Using High-Frequency Evaluations to Estimate Discrimination:
Evidence from Mortgage Loan Officers[*]

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Abstract

We develop empirical tests for discrimination that use high-frequency evaluations to address the problem of unobserved heterogeneity in a conventional benchmarking test. Our approach to identifying discrimination requires two conditions: (1) the subject pool is time-invariant in a short time horizon and (2) there is high-frequency variation in the extent to which evaluators can rely on their subjective assessments. We bring our approach to the residential mortgage market, using data on the near-universe of U.S. mortgage applications from 1994 to 2018. Monthly volume quotas reduce how much subjectivity loan officers apply to loans they process at the end of the month. As a result, the volume of new originations increases by 150% at the end of the month, while application volume and applicants' quality are constant within-month. Owing to within-month variation in loan officers' subjectivity, we estimate that Black mortgage applicants have 3.5% to 5% lower approval rates, which explains at least half of the observed approval gap for Blacks. When we use this approach to evaluate policies, we find that market concentration and FinTech lending have had no effect on lending discrimination, but that shadow banking has reduced discrimination presumably by having a larger presence in under-served communities.

Keywords: Performance Incentives, Loan Officers, Mortgages, FinTech Lending, Lending Discrimination

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1 Introduction

Racial and gender disparities have been documented in a range of fields, such as labor markets, the legal system, and credit markets. Yet whether these disparities are the result of discrimination by economic decision-makers—defined as an evaluator treating otherwise identical subjects from minority groups worse than subjects from the majority group—remains in dispute. There has been a growing trend toward using experiments and correspondence studies to test for discrimination (Bertrand and Duflo, 2017). Nonetheless, tests for discrimination that use observational data have several advantageous features. Such tests are accessible to a wide range of researchers, they are easy to replicate and scale, they can be used to estimate aggregate costs of discrimination in a given market, and policymakers can easily implement them.

However, tests for discrimination based on observational data face a number of econometric challenges that limit their appeal. The most straightforward test for discrimination is an audit or "benchmarking" test. Benchmarking tests claim to find discrimination when minority groups receive unfavorable evaluations relative to the majority group. But, benchmarking tests are vulnerable to criticisms of omitted variable bias—differences in group characteristics, which the researcher does not observe, can cause differences in evaluations across groups.

Alternatively, Becker (1957) proposed an "outcome test." Instead of comparing differences in how groups are evaluated, outcome tests compare the ex-post success of these evaluations. The marginal minority will have better ex-post outcomes than the marginal majority subject because minority groups face higher thresholds for inclusion when they are subject to discrimination. Though intuitively appealing, outcome tests are notoriously difficult to implement, most notably because of the "infra-marginality" problem—the average difference in ex-post outcomes can be a poor approximation of the difference in marginal outcomes (Ayres, 2002). Recent research has made significant progress to improve econometric methods (e.g., Arnold et al., 2018), but addressing the infra-marginality problem requires additional modelling and distributional assumptions (Simoiu et al., 2017). Furthermore, ex-post outcomes can be the result of self-fulfilling prophecies (e.g., female students underperform in math because gender stereotypes reduce investment in females' math education; Bordalo et al., 2016) and ex-post outcomes are often not easily measured (e.g., worker productivity can be difficult to measure and proxies for productivity, such as wages, can also be affected by discrimination).

We propose an alternative way to test for discrimination. The approach is motivated by the observation that evaluators' subjectivity can often vary substantially within short time intervals. For example, employers that have immediate staffing needs can ill afford to turn away job applicants. TSA agents might reduce their screening of travelers when they are at the end of their shifts or there are long queues. Police officers that have monthly quotas would issue tickets to all drivers that exceed the speed limit on the last day of the month. Our approach starts with a benchmarking test, but addresses the problem of omitted variables by exploiting such high-frequency evaluations. The approach requires two simple assumptions: time-varying discrimination and time-invariant unobserved characteristics both in a short time interval (e.g., a month). The identification rationale is straightforward. If the evaluations of a group vary within a short time interval, then these differences cannot be driven by unobserved subject characteristics, because the unobserved characteristics are time-invariant.

We apply our approach to high-frequency data on mortgage applications, to test for discrimination in the US residential mortgage market. We obtain the time-stamped version of the Home Mortgage Disclosure Act (HMDA) data, covering the near-universe of mortgage applications from 1994 to 2018 with 500 million loan applications across more than 28,000 lenders. Crucial to our empirical approach, we observe the exact application and decision date of each application.

Figure 1 demonstrates our key source of high-frequency variation in the mortgage market and the foundation of our empirical approach. The figure shows the volume of new originations and new applications relative to the first day of a given month. The total volume of new mortgage originations increases by more than 150% on the last day relative to the first day of a given month. At the same time, the number of submitted mortgage applications stays constant over the course of the month. These patterns reveal a crucial feature of the mortgage application process: loans are

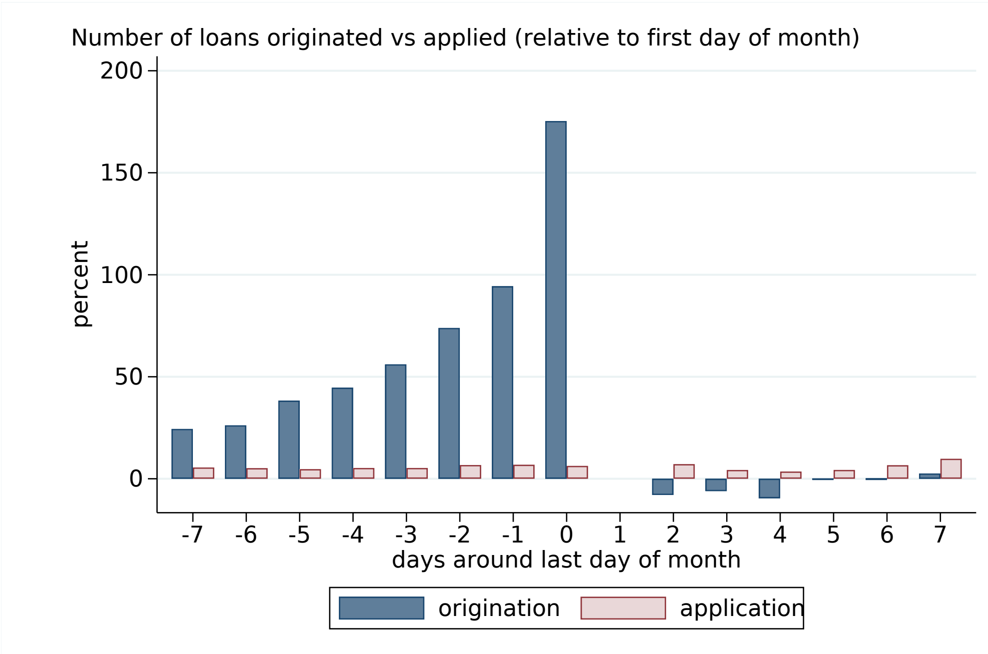

Figure 1: The Figure shows average percentage abnormal daily loan origination volume, and loan application volume (measured as number of originations and applications) in the U.S., for the last eight days of the month, and the first seven days of the following month. The Figure reports the average across all months over the sample period from January 1994 to December 2018 from the HMDA data. Abnormal volume is computed with respect to loan originations and applications on the first day of the following month.

processed by individual loan officers who have monthly performance targets that determine their compensation.[1] Moreover, this within-month pattern in loan approvals unveils the component of loan officers' decision-making that is orthogonal to observable and unobservable factors affecting loan originations (e.g., credit market conditions, applicant characteristics, and firm-level characteristics). Drawing from Becker (1957), a profit-maximizing agent can give disparate treatment to minority populations until market competition makes discrimination economically untenable. Loan officers have an economic incentive to meet end-of-month performance incentives. As such, loan officers' subjective favoritism toward applicants has to attenuate at the end of the month

[1]Though we do not directly measure the compensation of any individual loan officer, for the most part, commissions are set based on the number of loans and the loan amount originated. And the compensation scheme is common across employers. For example, see the following link for an article on the website of the Mortgage Bankers Association that discusses the industry standards for loan officers' compensation in the U.S. (*https://www.mba.org/publications/insights/archive/mba-insights-archive/2019/is-it-time-to-rethink-compensation-x253848*). Tzioumis and Gee (2013) also notes that loan officers face disciplinary actions if they fail to meet their quotas several months in a row. Given this non-linear incentive scheme, Tzioumis and Gee (2013) and Cao et al. (2020) document end-of-month bunching in a large U.S. commercial bank and in two Chinese banks, respectively.

relative to the beginning of the month. Therefore, the within-month pattern, combined with a conventional benchmark test, allows us to estimate the extent to which loan approval decisions can be attributed to loan officers' subjectivity towards applicants.

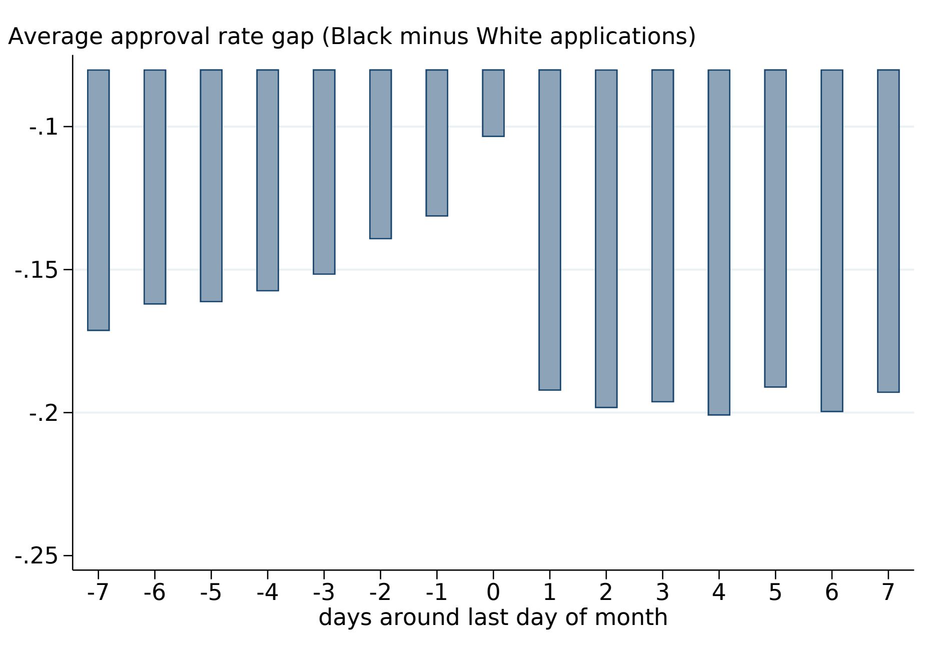

Figure 2: The figure reports the difference between the fraction of approved loans, out of all approved and denied loans in the U.S., for Blacks minus the one for Whites, on each of the last eight days of the month and the first seven days of the following month.

Exploiting this within-month variation, our tests for discrimination estimate the difference in approval rates between Black and white applicants at the start of the month relative to the end of the month. Our key finding is summarized in Figure 2, which shows the difference in application approval rates between Black and white applicants over the course of any given month. In the first seven days of the month, Black applicants have 20 percentage point lower approval rates than white applicants. The approval gap gets smaller over the course of the month. The approval gap between Blacks and whites is just 10 percentage points on the last day of the month. The regression tests that correspond to the graphical evidence in Figure 2 are saturated with a rich set of fixed effects that control for time-varying economic conditions at precise geographic levels, namely county-month and lender-month fixed effects. Confirming the graphical evidence, the difference in the Black-white approval gap between the start and the end of the month is 3 to 5 percentage points.

This constitutes a lower bound on the share of the Black-white approval gap that is due to loan officers' subjectivity, relative to the approval gap that can be attributed to unobservable group-differences. We estimate, in our most stringent regressions, that loan officers' subjective decision-making explains at least half of the overall difference in approval rates between Black and white applicants even after controlling for observable characteristics.

Our approach to estimating discrimination hinges on a set of simple assumptions that we derive and that are easily supportable, either in the data or via narrative, or both. The first assumption is that the loan officer has time-varying costs of being subjective. In our setting, loan officers have nonlinear contract incentives.[2] Loan officers that fail to meet their volume quotas will have reduced compensation and risk getting fired. The second assumption is that the characteristics of the subject pool are time invariant. Indeed, we find that application volume, the relative share of Black applications, and loan application quality (for both Black and white applications) are all constant over the course of the month. The remaining threat to identification is that there are differential trends by race in the quality of applications that get processed over the course of the month. As evidence against this explanation, we find that high-quality and low-quality Black mortgages have similar amounts of bunching toward the end of the month.

In contrast to other methodologies, our approach does not require ex-post outcomes to test for discrimination. Nevertheless, we show that a conventional outcome test is potentially misleading about the levels of discrimination in mortgage lending. We find that Black mortgages have significantly higher rates of default, which could be interpreted as evidence of *reverse* discrimination that favors minorities. Instead, this result is almost certainly caused by the infra-marginality problem – the fact that Black and white mortgage applicants have different risk distributions. We compare the subsequent default rates of applications approved at the start of the month to those approved at the end of the month. The within-month differential significantly shrinks the raw dif-

[2]Importantly, with volume quotas, the optimal strategy would be to approve all loan applications. However, in practice, there are several constraints on this strategy. Lenders set origination standards that the application has to exceed and loan officers may have a fixed quantity of mortgage credit that they can distributed within a month. Loan officers can use their discretion and work to sidestep the origination standards by either using risk-based pricing or appealing to other "soft" criteria, such as noting that the applicant is a customer of the bank.

ference between Black and white default rates. As such, these findings suggest that our approach potentially counteracts the shortcomings of a conventional outcome test.

Furthermore, our approach offers guidance, relative to both benchmarking and outcome tests, as to whether observed discrimination is caused by taste-based versus statistical discrimination. We develop an additional set of assumptions to distinguish between the two theories. Put simply, the case for statistical discrimination requires asymmetric information between evaluators and subjects. Because of the high-frequency nature of our data, statistical discrimination would require the loan officers' information set about applicants to change from the start to the end of the month. This explanation is unlikely because we show that the applicant pool is time invariant. Related, we consider the role of inaccurate beliefs (i.e., stereotypes Bordalo et al., 2016) and a similar logic precludes this explanation.

Finally, our approach is advantageous because it can easily be applied to evaluate the effect of market policies and market innovations on the quantity of discrimination. We consider three important features of modern mortgage lending: market concentration in banking, FinTech lending, and shadow banking. We find that the amount of discrimination due to loan officers' subjectivity is unaffected by both market concentration and FinTech lending. This result is largely consistent with the fact that our regressions include lender-by-month fixed effects and that the component of loan officer subjectivity our approach uncovers occurs *within-lender*. Moreover, despite these changes to the banking sector, loan officer compensation incentives have largely remained constant throughout our sample, and even mortgage lending at FinTech lenders involves significant discretion from human loan officers. On the other hand, we find that shadow banks have lower levels of subjective discrimination against Black applicants. This is likely the result of shadow banks—owing to their lower regulatory requirements—having a larger presence in under-served communities.

Related Literature

Our paper is related to advances in the literature on identifying discrimination by economic decision-makers. Our approach bears closest resemblance to empirical papers that use changes to evaluation settings to identify discrimination against minority groups. For example, Goldin and Rouse (2000) shows that blind auditions reduce employment discrimination against female orchestra musicians. Police officers are less likely at night than during the day to pull over Black motorists because the driver's race is difficult to identify (Pierson et al., 2020). These empirical papers identify discrimination by comparing situations in which evaluators know the subject's gender and race to situations in which they do not. Our approach is different because there is no change in the loan officer's knowledge of applicants' race. We show that discrimination can be identified under a set of simple assumptions about the applicant pool and loan officers' reliance on subjective assessments.

