0706***
Wyoming	-0.0081***	-0.0796***	0.0346***

Note: Alabama is taken as the base state. Discrimination levels in each state are computed by adding each interaction term to the appropriate female, minority, or Hispanic coefficient; Robust standard errors are reported in parentheses and clustered on the state level; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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