More specifically, our paper joins a large and important literature on discriminatory lending practices in consumer credit markets. Our empirical approach is grounded in evidence that loan officers have significant discretion in loan processing decisions (see e.g., Engelberg et al., 2012; Chen et al., 2016; Demiroglu et al., 2019). Most similar to our analysis, Cortés et al. (2016) also uses confidential HMDA data to disentangle application dates from processing dates to show that loan officers are more likely to approve mortgages on sunny days. Guided by this finding, we bring the confidential HMDA data to the question of lending discrimination. Several papers find compelling evidence that individual loan officers discriminate against other races and women.[3] We advance this literature in a few ways. With a few exceptions (e.g., Bohren et al., 2019; Dobbie et al., 2020), most papers are unable to distinguish between taste-based and statistical discrimination. Also, these papers use evidence from confidential internal data from one or two lending institutions. To the best of our knowledge, our paper is the first to use the universe of U.S. mortgage applications over a 25-year period to connect racial disparities in lending to the incentives of individual loan

[3] In no particular order, Fisman et al. (2017, 2020) use data from Indian banks to show that loan officers are more favorable to culturally proximate applicants. Beck et al. (2018) use evidence from an Albanian bank and Montoya et al. (2019) use a field experiment at a Chilean bank to uncover evidence of gender discrimination in consumer lending.

officers. This allows us to address crucial questions about external validity, investigate the effects of the market structure, and to quantify the scope of racial bias in mortgage markets.

Second, our paper contributes to a growing literature on how market structure and technology affect consumer lending. First, recent papers find support for classic theories arguing that competition reduces discrimination in consumer lending (Buchak and Jørring, 2017; Butler et al., 2019). Such papers suggest that racial discrimination declines because of changes to the composition of lending institutions. We find that discrimination by individual decision-makers can persist within organizations even when there are differences in institution-level competition across markets. Second, there is significant debate over how the growth of FinTech lending affects the allocation of credit, with a particular interest in the effects on disadvantaged borrowers. In theory, FinTech can reduce intermediation costs which can pass through to consumers (e.g., Tang, 2019) or improve screening (Berg et al., 2020a). However, the literature finds that FinTech algorithms either have no effect or negative effects on the supply of credit to disadvantaged consumers (see e.g., Fuster et al., 2017; Bartlett et al., 2019). Our contribution is to show that biases in human decision-making can survive advances in loan processing technology (similar to findings on the introduction of machine learning to judicial outcomes, as shown by Kleinberg et al., 2018).

Finally, we make a unique contribution to the literature on performance-based compensation, with a particular focus on financial intermediation. The effects of performance-based compensation have been studied in a range of settings, such as manufacturing (Oyer, 1998), software sales (Larkin, 2014), government contracts (Liebman and Mahoney, 2017), healthcare (Li et al., 2014; Gravelle et al., 2010), firm managers (Bandiera et al., 2007) and accounting (Murphy, 2000). The literature has also studied how performance incentives within banks affect loan officers' effort and performance (Agarwal and Ben-David, 2012; Cole et al., 2015), and information production (Hertzberg et al., 2010; Qian et al., 2015; Berg et al., 2020b). To the best of our knowledge, our paper is the first to study variation in performance incentives combined with racial biases in human decision-making.

2 Identifying Discrimination

This section presents a formal discussion of our empirical setup. We compare our approach to existing frameworks for identifying discrimination. Differences in unobserved characteristics of different subject groups pose a challenge for conventional tests for discrimination. Our approach is to filter out these unobserved differences across subject groups by using high frequency data.

Our approach extends conventional tests for discrimination, called either audit or benchmarking. These tests compare the conditional likelihood that a minority subject group receives disparate treatment relative to the majority group, after controlling for other observable characteristics from the point of view of the researcher. Consider the case of a Black mortgage applicant. The researcher claims to have uncovered discrimination when she rejects the null of no difference in the conditional likelihood of approval between Blacks and Whites, and instead finds that the likelihood is significantly smaller for Blacks. Specifically, the researcher claims discrimination when she finds that:

$$P(a|W, X) > P(a|B, X) \tag{1}$$

where $P(a|R, X)$ is the probability of loan application approval, conditional on race $R \in \{W, B\}$ (white or Black) and a vector of observable characteristics X to the researcher. However, this approach is exposed to the criticism that the difference in approval rates between white and Black applicants might be driven by unobserved characteristics that are relevant for the assessment of applicants' credit risk used by the loan officers, but are not included in the vector of controls X used by the researcher. To see that, assume, for simplicity that there is a binary unobserved variable $Z \in \{Z_L, Z_H\}$, such that the following assumptions are satisfied:

Assumptions Set (A)

No discrimination:	$P(a\|W, X, Z_k) = P(a\|B, X, Z_k)$ for $k \in \{H, L\}$
Higher quality predicts higher approval probability:	$P(a\|R, X, Z_H) > P(a\|R, X, Z_L)$
On average white applicants have better unobservables:	$P(Z_H\|W, X) > P(Z_L\|B, X)$

The inequality in approval rates formalized by equation (1) holds under the set assumptions above when omitting the variable Z, even though *decision-makers do not discriminate when all of the characteristics are accounted for* (see Appendix A.I). The differences in approval rates for different races simply captures the differences in the unobserved characteristics. In the mortgage-lending setting, Black and white applicants have substantially different observable characteristics (see Table 1). Such differences raise concern that there might be also substantial differences in unobservables.

In this paper, we show that we can refine existing approaches to addresses the identification problems due to the systematic differences in unobservables across subject groups. Rather than only testing for the differences in the likelihood of approval between white and Black applicants, we use high-frequency data to test whether those differences vary over a short period of time. Because discrimination is determined by the subjective judgement of the evaluators, under the null of no discrimination, and if applicants characteristics remain constant over time, there shall be no change in the approval rates over time. On the other hand, discrimination would predict a change in the relative approval rates over time.

To formalize this idea, let there be two time periods, $T \in \{Start, End\}$. Assume that evaluators have more scope to be subjective in period $Start$ relative to period End. Then, in the presence of time-varying discrimination we expect to find:

$$P(a|W, X, End) - P(a|B, X, End) < P(a|W, X, Start) - P(a|B, X, Start) \qquad (2)$$

where $P(a|., X, .)$ is the probability of approval, conditional on race (white or Black), a vector of observable characteristics X, and in a specific period ($Start$ or End). Note that the presence of unobservable quality characteristics systematically correlated with race cannot alone explain the effects in equation (2). Consider the following set of assumptions that characterize a situation in which there is no discrimination:

Assumptions Set (B)

No discrimination:	$P(a|W, X, Z_k, T) = P(a|B, X, Z_k, T)$
	for $k \in \{H, L\}$
Higher quality predicts higher approval probability:	$P(a|X, Z_H, T) > P(a|X, Z_L, T)$
On average white applicants have better unobservables:	$P(Z_H|W, T) > P(Z_H|B, T)$
No time pattern in applications quality:	$P(Z_H|R, X, Start) = P(Z_H|R, X, End)$

The first three assumptions are the same as in **Assumptions Set (A)**, while the last assumption states that the unobserved characteristics of the applicants, for both Whites and Blacks, are on average constant over time. Jointly, these assumptions imply (see Appendix A.I):

$$P(a|W, X, End) - P(a|B, X, End) = P(a|W, X, Start) - P(a|B, X, Start)$$

Thus, the condition in equation 2 indeed amounts to a rejection of the null of no discrimination.

2.1 Distinguishing Taste-Based from Statistical Discrimination

This section explores the extent to which our approach can distinguish between the two broad categories of discrimination. Under "taste-based" discrimination, minorities are subject to disparate treatment because evaluators have animus toward them. Under "statistical" discrimination, evaluators are uncertain about the abilities of any given subject. Evaluators form their beliefs after observing the subject's race. Minorities are subject to disparate treatment when evaluators have developed beliefs that minority subjects have worse abilities. Evaluators do not need to have accurate beliefs about minorities to apply disparate treatment (see e.g., Bohren et al., 2020).

We consider evaluators j who, over a short time-period, for example a month or a week, evaluate subjects i. Each evaluator j has perceived net benefits from making decisions that favor subject i equal to $U^j(X_i, Z_i, R_i, t)$, where X_i and Z_i are vectors of observable and unobservable (from the perspective of the researcher) characteristics, R_i is the subjects' race (e.g., $R_i = W$ for a white applicant and $R_i = B$ for a Black applicant), and t is the point in time in which the evaluation is conducted.

The evaluator's net benefits can be decomposed into two components:

$$U^j(X_i, Z_i, R_i, t) = b^j(X_i, Z_i, R_i, t) + E_j[u_i|X_i, Z_i, R_i, t], \tag{3}$$

where $b^j(X_i, Z_i, r_i, t)$ is the subjective net benefits of evaluator j conditional on all characteristics, and $E_j[u_i|V_i, Z_i, R_i, t]$ is the statistical component. The statistical component can be written as

$$E_j[u_i|X_i, Z_i, R_i, t] = E[u_i|X_i, Z_i, R_i, t] + \tau_j(R_i, t), \tag{4}$$

where $\tau_j(.)$ is the bias of decision maker j when forming expectations conditional only on the information about the race of an applicant.

We can then use our stylized framework to characterize different types of discrimination, for example against black subjects with respect to white subjects:

- Taste-based discrimination: $b^j(X_i, Z_i, W, t) > b^j(X_i, Z_i, B, t)$
- Statistical discrimination: $\tau_j(W, t) > \tau_j(B, t)$

The decision maker will take a decision favorable to subject i as long as net benefits is positive:

$$b^j(X_i, Z_i, r_i, t) + E_j[u_i|X_i, Z_i, R_i, t] + v_{i,j,t} > 0,$$

where $v_{i,j,t}$ is a random preference shock, i.i.d. across subjects and evaluators, and independent of information on subject characteristics and evaluators' beliefs. We can then introduce the variable $y_{i,j,t}$, which is equal to one if subject i receives a favorable decision from evaluator j at time t, and has likelihood function:

$$\mathcal{L}(y_{i,j,t}) = Pr(y_{i,j,t} = 1)^{I(y_{i,j,t}=1)}[1 - Pr(y_{i,j,t} = 1)]^{1-I(y_{i,j,t}=1)}$$
$$Pr(y_{i,j,t} = 1) = E[y_{i,j,t}|X_i, Z_i, R_i, j, t] = F(X_i, Z_i, R_i, j, t)$$

If we assume the function $F(X_i, Z_i, R_i, j, t)$ can be approximated with a liner specification, then we can write:

$$y_{i,j,t} = \beta_1 r_i + \beta_2 (r_i \times t) + \eta X_i + \phi Z_i + a_t + \epsilon_{i,j,t}. \tag{5}$$

where $r_i = 1$ if $R_i = B$. Equation 5 can be estimated in the data. Within this specific framework, we can state the predictions of our general discussion in the previous section along the following lines:

1. The two types of discrimination listed above (driven by taste or statistical) would cause estimates of $\beta_1 < 0$. However, as the previous section outlines, β_1 will be a biased estimate unless the researcher fully controls for observable (X_i) and unobservable (Z_i) characteristics, or r_i is uncorrelated with any omitted characteristics.

2. Estimates of β_2 will be different from zero if the magnitude of discrimination changes over time, regardless of the type of discrimination. If subject pool characteristics (X_i and Z_i) are not correlated with the evaluation time t, estimates of β_2 will be unbiased even if the researcher does not perfectly control for time-invariant characteristics.

How can this approach distinguish between different theories of discrimination? In principle, any type of discrimination can be subject to high-frequency fluctuations, and thus produce non-zero estimates of β_2. However, if the unobserved variation across subject pools and the evaluator's statistical inference problem are time-invariant, our approach allows the researcher to attribute discrimination to the source of time-variation in the evaluator's decision-making.

Consider the case of statistical discrimination. Statistical discrimination is caused by the evaluators' statistical inference problem. Therefore, the researcher can reasonably assume the findings are caused by statistical discrimination if she can provide evidence of time-variation in the evaluators' information set. Now consider taste-based discrimination. The evaluator's subjective preferences against minorities causes disparate treatment. The researcher can assume taste-based discrimination if she has evidence that evaluators' subjectivity is time-varying.

In the following empirical analysis, we focus on residential mortgage lending in the U.S. Our source of time-variation in evaluations is the fact that loan officers have monthly volume quotas. These monthly volume quotas generate within-month variation in loan officers' subjectivity. The volume quotas pressure the loan officer to increase their approval rates at the end of the month, whereas at the start of the month, loan officers have scope to apply their subjective preferences. At the same time, loan officers observe the same information about applications that they process at the start of the month relative to the end of the month. As such, any finding of discrimination due to within-month differences in evaluations can be attributed to loan officers' subjective preferences.

3 Data

The empirical results in this paper are based on the confidential version of the Home Mortgage Disclosure Act (HMDA) data available to researchers in the Federal Reserve System. The dataset contains the largest sample of mortgage applications available in the U.S. The public version of the data includes information on applicant characteristics – race, gender, reported income, and location of the property – and identifiers for the lenders that received the applications. The data cover the entire geography of the U.S. over the period from January 1994 through December 2018. Moreover, the data provide information on mortgage contract characteristics, such as whether the application is for a new home purchase or refinancing, the loan amount, the lien, and whether the property is owner-occupied. The primary distinguishing feature of the confidential version of the HMDA data is that it contains the exact date on which each application was submitted by a potential borrower and the date on which each application was processed by the lender (either approved or denied) or withdrawn by the applicant. This information has been employed in several prior papers (see e.g., Cortés et al., 2016).

In constructing our dataset, we drop mortgage applications with missing action date (the date on which the lender approves or denies the loan, or the date on which the application is withdrawn by the applicant). This results in dropping less than 200 out of a total of more than 500 millions observations.

Table 1, panel (a) shows summary statistics of the mortgage applications in our dataset, for each year from 1994 to 2018. Annual mortgage applications are between 10.1 and 37.3 millions, and originations between 7.4 and 23.7 millions. The number of active lenders by year is between 5,700 and 9,800, and the average number of originations per lender is between 750 and 2,900. Panel (b) shows statistics over the entire period from 1994 to 2018, and across different applicant groups based on race. Approximately 67% of applicants are white and 7% are Black. Other races are not separately identified and are grouped, along with applications that do not specify race, into a single category called "Other race" that includes 26% of all observations. Black applicants apply for smaller loans on average, have the highest fraction of low income applicants (59.8%, compared to 46% for Whites and 47.8% for other races), and have the lowest approval rate (63.25%, compare to 80.72% for Whites and 69% for other races). When considering approved loans, 73.7% are to Whites, 5.7% to Blacks and 20.6% to applicants of other races.

To obtain more detailed information on characteristics and performance of *originated* mortgage loans, we merge HMDA with the Black Knight McDash (McDash) dataset. We construct the merged sample with an algorithm similar to the one used by Rosen (2011). Individual observations in HMDA and McDash are merged using loan origination date, loan amount, zip code, lien type, loan type, loan purpose, and occupancy type (owner occupied, absentee or investment property). The match rate of the merge is about 60%.[4] McDash provides further information on individual

[4]Lender and consumer identities were anonymized for the merged dataset used in this analysis.

loan contracts, such as the mortgage interest rate, rate type (fixed or adjustable rate), the mortgage term, whether the loan is conforming, borrowers' FICO scores, and the quality of the supporting documentation submitted by the borrower.

4 Identifying Assumptions

Our identification strategy relies on high-frequency variation in evaluators' subjective decision making. This section provides support for the identification assumptions: (1) the pool of mortgage applicants is time-invariant and (2) there is time-variation in loan officers' reliance on their subjective assessments.

4.1 The Applicant Pool is Time-Invariant

The first identifying assumption in our tests for discrimination is that the composition of the applicant pool is time-invariant. Figure 3 shows how the composition of new applicants evolves over the course of the month. Panel (a) plots the average share of Black applicants submitted on each day of the month. The share of new applicants by Black applicants is roughly constant at approximately 7% on each day of the month. This confirms our identifying assumption that the racial composition of applicants is time-invariant.

We also verify that other characteristics of the applicant pool—characteristics that could correlate with race—are constant over the course of the month. The HMDA data has limited information on the creditworthiness of applicants. However, the data contain applicants' income, which is an important input into lender's decision-making and is likely correlated with other variables that determine whether an application is approved (e.g., credit scores). Figure 3, Panel (b) reports the fraction of applicants that have levels of personal income that are below the median of applicants within a county during a given year. Panel (c) shows the share of such applicants with the added restriction that the application becomes a new origination. In both panels, we divide the sample into applications submitted by Black and white applicants. As such, these figures explore whether the quality of applications within and across races changes within the month. These figures show that application quality is constant.

Lastly, Panel (d) studies the composition of the applicant pool with outstanding applications (i.e., applications that have been submitted but have yet to receive an approval decision) in the lenders' inventory over the course of the month. We explore this measure of application inventory because it captures what applications the loan officer has the opportunity to work on at any point during the month. Panel (d) also sorts the outstanding applications by incomes and by race. Again, we find that the applicant pool is constant over the course of the month, both in terms of the racial composition of the applicant pool and the quality of the applications outstanding.

4.2 Time-Variation in Subjective Assessments of Applicants

4.2.1 Loan Officers Have Monthly Volume Quotas

Mortgage loan officers tend to receive commissions calculated as a percentage of the total amount they originate over the month. They can also receive bonuses for meeting monthly origination targets, as well as face disciplinary actions or be fired for failing to meet volume targets.[5] The use of volume-based incentives is acknowledged by U.S. regulations and directives from the Consumer Financial Protection Bureau (CFPB). U.S. law permits the use of volume-based incentives, but it restricts the use of commissions based on the terms and performance of individual loans (see, most recently, the dispositions of Regulation Z, implementing the Truth in Lending Act).[6]

Seeing as loan officers have monthly volume targets, how would these non-linear contract incentives affect loan officer behavior? We consider several theories, even though such theories

[5] See Tzioumis and Gee (2013), and evidence from practitioners' research and discussions, such as what reported in the following articles on industry standards for loan officers' compensation in the U.S., published by the Mortgage Bankers Association (*https://www.mba.org/publications/insights/archive/mba-insights-archive/2019/is-it-time-to-rethink-compensation-x253848*), and by consumer websites (*https://www.investopedia.com/ask/answers/120214/whats-average-salary-loan-officer.asp* and *https://www.thetruthaboutmortgage.com/loan-officer-jobs/salary*).

[6] Volume-based incentives are the first form of compensation mentioned in the section on *Permissible Methods of Compensation* in the most recent revision of Regulation Z, available at *https://www.federalregister.gov/documents/2013/02/15/2013-01503/loan-originator-compensation-requirements-under-the-truth-in-lending-act-regulation-z*

are not distinguishable in our data, nor do we intend to establish a single theory. However, many such theories share a common feature: loan officers' decision criteria vary in a way that lessens their scope for subjective decision making as the end of month nears. Instead, in order to meet their volume quotas, loan officers have to approve more loans at the end of month irregardless of their preferences toward any given applicant. Nevertheless, the following outlines these theories to guide our understanding of the setting.

First, the end-of-month increase in new originations can be caused by rational loan officers that get dis-utility from exerting effort. Assume that loan officers prefer to work fewer than a certain number of hours per day. Whether or not the loan officer meets his volume target is a function of the effort he exerts, as well as how much effort it takes to finalize a loan approval. The amount of effort each loan takes is determined by random factors that the loan officer does not control, such as macroeconomic shocks and loan-specific idiosyncratic shocks. Assuming that new loan applications arrive randomly over the course of the month, then the loan officers' optimal strategy would be to increase their effort over the course of the month and as the end of month nears, increase their effort in order to exceed the volume threshold. This strategy by loan officers will cause large increases in loan originations at month-end. The strategy also implies that loan officers can be more subjective about loans processed at the start of the month, but need to be less discerning and seek approvals for all loans that they process at the end of the month.

Behavioral biases, such as procrastination (Akerlof, 1991), can also cause loan officers to delay the approval of loans until the end of the month. Alternatively, decision-makers can be overconfident—they overestimate their own abilities. Loan officers that have an overconfidence bias would overestimate their abilities to process loans over the course of the month and would have to work overtime at the end of the month in order to meet their quotas.

4.2.2 Monthly Volume Quotas Cause End-of-Month Bunching in Mortgage Originations

We find that monthly volume quotas cause large increases in new mortgage originations at the end of the month. Figure 1, described in the introduction, presents the average volume of new originations per day relative to the first day of any given month. The volume of new mortgage originations grows over the course of the month. The origination volume is more than 150% larger on the last day relative to the first day of a given month. The figure documents clear evidence of "bunching" at the end of any given month.

The end-of-month bunching in mortgage originations is robust across time and to seasonal factors. The end-of-month increase in originations occurs in every year of our sample, which suggests that the finding is not caused by business cycles and is therefore unlikely to be caused by fluctuations in the demand for mortgages (see Appendix Figure A.1). Also, the end-of-month bunching occurs in every month of the calendar year (see Appendix Figure A.2, which plots the average number of new originations on the first and last seven days of each month within a given year). This suggests that the finding is not caused by seasonality in mortgage demand.[7]

Building on our graphical evidence, we use regression analysis to show that the within-month pattern in originations is not caused by confounding factors. We estimate the following regression:

$$\log(N_t) = \beta_{lw} I_{lw} + \beta_{fw} I_{fw} + a_{ym} + a_{dow} + a_{holiday} + e_t \tag{6}$$

where the dependent variable $\log(N_t)$ is the log of the number of originated mortgages by lender i on day t. The regression includes year-month, day-of-week, and bank-holiday fixed effects, which are a_{ym}, a_{dow}, and $a_{holiday}$, respectively. I_{lw} and I_{fw} are dummies equal to one for days in the last week of the month and the first week of the following month. The coefficient of interest, β_{lw} (β_{fw}), measures the difference between the average origination volume in the last (first) seven days of the month, relative to the middle days of the month.

The regression estimates confirm that loan origination volume increases significantly in the last days of the month relative to the middle days. In Table 2, when origination volume is measured as the log number of loans, the point estimate of β_{lw} is 31%, and the estimate of β_{fw} is -15%. When origination volume is measured as the total dollar amount originated per day, the point estimates

[7] As a testament to the quality of our micro-level data, recurring-day bank-holidays are clearly visible in Figure A.2. Origination volume is abnormally low on the first day of January, on Christmas and on July 4th.

are 36% and -14%. This gives us estimates of the increase in origination volume between the first and last week of the month of 46% and 50%, which are qualitatively consistent with the evidence shown using the raw data in Figure 1. Our findings are unlikely to be explained by lending seasonality because the estimates are robust to including a rich set of calendar time fixed effects (see e.g., Murfin and Petersen, 2016).[8]

We also show that the end-of-month bunching in new originations is consistent with loan officers managing the inventory of applications over the course of the month. Figure A.3 in the Appendix shows the inventory of applications that await a decision (approval, denial, or withdrawal by the applicant) for each day within the month. There is a sharp drop in inventory over the last week of the month, driven by the spike in originations, and then a steady increase taking place over the first two weeks of the following month.

4.2.3 Linking Origination Volume to Loan Officers' Performance

Next, we connect loan officers' performance incentives to the end-of-month bunching in new originations. To do so, we consider how loan officers' monthly volume targets affect their economic incentive to approve and deny applications. Specifically, we expect that loan officers have to increase the pace of new originations when they are not on track to meet their quotas. Though our data does not contain the origination targets set by each lender, we infer that loan officers' volume targets are a function of mortgage lending seasonality and the lender's internal projections. As such, we expect that each lender will have their own month-by-month benchmarks that are a function of their origination volume in prior years (e.g., origination volume in March 2012 is a reasonable estimate of the volume target in March 2013).

Based on these observations, we construct a measure of whether or not loan officers at a given lender are likely to be on track to meet their performance targets. The measure relates the

[8]The month-end increase in originations is also robust across applicant characteristics. Table A.1 in the Appendix estimates equation 6 separately for different sub-samples: white applicants, Black applicants, and other applicants, as well as white and Black samples sorted into income quartiles. New origination volume increases substantially at the end of the month for all applicant sub-groups.

current month's origination volume relative to prior year's:

$$RelPerf_{i,ym} = \frac{AvgVol_{i,ym}}{AvgVol_{i,ym'}} \tag{7}$$

where $AvgVol_{i,ym}$ is the average daily volume of mortgage loans that have been issued by lending institution i and in year and month ym, excluding the last 7 days of the month. The denominator is the average daily volume of mortgage loans issued by the same lending institution in month ym', exactly one year before ym. We conjecture that the denominator of equation 7 proxies for the volume target for institution i, which is based on the performance in the same month of the previous year. We expect loan officers to be behind their volume targets when the value of $RelPerf_{i,ym}$ is small. Loan officers that are behind their volume targets would be motivated to increase their lending at the end of the month.

Indeed, origination volume at the end of the month increases by a larger amount when loan officers are more likely to miss their quotas. Figure 4(a), Panel (a) shows origination volume around the end of the month. The figure splits the sample into lenders that have values of $RelPerf_{i,ym}$ in the top quartile of lenders in a given month and one for lenders with values of $RelPerf_{i,ym}$ in the bottom quartile. The month-end increase in originations is substantially larger when $RelPerf_{i,ym}$ is in the bottom quartile. This provides evidence that loan officers increase the pace of new originations at the end of the month in order to meet their performance targets, and suggests that the end-of-month increase in origination volume is caused by loan officers' monthly volume quotas.[9]

4.2.4 Alternative Explanation for the End-of-Month Bunching

Though we attribute the increase in new originations at the end of the month to loan officers' monthly volume quotas, we consider alternative explanations. The leading alternative explanation is that consumer lending regulations incentivize lenders to increase origination volume at the

[9]Figure 4(b), Panel (b) replicates these findings using approval rates rather than origination volume.

end of the month. Lenders have incentive to "window-dress" prior to regulatory examinations by increasing originations of certain types of loans.

We test the "window-dressing" explanation by exploring how origination volume changes when lenders are subject to examinations conducted under the Community Reinvestment Act (CRA). CRA exams are conducted every two years for large banks and every five years for small and medium size lenders. Lenders know in advance the exam dates. CRA exams consist of a review of the lender's fair lending practices, designed to ensure that lenders meet the credit needs of disadvantaged communities in markets that they serve. The primary alternative explanation for the month-end effect would be that lenders increase originations to disadvantaged neighborhoods in an effort to meet the requirements of upcoming CRA examinations. Indeed, prior research shows that the CRA encourages high-risk lending (see e.g., Bhutta, 2011; Agarwal et al., 2012; Akey et al., 2020).

We test whether the increase in new originations at the end of the month is caused by upcoming CRA examinations. We sort lenders by whether or not they have a CRA exam scheduled in the following month. Then, separately for the two samples, we estimate the specification in equation 6 where the dependent variable is the logarithm of daily origination volume. Table 2 reports the regression estimates in columns (5) and (6). We find that the month-end effect occurs regardless of whether the lenders are subject to CRA examinations. Surprisingly, the end-of-month increase in lending is smaller for institutions that are subject to CRA exams. Lenders that have (do not have) CRA exams increase their origination volume by 29% (54%) at the end of the month.[10]

4.2.5 Performance Incentives Affect Loan Officers' Decision-Making

The previous section shows that monthly volume quotas motivate loan officers to increase the volume of originations at the end of the month. Next, we show that such volume quotas affect loan officers' decision-making on individual loan applications. Specifically, we study mortgage

[10]We also use approval rates to confirm that CRA examinations do not cause the increase in originations at the end of the month. We expand regression equation 8 to include controls for past and upcoming CRA exams. Our estimates are reported in Table A.2 in the Appendix. We find that controlling for CRA exams does not significantly affect the coefficient estimates on the indicator variables for start-of-month and end-of-month loans.

approval and rejection decisions and how they vary over the course of the month. Holding constant the characteristics of the application, a loan approval (denial) implies that the loan officer was more (less) favorable toward the applicant. The within-month variation in loan approval decisions gives us an estimate of loan officers' subjectivity towards individual loan applications.

Figure 5 shows the average approval rate in the U.S. for mortgage applications processed in each of the last eight days of the month, and each of the first seven days of the following month. There is roughly a 15% difference in the approval rates between the start and end of the month. The approval rate gradually increases from 76% seven days before month-end to more than 86% on the last day of the month. Then, it drops abruptly at the start of the following month, reaching a bottom value of 71% on the second day of the month.

We use regression analysis to show that the within-month increase in approval rates is robust to a rich set of fixed effects for time, seasonality, and supply-side factors. We estimate:

$$Appr_{i,t} = \gamma_{lw} I_{last-week} + \gamma_{fw} I_{first-week} + a_{ym} + a_i + a_{dow} + a_{holiday} + u_{i,t} \tag{8}$$

where $Appr_{i,t}$ is the approval rate for lender i on day t. a_{ym} is a year-month fixed effect, a_i is a lender fixed effect, and a_{dow} and $a_{holiday}$ are day-of-the-week and holiday fixed effects. The coefficients of interest, γ_{lw} and γ_{fw}, capture abnormal approval rates in the first and last week of the month, *for the same lender in the same month*. The specification in equation 8 is strict. If month-end effects are explained by persistent differences across lenders, or by transitory differences in each specific month, then estimates of γ_{lw} and γ_{fw} would be indistinguishable from zero. Moreover, because the dependent variable is the approval rate, if month-end increases in originations are caused by lagged demand, but not by higher propensity to originate loans, γ_{lw} and γ_{fw} will not be different from zero.

Table 3 reports estimates of the coefficients in equation 8. Column (1) reports results based on approval rates for all processed applications. We find that estimates of γ_{lw} and γ_{fw} are statistically significant, and show higher approval rates than average in the last week of the month, and lower approval rates than average in the first week of the month. The difference $\gamma_{lw} - \gamma_{fw}$ measures the increase in approval rates around month-end, and is equal to 4.5% and highly statistically significant. The other columns sort the data by various applicant characteristics, namely racial groups, income quartiles, and for various loan characteristics. We find that the increase in approval rates is present across all groups, but is particularly pronounced for Black applicants, for which it is equal to 7.6%. Because the average approval rate for Black applicants is 63%, our estimates imply a 12% relative decline in approval rates for this group of applicants when comparing the last and first week of the month.

5 Testing for Lending Discrimination Using High-Frequency Evaluations

This section uses the framework developed in Section 2 to test for discrimination in the mortgage lending data. Our approach exploits a change in the propensity for evaluators (in this case, mortgage loan officers) to rely on their subjective judgement in decision making. In our setting of mortgage lending, monthly volume quotas compel loan officers to generate more originations near the end of the month. While loan officers can reject applications at the start of the month based on their subjective assessments and personal biases, they will be less willing to do so at the end of the month when they face pressure to meet their volume quotas.

We can then exploit within-month variation—comparing the fist to the last week of the month—in the difference in approval rates between Whites and Blacks to conduct the formal discrimination test presented in equation 2. Under the assumption that there is *no discrimination*, and that application quality is constant within the month, we should find that the difference in approval rates between Black and white applicants is constant over the course of the month. However, we find that Black applicants are relatively more likely to be approved at the end of the month. These findings point toward taste-based discrimination against Black applicants in mortgage loan approval decisions.

5.1 Empirical Evidence

We start our analysis by examining the aggregate (U.S.-level) differences in mortgage origination volume for different groups of applicants around month-end. Figure 6 shows daily origination volume in percentages relative to the first day of the month for Whites, Blacks and others. All three groups experience increased origination volume at the end of the month. However, the magnitude is substantially larger for Blacks—the number of originations is on average more than 240% larger on the last day of the month than on the first day of the following month. Even after controlling for seasonality, the results in Table A.1 show that the average increase in daily originations from the first week of the month to the last week of the month is 11% larger for Blacks rather than Whites.

5.2 Testing for lending discrimination

We test for discrimination in mortgage lending by examining within-month differences in approval rates across races. Our tests use the following regression specification:

$$\begin{aligned} Appr_j = {} & \delta_{lw,Black}\left(I_{lw} \times I_{Black}\right) + \delta_{fw,Black}\left(I_{fw} \times I_{Black}\right) + \delta_{lw} I_{lw} + \delta_{fw} I_{fw} + \\ & + \delta_{Black} I_{Black} + BX_j + a_{ym,c} + a_{ym,i} + a_{dow} + a_{holiday} + u_{j,t} \end{aligned} \tag{9}$$

where the unit of observation is the individual loan application. The dependent variable $Appr_j$ equals one if the loan is approved. Independent variables I_{fw} and I_{lw} equal one when the application decision is made in the first or the last week of the month, respectively. I_{Black} is equal to one for Black applicants. X_j is a vector that contains characteristics for mortgage application j and the corresponding applicant: loan amount, conforming loan status, loan type (conventional, or government guaranteed or insured, such as FHA, VA, and USDA loans), occupancy type (owner occupied or absentee), loan purpose (new purchase or refinancing), and applicant income. Year-month-county, year-month-lender, day of the week, and holiday fixed effects are $a_{ym,c}$, $a_{ym,i}$, a_{dow}, and $a_{holiday}$, respectively. The coefficients of interest, $\delta_{lw,Black}$ and $\delta_{fw,Black}$, capture the abnormal approval rate for Black applicants in the last and first week of the month.

We begin the regression analysis by reporting split-sample tests of Black and white applicants that compare approval rates at the start to the end of the month (Table 4). We find that approval rates for Black applicants are 12 percentage points larger in the last week of the month relative to the first week (column 1). Approval rates for white (and other) applicants are 8 percentage points larger in the last week (column 2). Comparing these results, Black applicants gain an additional 4 percentage point increase in approval rates over the course of the month relative to white applicants.

Next, we use the entire sample of HMDA data to test the regression model in equation 9 that contains the complete set of interaction terms between Black applicants and applicants of other races (Table 4, columns 3 through 6). Because we find that the estimates are robust across specifications, we describe the most restrictive specification: column (6). The point estimate of $\delta_{lw,Black}$, the abnormal approval rate for Black applicants in the last week of the month, is equal to 2.7 ppt. The estimate of $\delta_{fw,Black}$, the abnormal approval rate in the first week of the month, is equal to -0.7 ppt. This implies that the relative likelihood of approval for Black applications increases by 3.4 ppt if the application is processed in the last seven days of the month.

The estimates of the within-month difference in approval rates for Black applicants are large. For context, we estimate a baseline 6.8 ppt difference in approval rates between Black applicants and applicants of other races (the coefficient estimate on I_{Black}). This estimate is equivalent to what a conventional benchmarking test would estimate as the amount of discrimination against Black applicants. However, a conventional benchmarking test is unable to determine whether the 6.8 ppt difference is caused by racial biases or whether it reflects the unobserved heterogeneity across races. On the other hand, because our empirical design suppresses the cross-sectional variation across applicants' races, we can confidently attribute the within-month approval gap of 3.4 ppt to loan officers' subjectivity. As such, the ratio of the within-month difference to the unconditional difference—3.4 divided by 6.8, or 50%—approximates the share of the observed racial gap in approval rates that can be attributed to subjective decision-making. In other words, we attribute at least half of the racial gap in approval rates to racial bias.

Our finding that the approval gap for Black applicants is reduced at the end of the month is highly robust (see Appendix Table A.3 for the following robustness tests). The estimates are not much changed across different types of mortgage applications – new home purchases, conforming mortgages, and refinances. Controlling for the applicant's gender and including black-year fixed effects also do not affect the estimates. Lastly, the results are robust to replacing calendar month fixed effects with fixed effects that span the end and start of successive calendar months (e.g., January 15 to February 14).

These regression tests confirm the graphical evidence that the approval gap between Black and other applicants converges over the course of the month (presented in Figure 2 and described in the Introduction). We augment this aggregate evidence by plotting how the approval gap changes over the course of the month estimated from the saturated regression model in Table 4, column (6). Figure 7(b) plots the average day-by-day residual difference in approval rates after controlling for application characteristics. The approval gap in the first seven days of the month is approximately equal to 7 ppt. The approval gap during the last seven days of the month shrinks to approximately 1 ppt on the last day of the month. Therefore, after controlling for loan characteristics, there is almost no difference in application approval rates across races on the last day of any given month.

The regressions in Table 4 also convey insight into how differences across lending institutions affects mortgage credit for Black applicants. Notably, the literature has argued that much of the difference in approval rates between Black and white applicants can be attributed to different lending institutions catering to different types of borrowers and that different applicants choose to apply for mortgages at certain types of institutions. We gain insight into the role of selection across institutions by examining how including lender fixed effects affect the regression estimates. Including lender fixed effects reduces the magnitude of the un-interacted coefficient on I_{Black} from -0.10 in column (2) to -0.07 in column (3). This result implies that lender fixed effects are a crucial source of unobservable variation driving the Black-white approval gap. On the other hand, lender fixed effects have a negligible effect on the within-month approval gap. The difference in approval gaps between the start and end of the month is 0.040 without and 0.035 with lender fixed effects. These results suggest that we capture a component of loan officer decision-making that exists within lenders and is consistent across institutions. These results are reassuring for our empirical design and the interpretation of the findings, because loan officer compensation schemes do not vary much across lending institutions.

We also provide evidence that the within-month reduction in approval gap for Black applicants can be linked to the inventory of loan applications that lenders have in their queue. Figure 8(a) plots the share of all approved applications on a given day are submitted by Black applicants. On the first day of the month, Black applicants account for approximately 4.4% of approved loans. In the last week of the month, the share increases steadily, reaching just over 6% on the last day of the month.

Furthermore, we study whether the within-month convergence in approval gap is sensitive to the share of Black applicants that a lender processes. Figure 8(b) shows that the within-month change in approvals occurs across the full range of lenders. The figure reports the median share of approved loans from Black applicants, along with the 25th and 75th percentile, across lenders that issued at least 10 loans per day on average over the year. The median share is close to 5.5% in the first two weeks of the month. However, it steadily increases in the last week of the month. The shift involves the entire distribution. On the last day of the month, the median share is above 6%, the 25th percentile is approximately 4% and the 75th percentile is close to 10%. On the first day of the month, the median is below 5.5% the 75th percentile shrinks close to 9% and the 25th percentile falls below 3.5%.

5.3 Alternative Explanations

The evidence that the approval gap for Black applicants declines at the end of the month is consistent with loan officers having less scope for subjective decision-making when they have monthly volume quotas, consistent with the framework outlined in Section 2. Yet, we consider plausible alternative explanations, other than taste-based discrimination, for the change in approval rates over the course of the month.

Before considering specific alternative explanations, we describe how the empirical design limits the the scope for alternative theories. First, it is unlikely that the within-month variation in approval rates can be explained by variation across lenders because the estimates are hardly changed by the inclusion of lender fixed effects.

Second, our empirical strategy rules out the possibility of unobserved differences across applicant groups. Therefore, any candidate alternative explanation has to have within-month variation and also has to have differential effects on Black applicants relative to other applicants. Not only does this confine alternative explanations to factors that vary within the month, it gives us an avenue to test alternative theories. In particular, suppose that the indicator variable for Black applicants reflects other unobserved characteristics, such as the riskiness of the loan, and that loan officers delay processing high-risk applications. If application risk explains the convergence in approval rates across races over the course of the month, then the observed riskiness of the loan application would explain within-month changes in approval rates. Put simply, we would expect to find that originations of observably high-risk applications submitted by Black applicants would bunch at the end of the month, whereas low-risk applications would be relatively more evenly distributed throughout the month.

Guided by these bounds on alternative theories, we take a holistic approach to confronting alternative explanations by examining the within-month quantity of loan originations sorted by credit scores (and applicant incomes). We study credit scores because they are possibly the most important ingredient in loan approval decisions and mortgage pricing. They would also correlate with the most plausible alternative explanations: they directly measure the ex-ante risk of the application and low credit score applicants would be more likely to file low-documentation applications. As section 3 describes, the data only contains credit scores for applications that are approved. As such, we study the quantity of new originations over the course of the month instead of approval rates. However, such tests would be nearly equivalent to testing approval rates because we have shown that mortgage demand does not vary within the month.

We find that alternative explanations related to application quality are unlikely to explain the within-month approval gap. Figures 9 and 10(a) plot the quantity of new originations sorted by credit scores and incomes for applications submitted by Blacks and whites, respectively. Strikingly, the volume of originations for prime-credit-score (FICO $\geq$ 660) and subprime (FICO $<$ 660) Black applicants are nearly identical over the course of the month (Figure 9(a)). We would have expected to find relatively more end-of-month bunching for subprime Black applicants if the results simply reflected characteristics—such as risk—that correlate with applicants' credit scores. Also, the end-of-month bunching of originations is larger for Blacks than whites for both prime and subprime applicants (comparing the levels in Figure 9(a) to those in Figure 10(a)). The difference between Black and white originations would have been attenuated for prime applicants if characteristics related to credit scores explained the within-month approval gap.

We find similar evidence when we sort the volume of new originations into quartiles by applicant incomes (Figure 9(b) and Figure 10(b)). Testing for end-of-month bunching across applicant incomes not only fortifies evidence from sorting by credit scores but it also allows us to present evidence from the full HMDA sample. We find that there is substantial end-of-month bunching for all four income quartiles. Moreover, in each corresponding quartile, the end-of-month bunching for Black applicants is significantly larger than for white applicants. These findings cast doubt on alternative explanations related to within-month variation in application quality.

We provide additional evidence that racial differences in approval rates over the course of the month do not merely reflect the possibility that race proxies for other loan characteristics. We obtain such evidence by directly testing whether certain types of loans are more or less likely to be approved over the course of the month. Specifically, Table 6 tests the regression specification in equation 9, but replaces the dependent variable with variables that measure loan quality: an indicator for subprime loans (column 1), loan-to-value (LTV) ratios (column 2), an indicator for low-documentation loans (column 3), and the interest rate (column 4). We find that, of the four loan characteristics, only low documentation loans are more likely to be originated in the last week of the month, but the effect is only weekly statistically significant. Furthermore, Black applicants with low documentation applications are relatively *less* likely than white applicants to be originated in the last week of the month. These results, combined with the above tests, suggest that race has effects that are are independent from loan characteristics—characteristics that vary by race in the cross-section—over the course of the month.

Finally, we consider the possibility that our estimates of the within-month approval gap are caused by the selection of when loan officers choose to evaluate loan applications. Notably, if loan officers delay processing applications by Black applicants this would be an act of discrimination. However, the primary alternative explanation regarding the timing of application processing is that Black applications are more difficult for lenders to process and therefore, spend a longer time in inventory. We confront this alternative explanation in a few ways. Table 5, column (1) shows that controlling for time-to-action (approval or denial) in equation 9 does not affect the regression estimates of the within-month approval gap. Table 5 also estimates the approval gap using sub-samples of the data sorting on time-to-action: 1 to 30 days, 31 to 60 days, 61 to 90 days and more than 90 days (columns 2 through 4, respectively). We find that the within-month approval gap for Black applicants holds in all four sub-samples. Furthermore, there are no patterns across sub-samples that would suggest that the approval gap is affected by the time that the application is held in loan officers' inventory. These findings are inconsistent with the explanation that the approval gap is caused by the timing of when applications are processed.[11]

5.4 Outcome tests

Four our final test, we turn to outcomes, and in particular to the performance of originated loans. One may argue that there can still be differences in unobservable characteristics of approved loans around month-end, that are not spanned by FICO, loan-to-value, documentation quality, applicant and application characteristics, and that are not priced in mortgage interest rates. However, if such differences, orthogonal to *ex-ante* observable characteristics, exist, they shall then be reflected

[11] Also, Table A.4 in the Appendix tests whether there are differences across races over the course of the month in time-to-origination, time-to-denial, and time-to-action (approval or denial). We do not find economically significant differences for Black applicants.

in *ex-post* loan performance. In other words, if loans originated at month-end are riskier due to any unobservable characteristics correlated with race, then we should see these characteristics reflected in differences in average loan performance for loans originated in the last and first week of the month, after controlling for observables. Most importantly, we should find a stronger difference in loan performance around month-end for Black applicants, after controlling for all other characteristics.

We set out to conduct this test in Table 7. We use the same regression specification as in Table 6, and set the dependent variable as a dummy equal to one for mortgages that defaulted within 5 years after origination.[12] In column (1), the sample contains loans across the entire observable quality distribution, while in columns (2), (3) and (4) the sample is restricted to difficult to evaluate and risky loans. Estimates are based in column (2) on subprime loans ($FICO < 660$), in column (3) on high loan-to-value loans ($LTV > 80\%$), and in column (4) on low documentation loans. When considering the baseline differences between the last and first week of the month for white applicants and applicants of other races, we find no statistically significant effects after controlling for observables. However, we do find that, for black applicants, after controlling for observables, default rates are systematically lower than average in the last week of the month, and systematically higher in the first week of the month, both when considering all applications and when considering only subprime, high LTV and low documentation applications. This effect is not negligible; when considering the entire sample of application, roughly 1.7% of mortgage loans default within 5-years. Black applicants' loans are 0.33% less likely to default when originated in the last rather than in the first week of the month. Thus, the quality of black applicants approved in the last week of the month is higher, which is in direct contrast with the predictions of the risk-taking explanation.

[12]In Table A.5 in the Appendix we repeat the same analysis, but set the dependent variable as a dummy equal to one for loans terminated (due to default or refinancing) within 5 years after origination. Results are similar to the ones for defaults reported in Table 7.

6 Lenders, Market Structure and Discrimination

Our empirical approach to estimating discrimination presents an avenue to study the effects of policy on the quantity of discrimination. In this section, we explore how two important features of the mortgage lending market—financial innovation and competition across lenders—affect the estimates of the approval gap for black applicants that can be attributed to loan officers' subjectivity. We explore two features of the market for mortgage lending: financial innovation and competition across institutions. Intuitively, innovation in financial technologies is supposed to mitigate subjective decision-making by individuals, and the same could be said of innovation promoting more lean and efficient organizational structures, such as shadow banks. Moreover, according to theory (Becker, 1957), increased competition should eliminate a profit-maximizing agent's ability to engage in taste-based discrimination. Then, both factors should reduce the scope for subjective taste in loan decisions. The weaker is the role of taste-based discrimination in normal days, the weaker should be month-end effects, and the narrower should be the approval gap between Whites and Blacks.

6.1 FinTech and Shadow Bank Lending

This section studies the effects of the recent growth of financial technologies and new forms of lending institutions on the racial lending gap. The rise of FinTech and shadow banks has been a major trend in mortgage lending over the last decade in the United States.[13] First, we compare FinTech lenders to non-FinTech lenders. FinTech lenders rely on complex models rather than human decisions in loan approvals and have been shown to improve the speed of the origination process (Fuster et al., 2019). Second, we compare shadow banks to mortgage originators from "traditional" depository institutions. Shadow banks are less regulated than traditional banks. Buchak et al. (2018) shows that having fewer regulations allows shadow banks to have a larger operating presence in underserved communities. However, the overall effect of FinTech and shadow banking

[13] Buchak et al. (2018) show that the market share of shadow banks has nearly doubled, from 30% in 2007 to more than 50% in 2017.

on minorities' access to credit is still an open question (see e.g., Fuster et al., 2017; Bartlett et al., 2019). We use our novel empirical strategy to shed new light on this important topic.

Our analysis uses the classifications of FinTech lenders and shadow banks provided by Buchak et al. (2018).[14] Their hand-collected classification defines FinTech lenders as those that have a large online presence and that process the majority of mortgage application online. However, the authors note that human interaction is not completely absent for FinTech lenders. Mortgage applicant have to engage with a loan officer during the closing process even if applications are submitted online. On the other hand, shadow banks have a straightforward classification. The authors define non-shadow banks as mortgage originators that also take deposits, and classify all other mortgage lenders as shadow banks. In this section, we restrict the sample of mortgage applications from HMDA to the period between 2014 and 2018, since the rise in FinTech and shadow banking is a recent phenomenon.

In Table 8 we study approval patterns around month-end for FinTech lenders and shadow banks, after carefully controlling for differences in loan and applicant characteristics, using the same set of controls that we introduce in column (6) of Table 4.[15] Starting from the comparison between Fintech and non-Fintech lenders, in columns (1) and (2), we restrict the sample to each one of these two categories, and separately estimate equation 9. We find that for FinTech lenders the increase in approvals is 9% for Whites and 13% for Blacks, while the increases are only 5.6% and 9.2% for non-Fintech lenders. When considering shadow banks (columns 4 and 5), the increase in approval rates is only 5% for Whites and 7.3% for Blacks in shadow banks. The same differences are larger for non-shadow banks, equal to 7.7% and 12%, respectively.

[14]Fuster et al. (2019) use loan processing times to classify FinTech lenders. Though we find this measure appealing, it would not be well-suited to our analysis. Our analysis focuses on the differences in loan processing across races. To the extent that there could be differences in the processing times across races, such an analysis would confound the classification of FinTech lenders.

[15]Figures 4(a) and 4(b) in the Appendix provide a first look at approval patterns around month-end for FinTech lenders and shadow banks, based on the raw data.

To provide a test for the differences between Fintech and non-Fintech lenders, and shadow and non-shadow banks, we estimate a new regression equation:

$$
\begin{aligned}
Appr_j = {} & \delta_{lw,Black,Z} \left(I_{lw} \times I_{Black} \times Z_i \right) + \delta_{fw,Black,Z} \left(I_{fw} \times I_{Black} \times Z_i \right) + \\
& + \delta_{lw,Black} \left(I_{lw} \times I_{Black} \right) + \delta_{fw,Black} \left(I_{fw} \times I_{Black} \right) + \delta_{lw} I_{lw} + \delta_{fw} I_{fw} + \\
& + \delta_{lw,Z} \left(I_{lw} \times Z_i \right) + \delta_{fw,Z} \left(I_{lw} \times Z_i \right) + \delta_{Black} I_{Black} + \delta_{Black,Z} \left(I_{Black} \times Z_i \right) \\
& + BX_j + a_{ym,c} + a_{ym,i} + a_{dow} + a_{holiday} + u_{j,t}
\end{aligned}
\tag{10}
$$

This specification is constructed by augmenting equation 9 with interaction terms, capturing the effect of lender characteristic Z_i on approval rates (coefficients $\delta_{lw,Z}$ and $\delta_{fw,Z}$), and on the approval rates for Black applicants (coefficients $\delta_{lw,Black,Z}$ and $\delta_{fw,Black,Z}$). The variable Z_i will consists of either a dummy equal to one for FinTech lenders, or a dummy equal to one for shadow banks.

Our results for FinTech lenders are reported in column (3). Interestingly, the coefficient $\delta_{lw,Z}$ is positive and statistically significant, and close to 3%. Thus, there is a higher increase in approval rates for white applicants in the last week of the month for FinTech lenders. However, the incremental effects on Black applicants are not significant. The coefficients on the individual dummies $\delta_{lw,Black,Z}$ and $\delta_{fw,Black,Z}$ are statistically indistinguishable from 0, and their difference is also not statistically significant at conventional confidence levels.

In column (6) we turn to shadow banks. The coefficient $\delta_{lw,Z}$ is negative, while $\delta_{fw,Z}$ is positive, thus taking the opposite signs as the baseline month-end fluctuation in approval rates. Both are statistically significant. For white applicants, the increase in approval rates is smaller for shadow, rather than non-shadow, banks by roughly 2.8%. Moreover, the marginal increase in approval rates for Black applicants ($\delta_{lw,Black,Z} - \delta_{fw,Black,Z}$) is smaller by 1.8% (significant at the 95% confidence level) for shadow banks. Thus, shadow banks seem to experience smaller month-end effects in general, and in particular for Black applicants. Consistent with this finding, the coefficient on the interaction between the Black applicant and the shadow bank dummy reveals that in normal days (outside the last and first week of the month) approval rates for Black applicants are 5% higher for shadow banks than for traditional depository institutions. There is again no difference when comparing FinTech and non-Fintech lenders.

Summing up, shadow banks appear to have smaller month-end effects, and a more equal treatment of white and Black applicants. This is consistent with our conjecture that more efficient institution would leave less room for taste-based discrimination. However, quite surprisingly, this does not seem to be the case for FinTech lenders, which experience larger month-end spikes in approvals, and are subject to a similar degree of taste-based discrimination as non-FinTech lenders.

There are two potential explanation for this result. First, the criteria currently used in the literature to identify FinTech companies might be flawed, or noisy. Second, while up-to-date statistical and machine learning models may provide loan officers with more accurate insights on credit risk, FinTech lenders may still leave loan officers free to blend model insights with their own subjective judgement. Both explanations have potentially important implications for our current assessment and understanding of the role of FinTech lenders in the mortgage market, and deserve further investigation in future research.

6.2 Market Structure and Competition

While the previous section has focused on lender characteristics, we now turn to the relationship between lending market structure and month-end fluctuations in approval rates, and ultimately the relationship between market structure and discrimination.

We first focus on local (county-level) market concentration. To measure concentration, in each county and year in our sample we construct two measures based on the number of mortgage originations by lender using the HMDA data: the share of total mortgages originated by the 4 institutions with the largest number of originations, and the Herfindhal-Hirschman Index (HHI) based on within county shares of mortgage originations in the previous year. Our analysis is reported in Table 9.[16] In columns (1) and (2) we restrict the sample to counties with top 4 share

[16]Results based on the raw data are reported in figures 5(a) and 5(b) in the Appendix.

above and below median. We find that the magnitude of the increase in approval rates for Blacks is, in relative terms, 50% larger than the one for Whites in both groups. In general, the magnitude of the increases for Blacks and Whites are roughly the same for high and low top 4 share counties. The same is true when comparing counties with HHI above and below median, as shown in columns (4) and (5). In columns (3) and (6) we report estimates from the specification in equation 10 (with Z now a dummy equal to one for above median top 4 share or above median HHI counties), which we use to test the triple interaction effects between last and first week of the month, Black applicant and market concentration. We find that these effects are not statistically significant. Differences between high and low concentration counties in the month-end approval rates increase for Whites are significant, but quantitatively negligible.

If we interpret concentrations as a proxy for local competition among lenders (Cetorelli and Strahan, 2006), then this evidence suggests that local competition among lenders does not translate into higher competition and smaller room for subjective decision making and biases at the level of individual loan officers.

An alternative channel through which we may capture the effects of local competition is by comparing large and small lenders. Small lenders are naturally more concentrated in a small number of markets, and might compete more fiercely in those markets. Thus, we construct a proxy for lender size, equal to the average number of mortgage originations per year. We compute the overall average annual mortgage origination volume for each lender and split lenders into two groups, depending on whether their size is above or below the median across lenders in the United States. In Table 10 we conduct regression tests analogous to the ones in Tables 8 and 9.[17] When splitting the sample between lenders with above and below median size, we find that for the former group the increase in approval rate around month-end is 7.2% for white applicants and 10% for Black applicants. For the latter group, the increases are smaller: 5.2% and 8.9%. Nonetheless, in column (3) we find that the magnitude of the change in the approval gap for Black applicants around month-end is indistinguishable between large and small size lenders. Overall, our results suggest

[17]See figure A.6 for the results from the raw data.

that, even when market forces increase competition across institutions, discriminatory practices persist *within* institutions.

7 Conclusions

Tests for taste-based discrimination are often unconvincing because subject groups tend to have different unobserved characteristics. We show that high-frequency evaluations can help address the omitted variable problem when there is variation in the degree to which decision-makers rely on subjective evaluations. Under the null that decision-makers do not engage in taste-based discrimination, and assuming that the applicant pool is constant, a decrease in the degree of subjectivity should have no impact on the likelihood of favorable decisions for minority subjects relative to majority subjects. A reduction in disparate treatment for minority subjects would instead reveal the presence of taste based discrimination.

We use our approach to provide new evidence of discrimination in mortgage lending in the U.S. First, we document an "end-of-month effect" in which the volume of new mortgage originations increases by over 150% relative to the start of the month. This increase is caused by the performance incentives of loan officers – the fact that loan officers have monthly performance targets. Next, we show that the within-month pattern of loan approvals varies by the mortgage applicants' race. The gap in approval rates between white and Black applicants attenuates by half at the end of the month, when loan officers need to approve more applications to meet their performance targets. There are no observable within-month racial patterns in application volume and no within-month patterns of application quality that could explain the results.

Our findings have important policy implications for the distribution of credit in consumer credit markets. Legislation such as the Consumer Reinvestment Act and the Equal Credit Opportunity Act have been implemented over the past several decades to counteract historical inequities in credit access (e.g., red-lining; Appel and Nickerson, 2016; Aaronson et al., 2017). A crucial aspect of such legislation is that it intends to modify the behavior of lending institutions. We show that patterns of discriminatory behavior by loan officers exist *within-institution* and such behavior is not mitigated by important features of the market structure of lending markets—namely FinTech, institution size, and competition across lenders. This suggests that policies targeted toward institutions will have limited effects so long as individuals use their discretion to allocate credit.

Seeing as institution-level policies do not eliminate biases held by individuals, it calls to question what policies would be effective. In accordance with classic economic theories of discrimination (Becker, 1957), competition reduces taste-based discrimination. Such competition occurs in the labor market for loan officers. Loan officers have to meet monthly performance targets otherwise they would have less compensation and risk being fired. However, loan officers' preference for discrimination is not fully undone by labor market competition, suggesting that there are barriers to entry in the labor market. Indeed, loan officers need at least a bachelor's degree in a field related to finance or business, and they have to obtain and maintain a license.

There are two recommendations that emerge from our study. First, the collection of high-frequency data on evaluations, combined with our approach, can be used to estimate the amount of discrimination across a variety of contexts and markets. Second, enhancing the data collection to go beyond the institution and down to individual decision-makers can provide further insight into the factors that determine discrimination. Such data can be used by researchers and policy-makers, as well as by consumers, for instance when shopping for credit in the mortgage market.

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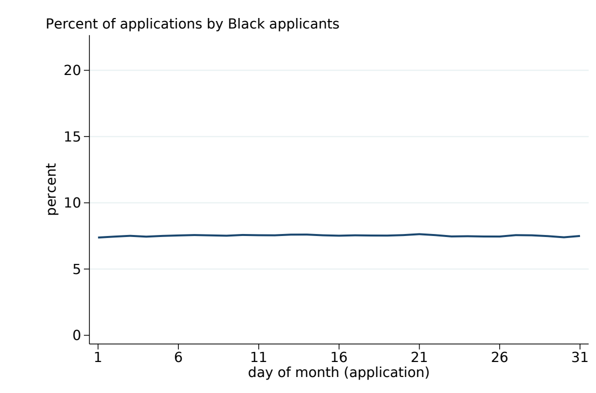
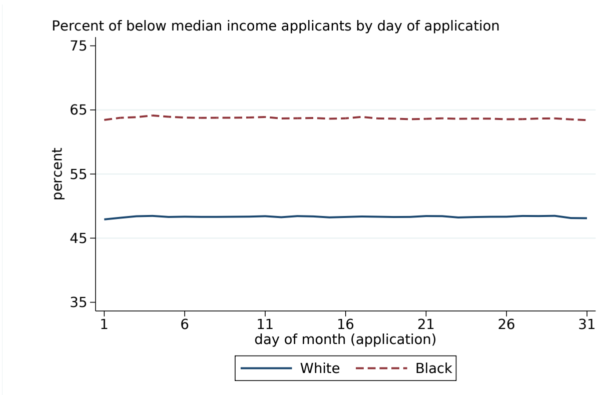
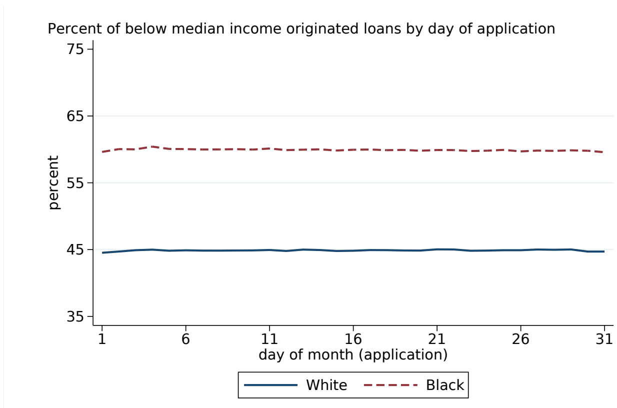
Figures



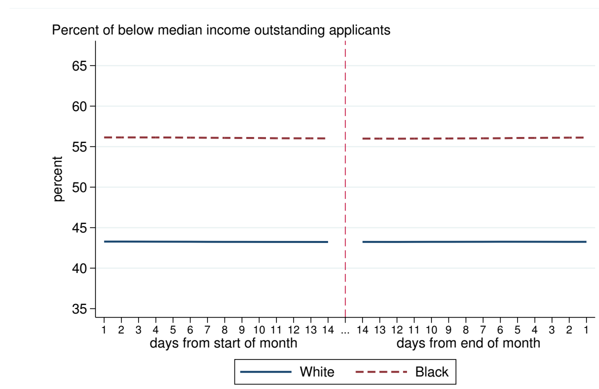
(a) Share of Black Applicants



(b) Originated Loans

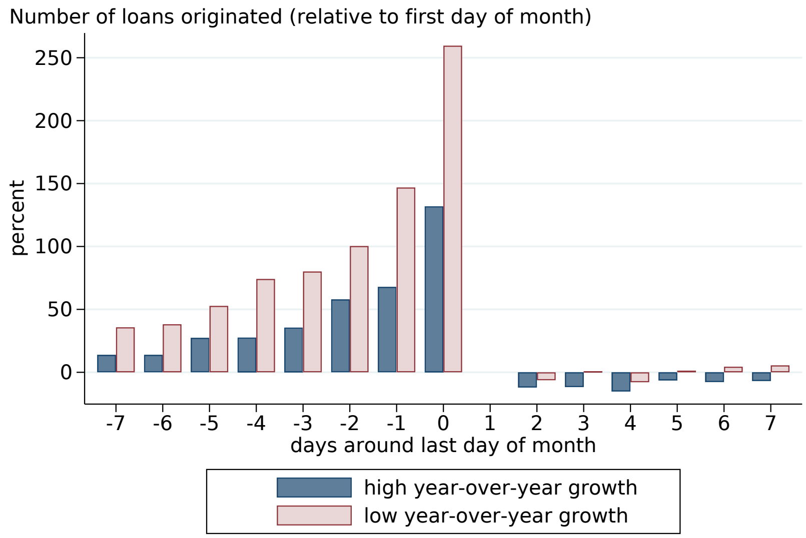


(c) All Applications

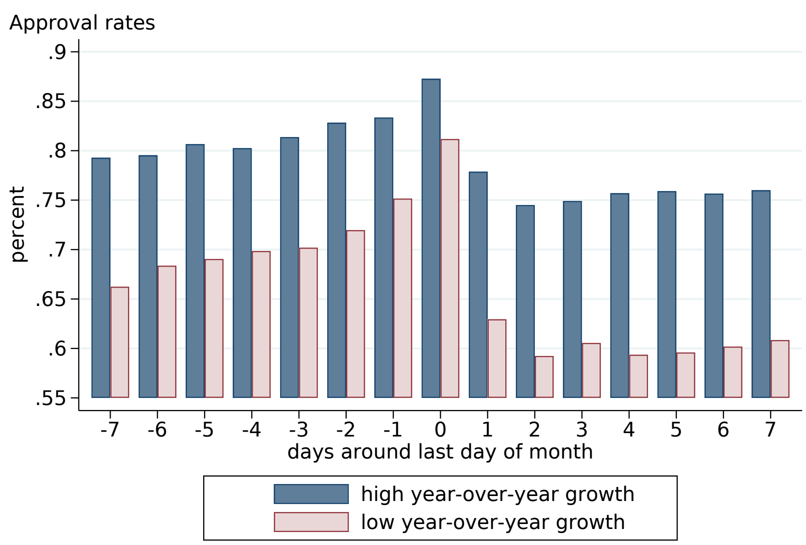


(d) Low Income, Outstanding Applications

Figure 3: Panel (a) of the Figure shows the average fraction of applications by Blacks (out of all applications) based on the day of the month in which the application was filed. Panel (b) shows the fraction of applications by White and Black applicants with income below the county median in the year, based on the day of the month in which the applications were filed. Panel (c) shows the fraction of loans originated to White and Black applicants with income below the county median in the year, based on the day of the month in which the original applications were filed. Panel (d) shows the fraction of applications with income below the county median in the year, out of all applications outstanding on each day of the month, for White and Black applicants. The results in all panels of the Figure are based on the HMDA data from January 1994 to December 2018.



(a) Effects of YoY Performance: Volume



(b) Effects of YoY Performance: Approval Rates

Figure 4: Panel (a) of the figure shows average percentage abnormal daily loan origination volume in the U.S., separately for lenders that, on each day, have high (top quartile across all lenders in the year) and low (bottom quartile across all lenders in the year) performance growth relative to the same month in the previous year (defined according to equation 7). The darker bars are for lenders with high performance growth, while the lighter bars are for lenders with low performance growth. Abnormal origination volume is reported for the last eight days of the month, and the first seven days of the following month, and is computed with respect to volume on the first day of the month. Panel (b) of the figure shows the approval rate, across all decisions taken on loan application on each day in the U.S., separately for high and low performance growth lenders, and for the last eight days of the month and the first seven days of the following month. The results in both panels of the figure are based on the HMDA data from January 1994 to December 2018.

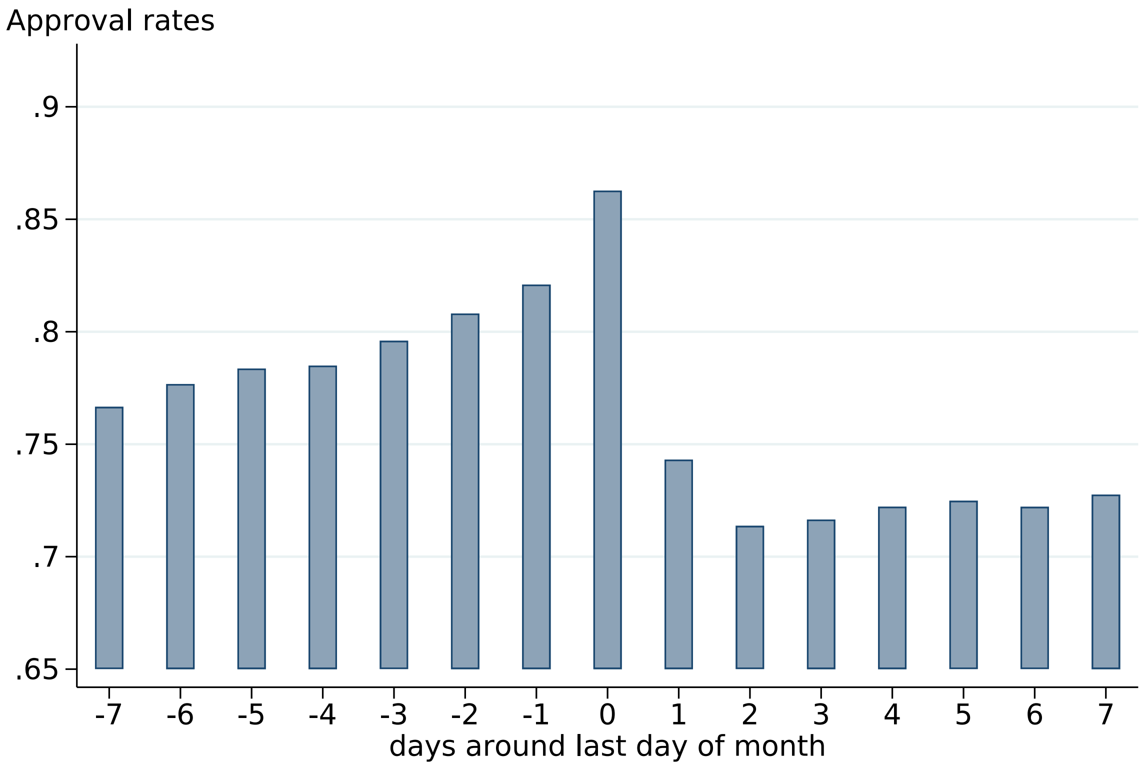


Figure 5: The figure shows the average approval rate (approved applications over approved and denied applications) at the level of the entire United States, for the last eight days of the month, and the first seven days of the following month. The results in the figure are based on the HMDA data from January 1994 to December 2018.

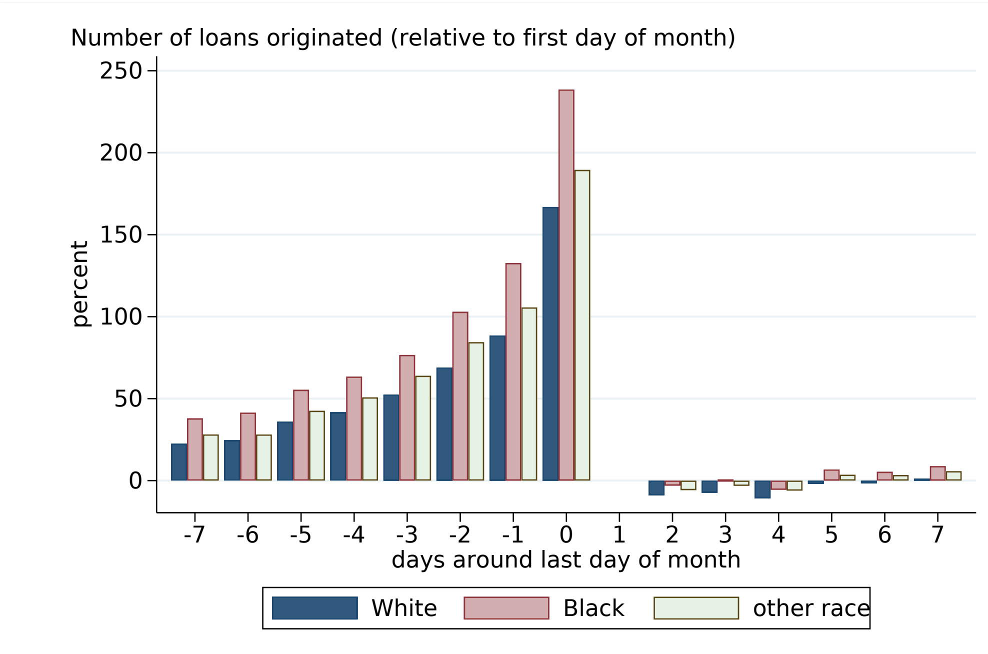
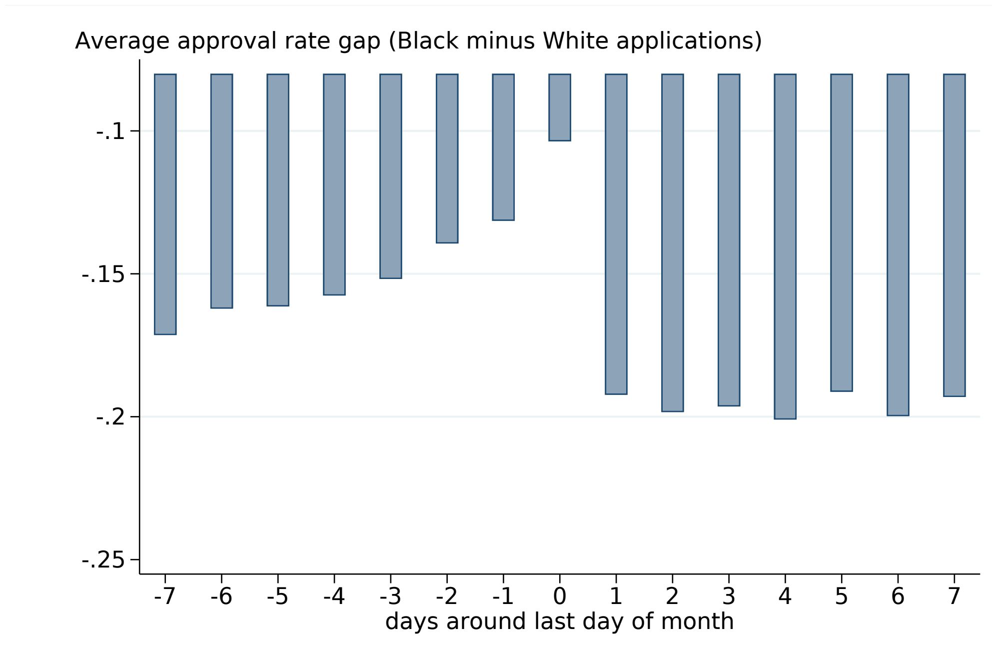
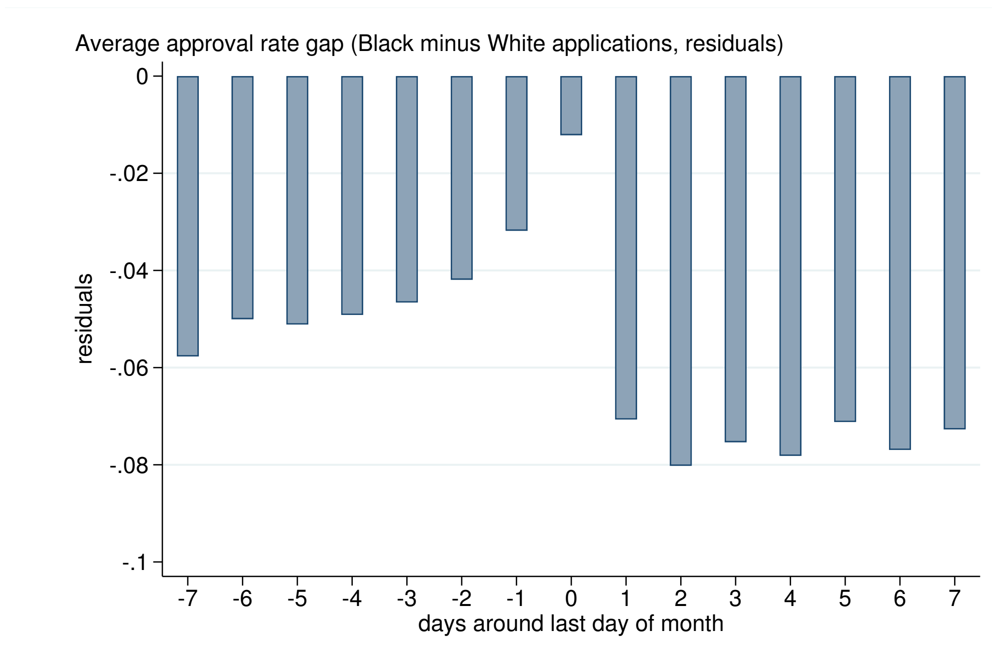


Figure 6: The figure shows average percentage abnormal daily loan origination volume in the U.S., by race group (Whites, Blacks and other races). Abnormal volume is reported for the last eight days of the month, and the first seven days of the following month, and is computed with respect to loan origination volume on the first day of the following month, for each group of applicants. The results in the figure are based on the HMDA data from January 1994 to December 2018.

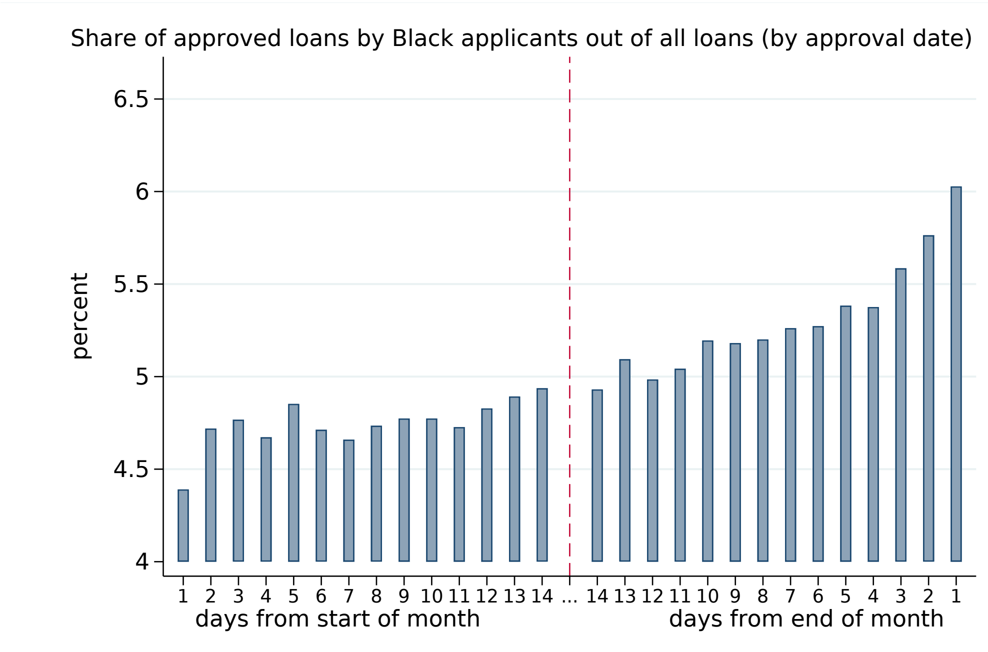


(a) Approval Gap (Raw Data)

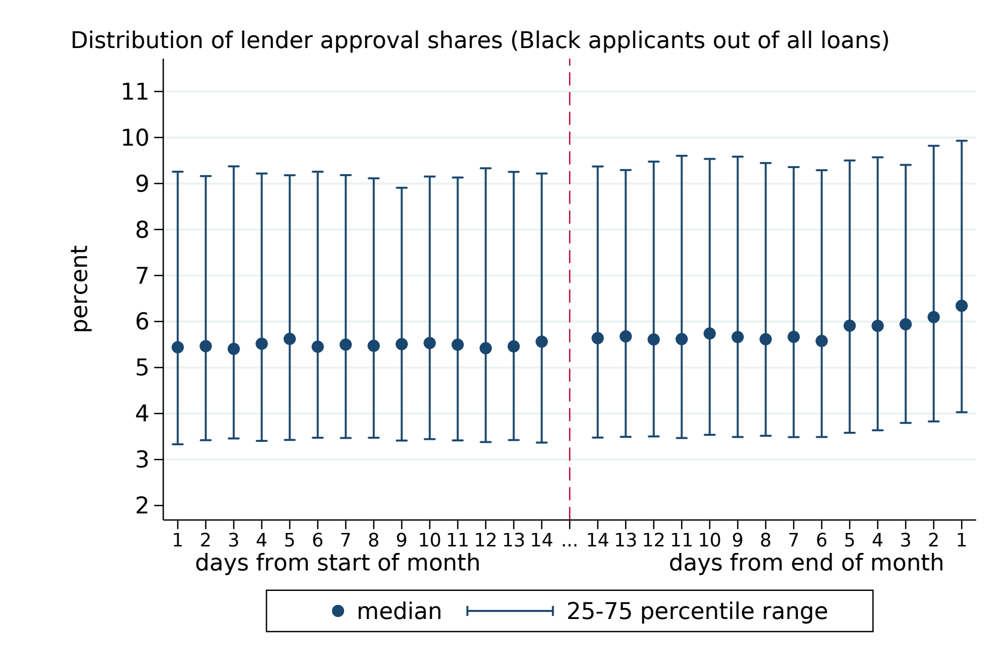


(b) Approval Gap (Residuals)

Figure 7: The figure shows the approval gap for Blacks. Panel (a) reports the difference between the fraction of approved loans, out of all approved and denied loans in the U.S., for Blacks minus the one for Whites, on each of the last eight days of the month and the first seven days of the following month. Panel (b) reports residual differences in approval rates after controlling for loan applicant characteristics. The day-by-day difference in approval rates is attained by first estimating the complete specification of equation 9 (see column 6 of Table 4), but omitting the dummies for actions taken in the first and last week of the month. We then average regression residuals on each day, separately for Black and White applicants, and compute the difference between the daily averages to estimate the (controlled) approval gap on each day. Estimates are based on a 5% sample of the HMDA data from January 1994 to December 2018.

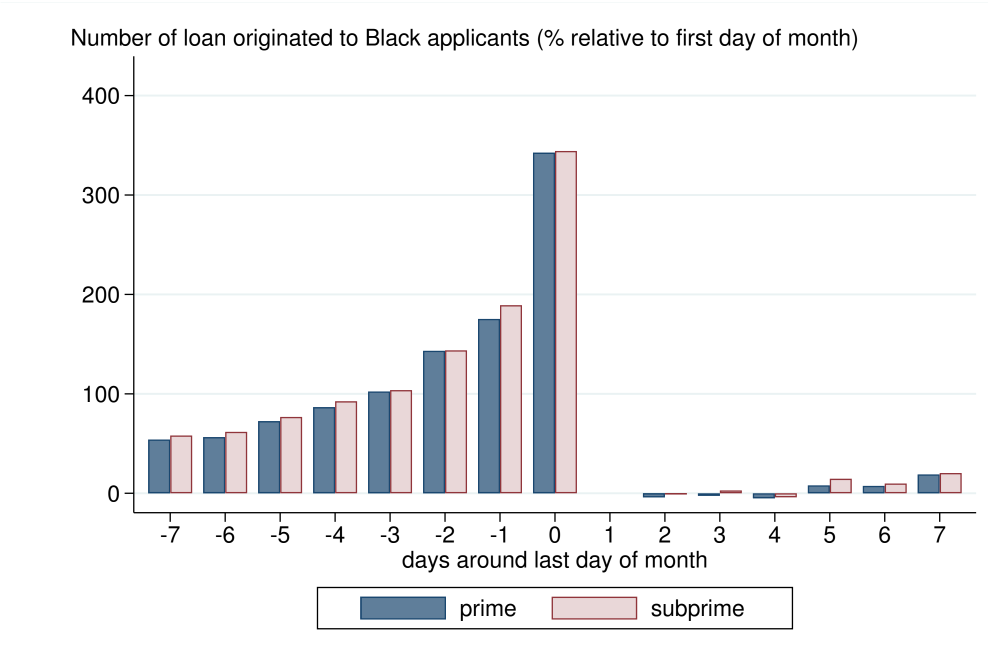


(a) United States

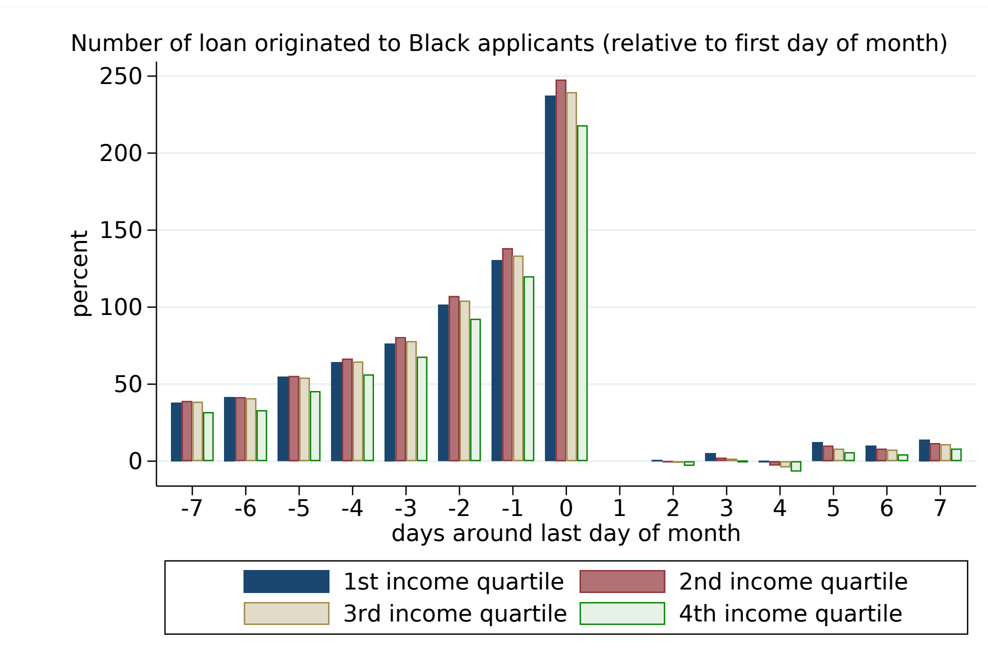


(b) Individual Lenders

Figure 8: Panel (a) of the figure shows the share of approved applications form Black applicants, out of all approved applications on each day in the two weeks before and after the end of the month in the United States. The results in this panel are based on a 5% random sample of the HMDA data from January 1994 to December 2018. Panel (b) shows the distribution (median, 25th percentile and 75th percentile) of the share of approved applications from Blacks at the lender level on each day, for all lenders that originate on average at least 10 loans per-day. The results in this panel are based on the whole HMDA sample from January 1994 to December 2018.

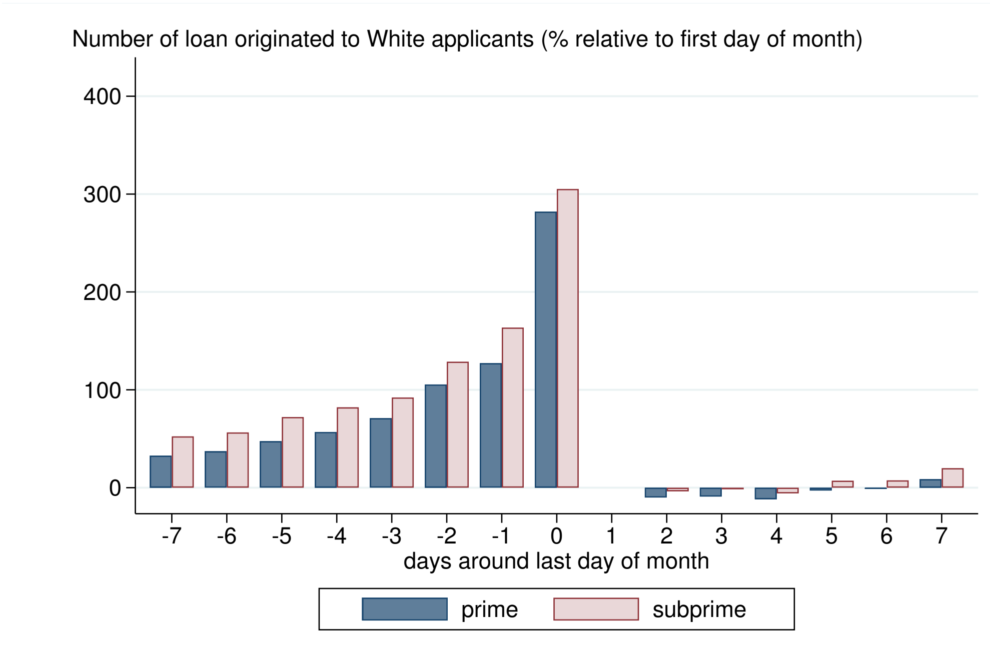


(a) Effects for Prime/Subprime Black Applicants

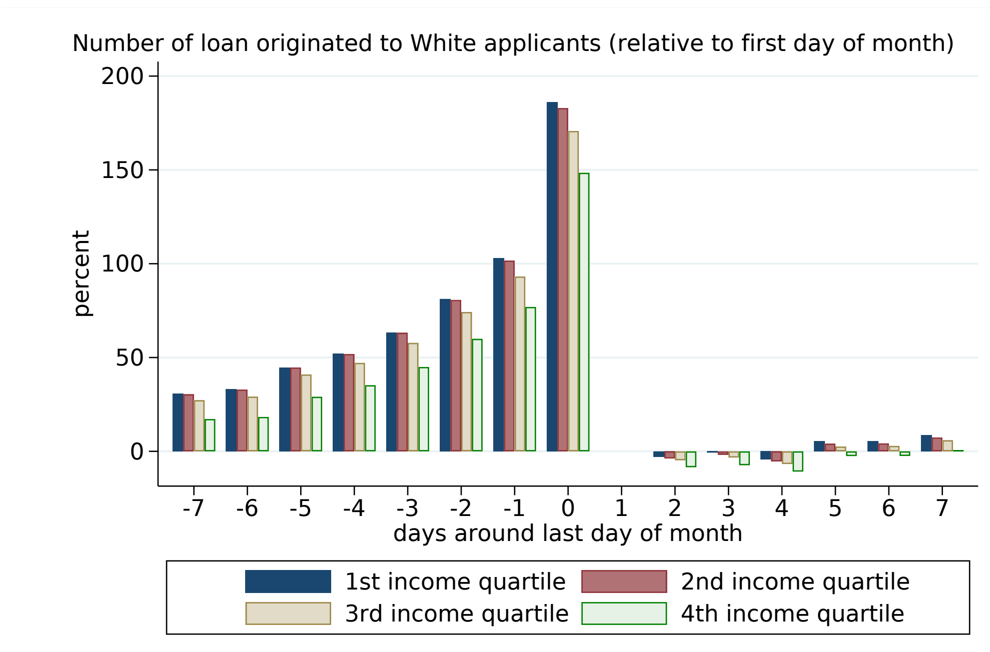


(b) Effects by Income Quartile Black Applicants

Figure 9: Panel (a) of the figure shows average percentage abnormal daily loan origination volume in the U.S., for Blacks with prime (660 or higher) and subprime FICO. Abnormal volume is reported for the last eight days of the month, and the first seven days of the following month, and is computed with respect to loan origination volume on the first day of the following month for each applicant group. Estimates are based on the merged sample of HMDA and Black Knight McDash data from 1994 to 2018. Panel (b) of the figure shows average percentage abnormal daily loan origination volume separately for Blacks belonging to different income quartiles within county. The results in this panel are based on the HMDA sample from January 1994 to December 2018.



(a) Effects for Prime/Subprime White Applicants



(b) Effects by Income Quartile White Applicants

Figure 10: Panel (a) of the figure shows average percentage abnormal daily loan origination volume in the U.S., for Whites with prime (660 or higher) and subprime FICO. Abnormal volume is reported for the last eight days of the month, and the first seven days of the following month, and is computed with respect to loan origination volume on the first day of the following month for each applicant group. Estimates are based on the merged sample of HMDA and Black Knight McDash data from 1994 to 2018. Panel (b) of the figure shows average percentage abnormal daily loan origination volume separately for Blacks belonging to different income quartiles within county. The results in this panel are based on the HMDA sample from January 1994 to December 2018.

Tables

Panel (a): Statistics by Year

Year	Apps Number (Millions)	Orig Number (Millions)	Loan Amount ($ Billions)	Lenders Number	Average Orig Number Per Lender	Average Loan Size ($ 1,000)
1994	12.22	8.25	774.16	9876	835.62	93.81
1995	11.22	7.15	648.27	9544	748.90	90.70
1996	14.42	8.61	799.96	9333	922.24	92.94
1997	15.56	8.78	876.75	7931	1106.87	99.87
1998	23.24	13.75	1531.01	7846	1752.67	111.33
1999	21.71	11.68	1315.98	7824	1492.54	112.69
2000	18.42	9.37	1084.18	7705	1215.83	115.73
2001	23.87	13.69	1856.97	7628	1794.62	135.65
2002	29.06	18.12	2739.76	7780	2329.56	151.17
2003	37.26	23.65	3736.00	8117	2913.08	158.00
2004	30.41	16.41	2782.34	8864	1851.35	169.55
2005	32.13	16.78	3077.99	8859	1894.14	183.43
2006	29.28	15.03	2792.80	8893	1689.79	185.85
2007	23.84	12.00	2359.11	8632	1389.98	196.62
2008	16.15	8.16	1617.75	8418	969.82	198.16
2009	15.91	9.34	1903.12	8148	1146.43	203.74
2010	13.52	8.14	1701.14	7929	1026.50	209.01
2011	12.38	7.43	1563.70	7677	968.46	210.32
2012	16.24	10.37	2266.83	7429	1396.37	218.52
2013	15.19	9.52	2086.19	7201	1322.66	219.03
2014	10.12	5.98	1386.26	7050	848.17	231.83
2015	12.27	7.40	1847.68	6907	1071.99	249.54
2016	14.10	8.38	2180.81	6756	1240.07	260.31
2017	12.23	7.36	2042.92	5860	1255.25	277.73
2018	13.12	7.72	1985.78	5678	1359.87	257.18

Panel (b): Statistics by Applicant Race (1994:2018)

Race	Share of Applications	Average Loan Amount ($ 1,000)	Share Low Income Apps	Share Conforming	Share Primary Residence	Share New Purchases	Approval Rate	Share of Approved Loans
White	66.95%	156.21	46.03%	87.24%	91.08%	41.64%	80.72%	73.72%
Black	7.34%	125.12	59.75%	89.23%	91.40%	42.73%	63.25%	5.73%
Other Race	25.71%	176.69	47.80%	87.09%	90.25%	32.95%	69.00%	20.55%

Table 1: Summary statistics for the HMDA loan applications data, covering the whole United States. Panel (a) reports statistics for each year from 1994 to 2018. Panel (b) reports statistics by groups based on applicant race. In panel (b), *Share of Applications* is the share of applications belonging to each group out of the total, *Share Low Income Apps* is the fraction of applicants with income below the median in the county and year of the application, within each group, *Share Conforming* is the fraction of conforming loans, within each group, *Share Primary Residence* is the fraction of loans for which the collateral is the primary residence of the applicant, within each group, *Share New Purchase* is the fraction of loans for new house purchase, within each group, *Approval Rate* is the fraction of approved loans, within each group, and *Share of Approved Loans* is the fraction of approved loans belonging to each group of applicants, out of the total.

	U.S.-Level					
	(1)	(2)	(3)	(4)	(5)	(6)
	log(Num Loans)	log(Num Loans)	log(Num Loans)	log($ Amount)	log(Num Loans) CRA	log(Num Loans) non-CRA
$lastweek$	0.25***	0.31***	0.31***	0.36***	0.18***	0.36***
	(0.052)	(0.016)	(0.012)	(0.013)	(0.013)	(0.013)
$firstweek$	-0.22***	-0.15***	-0.15***	-0.14***	-0.11***	-0.18***
	(0.052)	(0.016)	(0.012)	(0.013)	(0.013)	(0.013)
Holiday FE	NO	YES	YES	YES	YES	YES
Day-of-Week FE	NO	YES	YES	YES	YES	YES
Month FE	NO	YES	NO	NO	NO	NO
Month-Year FE	NO	NO	YES	YES	YES	YES
$last - first$	0.47	0.46	0.46	0.50	0.29	0.54
$p - value$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
N	9131	9131	9131	9131	9131	9131
r2	0.0064	0.91	0.95	0.95	0.95	0.94

Table 2: The table reports regression estimates of the abnormal loan originations volume in the last and first week of the month (see equation 6). In columns (1) to (3) the dependent variable is the log of the number of originations per day in the United States. In column 4, the dependent variable is the total Dollar amount of loan applications per day in the United States. In columns 5 and 6 the dependent variable is the log number of originations, respectively, for lenders subject to CRA examination and not subject to CRA examination. $lastweek$ and $firstweek$ are dummies equal to one, respectively, in the first and last week of the month. The different columns present estimates based on different choices of lender and seasonality fixed effects. Estimates are based on the sample of HMDA mortgage originations from 1994 to 2018.

	(1) All	(2) Male	(3) White	(4) Black	(5) Other Race	(6) Income $>$ Med	(7) Income $\leq$ Med	(8) Income Q1	(9) Income Q2	(10) Income Q3	(11) Income Q4	(12) Loan $>$ Med	(13) Loan $\leq$ Med
$lastweek$	0.029***	0.028***	0.026***	0.050***	0.028***	0.024***	0.034***	0.038***	0.031***	0.026***	0.023***	0.031***	0.028***
	(0.00088)	(0.00091)	(0.00090)	(0.0014)	(0.00087)	(0.00083)	(0.0010)	(0.0012)	(0.0011)	(0.00090)	(0.00087)	(0.0011)	(0.00087)
$firstweek$	-0.016***	-0.016***	-0.016***	-0.025***	-0.016***	-0.015***	-0.019***	-0.021***	-0.019***	-0.016***	-0.013***	-0.018***	-0.017***
	(0.0011)	(0.0011)	(0.0011)	(0.0018)	(0.0010)	(0.00094)	(0.0011)	(0.0013)	(0.0011)	(0.00097)	(0.00091)	(0.00095)	(0.0012)
Holiday FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Day-of-Week FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Month-Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Lender FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
$last - first$	0.045	0.044	0.042	0.076	0.044	0.038	0.052	0.058	0.050	0.043	0.037	0.049	0.045
$p - value$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
N	5749198	5468592	5457749	2561526	5711340	5209254	5177984	4496837	4541807	4560944	4509888	5027344	5279720
r2	0.35	0.32	0.32	0.26	0.35	0.32	0.31	0.29	0.28	0.28	0.30	0.32	0.32

Table 3: The table reports regression estimates of abnormal approval rates in the last and first week of the month (see equation 8). The dependent variable is the approval rate (approval decisions over approval and denial decisions) per day and lender. Column (1) reports results for all applicants, while the other columns report results for subgroup of applicants based on sex, race, income and loan amount. *Income* $\leq$ *Med* and *Loan* $\leq$ *Med* are income and loan amount smaller or equal than the median in the county and year. *Income Q1*, *Income Q2*, *Income Q3* and *Income Q4* are quartiles of the income distribution in each county and year. $lastweek$ and $firstweek$ are dummies equal to one, respectively, in the first and last week of the month. Standard errors are clustered by lender and year. Estimates are based on the sample of HMDA mortgage applications and originations from 1994 to 2018.

	(1) approval Black	(2) approval White & Other	(3) approval All	(4) approval All	(5) approval All	(6) approval All
$lastweek$	0.090***	0.057***				
	(0.0043)	(0.0037)				
$firstweek$	-0.032***	-0.022***				
	(0.0028)	(0.0025)				
$black$			-0.12***	-0.10***	-0.070***	-0.068***
			(0.0069)	(0.0062)	(0.0053)	(0.0043)
$lastweek$			0.057***	0.048***	0.044***	0.043***
			(0.0037)	(0.0035)	(0.0031)	(0.0031)
$black \times lastweek$			0.036***	0.032***	0.028***	0.027***
			(0.0021)	(0.0023)	(0.0022)	(0.0023)
$firstweek$			-0.022***	-0.021***	-0.019***	-0.020***
			(0.0025)	(0.0021)	(0.0018)	(0.0017)
$black \times firstweek$			-0.010***	-0.0081***	-0.0073***	-0.0072***
			(0.0015)	(0.0014)	(0.0024)	(0.0015)
log(income)				0.095***	0.073***	0.071***
				(0.0061)	(0.0039)	(0.0036)
log(loan amount)				0.031***	0.0089***	0.0076***
				(0.0075)	(0.0029)	(0.0023)
is conforming				0.13***	0.092***	0.090***
				(0.0093)	(0.0057)	(0.0057)
Loan-Level Controls	NO	NO	NO	YES	YES	YES
Holiday FE	YES	YES	YES	YES	YES	YES
Day-of-Week FE	YES	YES	YES	YES	YES	YES
Month-Year FE	YES	YES	YES	YES	YES	NO
County FE	YES	YES	YES	YES	YES	NO
Lender FE	NO	NO	NO	NO	YES	NO
Month-Year-County	NO	NO	NO	NO	NO	YES
Month-Year-Lender	NO	NO	NO	NO	NO	YES
$last - first$	0.12	0.079	0.079	0.068	0.063	0.063
$p - value$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
$last - first\ (black)$			0.13	0.11	0.099	0.097
$p - value\ (black)$			0.0000	0.0000	0.0000	0.0000
$last - first\ (black - other)$			0.046	0.040	0.035	0.034
$p - value\ (black - other)$			0.0000	0.0000	0.0000	0.0000
N	1440405	18200483	19641147	18464497	18463245	17898939
r2	0.050	0.034	0.041	0.092	0.23	0.32

Table 4: The table reports individual loan-level regression estimates of abnormal approval rates in the last and first week of the month (see equation 9). The dependent variable is a dummy that takes value 1 if a loan application is approved and 0 if it is denied. $lastweek$ and $firstweek$ are dummies equal to one, respectively, if the decision on the application is taken in the first and last week of the month. $black$ is a dummy equal to one for Black applicants. In columns (1) and (2), the sample is restricted to, respectively, Blacks and Whites or other race applicants. The table also reports estimates of the difference between the coefficients for the dummies $lastweek$ and $firstweek$, and for the difference of the interaction coefficients for $black$ applicants, along with the *p-value* of tests of the null that each difference is equal to 0. Standard errors are clustered by lender and year. Estimates are based on a 5% random sample of the HMDA data from 1994 to 2018.

	(1) approval	(2) approval 1-30 Days TTA	(3) approval 31-60 Days TTA	(4) approval 61-90 Days TTA	(5) approval $>$ 90 Days TTA
$lastweek$	0.038***	0.053***	0.027***	0.027***	0.023***
	(0.0026)	(0.0033)	(0.0031)	(0.0030)	(0.0034)
$firstweek$	-0.019***	-0.016***	-0.017***	-0.019***	-0.017***
	(0.0018)	(0.0017)	(0.0017)	(0.0027)	(0.0027)
$black$	-0.056***	-0.072***	-0.043***	-0.037***	-0.030***
	(0.0039)	(0.0050)	(0.0032)	(0.0035)	(0.0032)
$black \times lastweek$	0.023***	0.023***	0.021***	0.015***	0.015***
	(0.0020)	(0.0025)	(0.0020)	(0.0023)	(0.0037)
$black \times firstweek$	-0.0094***	-0.0043**	-0.015***	-0.0053	-0.0056
	(0.0017)	(0.0019)	(0.0027)	(0.0033)	(0.0036)
log(TTA)	0.11***				
	(0.0069)				
log(income)	0.058***	0.083***	0.038***	0.040***	0.036***
	(0.0029)	(0.0048)	(0.0026)	(0.0029)	(0.0035)
log(loan amount)	-0.021***	0.0022	-0.013***	-0.017***	-0.012***
	(0.0026)	(0.0029)	(0.0020)	(0.0026)	(0.0035)
is conforming	0.058***	0.10***	0.039***	0.035***	0.033***
	(0.0044)	(0.0072)	(0.0043)	(0.0042)	(0.0035)
$last - first$	0.057	0.069	0.044	0.046	0.040
$p - value$	0.0000	0.0000	0.0000	0.0000	0.0000
$last - first\ (black)$	0.089	0.096	0.080	0.065	0.061
$p - value\ (black)$	0.0000	0.0000	0.0000	0.0000	0.0000
$last - first\ (black - other)$	0.032	0.027	0.036	0.020	0.021
$p - value\ (black - other)$	0.0000	0.0000	0.0000	0.0000	0.0000
N	16503563	9038519	4907587	1420393	1332868
r2	0.35	0.40	0.29	0.37	0.42

Table 5: The table reports individual loan-level regression estimates of abnormal approval rates in the last and first week of the month (see equation 9), controlling for time to action (TTA), defined as the number of days between the application date and the date in which action (approval or denial) of the loan is taken. In column (1), the log of TTA is included as a control. In columns 2 to 5, the sample is restricted to loans with TTA, respectively, between 1 and 30 days, between 31 and 60 days, between 61 and 90 days, and longer than 91 days. The dependent variable is a dummy that takes value 1 if a loan application is approved and 0 if it is denied. $lastweek$ and $firstweek$ are dummies equal to one, respectively, if the decision on the application is taken in the first and last week of the month. $black$ is a dummy equal to one for Black applicants. The table also reports estimates of the difference between the coefficients for the dummies $lastweek$ and $firstweek$, and for the difference of the interaction coefficients for $black$ applicants, along with the *p-value* of tests of the null that each difference is equal to 0. Standard errors are clustered by lender and year. Estimates are based on a 5% random sample of the HMDA data from 1994 to 2018.

	(1) Subprime (FICO $<$ 660)	(2) Origination LTV (%)	(3) Low Documentation	(4) Origination Interest Rate
$lastweek$	0.00029	0.0062	0.042*	0.00096
	(0.00079)	(0.070)	(0.023)	(0.0011)
$firstweek$	0.00059	-0.15***	-0.0012	0.00016
	(0.00042)	(0.028)	(0.0012)	(0.00094)
$black$	0.12***	3.09***	0.0014	0.0013
	(0.0066)	(0.24)	(0.0034)	(0.0019)
$black \times lastweek$	0.0020	-0.32***	-0.018**	-0.00076
	(0.0014)	(0.081)	(0.0068)	(0.00068)
$black \times firstweek$	0.0031*	0.098*	-0.00042	0.00022
	(0.0016)	(0.054)	(0.0011)	(0.00071)
LTV	0.0016***		0.00032	0.00043
	(0.00035)		(0.00055)	(0.00044)
log(income)	-0.011***	-9.02***	0.013**	0.000068
	(0.0039)	(0.84)	(0.0051)	(0.0081)
log(loan amount)	-0.041***	19.8***	-0.028	-0.049***
	(0.0061)	(1.60)	(0.022)	(0.012)
is conforming	-0.0061**	7.98***	0.053***	-0.036***
	(0.0030)	(0.67)	(0.012)	(0.0062)
FICO 620:659		-1.59***	0.019	-0.00015
		(0.46)	(0.025)	(0.010)
FICO 660:719		-2.83***	0.043	-0.020*
		(0.56)	(0.040)	(0.011)
FICO 720:759		-3.99***	0.051	-0.036***
		(0.71)	(0.051)	(0.011)
FICO 760:799		-7.34***	0.052	-0.051***
		(0.74)	(0.054)	(0.0099)
FICO $\geq$ 800		-10.6***	0.060	-0.065***
		(0.67)	(0.052)	(0.0081)
$last - first$	-0.0003	0.1500	0.0430	0.0008
$p - value$	0.7600	0.0830	0.0690	0.6800
$last - first\ (black)$	-0.0014	-0.2600	0.0250	-0.0002
$p - value\ (black)$	0.6100	0.0077	0.1500	0.9100
$last - first\ (black - other)$	-0.0011	-0.4200	-0.0180	-0.0010
$p - value\ (black - other)$	0.6600	0.0005	0.0130	0.3700
N	27701585	27701585	18125835	24187005
r2	0.26	0.51	0.51	0.78

Table 6: The table reports regression estimates of the difference in characteristics between mortgages originated in the last and first week of the month. The dependent variables are a dummy equal to one for subprime loans (with FICO $<$ 660, see column (1)), the mortgage LTV at origination (column (2)), a dummy equal to one for mortgages for which the applicant provided low documentation (column (3)), and the mortgage interest rate at origination (column (2)). $lastweek$ and $firstweek$ are dummies equal to one in the first and last week of the month. $black$ is a dummy equal to one for Black applicants. The table also reports estimates of the difference between the coefficients for the dummies $lastweek$ and $firstweek$, and for the difference of the interaction coefficients for $black$ applicants, along with their *p-value*s. Standard errors are clustered by lender and year. Estimates are based on the merged sample of HMDA and Black Knight McDash data from 1994 to 2018.

	(1) 5-Year Default	(2) 5-Year Default FICO < 660	(3) 5-Year Default LTV $> 80\%$	(4) 5-Year Default Low Docs
$lastweek$	-0.00011	-0.00016	-0.00031	0.00042
	(0.00027)	(0.00047)	(0.00033)	(0.00077)
$firstweek$	0.00044	0.0011	0.00097*	0.00049
	(0.00027)	(0.00064)	(0.00054)	(0.00041)
$black$	0.0033**	0.0011	0.0017	0.0075***
	(0.0012)	(0.0012)	(0.0015)	(0.0024)
$black \times lastweek$	-0.0013**	-0.0020	-0.0022***	-0.0039**
	(0.00059)	(0.0011)	(0.00062)	(0.0016)
$black \times firstweek$	0.0020***	0.0011	0.0025**	0.0033***
	(0.00060)	(0.00096)	(0.00095)	(0.0011)
LTV	0.00032**	0.00049**	-0.00016	0.00079**
	(0.00012)	(0.00018)	(0.00030)	(0.00033)
log(income)	-0.0020	-0.011***	-0.012***	-0.0039**
	(0.0016)	(0.0036)	(0.0022)	(0.0016)
log(loan amount)	-0.0027	0.0021	0.0061***	0.0029
	(0.0035)	(0.0076)	(0.0021)	(0.0038)
is conforming	-0.0037**	-0.013***	-0.0075**	-0.0051**
	(0.0016)	(0.0044)	(0.0032)	(0.0021)
FICO 620:659	-0.0063	-0.0040	-0.013***	0.0030
	(0.0045)	(0.0042)	(0.0030)	(0.0050)
FICO 660:719	-0.020***		-0.026***	-0.014***
	(0.0048)		(0.0044)	(0.0038)
FICO 720:759	-0.029***		-0.035***	-0.028***
	(0.0058)		(0.0063)	(0.0073)
FICO 760:799	-0.033***		-0.040***	-0.034***
	(0.0069)		(0.0077)	(0.0096)
FICO $\geq$ 800	-0.033***		-0.042***	-0.030***
	(0.0072)		(0.0082)	(0.0089)
$last - first$	-0.0006	-0.0012	-0.0013	-0.0001
$p - value$	0.2800	0.2300	0.1400	0.9400
$last - first\ (black)$	-0.0038	-0.0043	-0.0060	-0.0073
$p - value\ (black)$	0.0015	0.0036	0.0023	0.0003
$last - first\ (black - other)$	-0.0033	-0.0031	-0.0047	-0.0072
$p - value\ (black - other)$	0.0003	0.0380	0.00080	0.0020
N	20732913	3729582	6606008	5617655
r2	0.12	0.16	0.15	0.22

Table 7: The table reports regression estimates of the difference in performance between mortgages originated in the last and first week of the month. The dependent variable is a dummy equal to one for mortgage that defaulted within 5 years after origination. In column (2), the sample is restricted to subprime loans (FICO < 660). In column (3) the sample is restricted to high loan-to-value loans (LTV$> 80\%$), and in column (4) to loans with low documentation. $lastweek$ and $firstweek$ are dummies equal to one in the first and last week of the month. $black$ is a dummy equal to one for Black applicants. The table also reports estimates of the difference between the coefficients for the dummies $lastweek$ and $firstweek$, and for the difference of the interaction coefficients for $black$ applicants, along with their *p-value*s. Standard errors are clustered by lender and year. Estimates are based on the merged sample of HMDA and Black Knight McDash data from 1994 to 2018.

	(1) approval Fintech	(2) approval Non-Fintech	(3) approval All	(4) approval Shadowbanks	(5) approval No-Shadowbanks	(6) approval All
$lastweek$	0.064***	0.036***	0.035***	0.034***	0.053***	0.054***
	(0.011)	(0.0030)	(0.0031)	(0.0037)	(0.0081)	(0.0081)
$firstweek$	-0.026***	-0.020***	-0.020***	-0.017***	-0.024***	-0.024***
	(0.0045)	(0.0034)	(0.0034)	(0.0030)	(0.0037)	(0.0037)
$black$	-0.10***	-0.096***	-0.093***	-0.069***	-0.11***	-0.11***
	(0.0059)	(0.0037)	(0.0043)	(0.0050)	(0.0035)	(0.0038)
$black \times lastweek$	0.034***	0.028***	0.027***	0.021***	0.031***	0.031***
	(0.0038)	(0.0037)	(0.0034)	(0.0040)	(0.0034)	(0.0035)
$black \times firstweek$	-0.0063*	-0.0086***	-0.0074***	-0.0018	-0.0081***	-0.0087***
	(0.0033)	(0.0023)	(0.0024)	(0.0043)	(0.0025)	(0.0024)
$black \times fintech$			-0.013			
			(0.0089)			
$fintech \times lastweek$			0.029***			
			(0.010)			
$fintech \times firstweek$			-0.0069			
			(0.0046)			
$black \times fintech \times lastweek$			0.0072			
			(0.0049)			
$black \times fintech \times firstweek$			0.00063			
			(0.0033)			
$black \times shadowbank$						0.050***
						(0.0076)
$shadowbank \times lastweek$						-0.020**
						(0.0086)
$shadowbank \times firstweek$						0.0075*
						(0.0042)
$black \times shadowbank \times lastweek$						-0.0095**
						(0.0046)
$black \times shadowbank \times firstweek$						0.0083*
						(0.0049)
log(income)	0.075***	0.077***	0.077***	0.058***	0.082***	0.077***
	(0.0045)	(0.0040)	(0.0031)	(0.0070)	(0.0041)	(0.0031)
log(loan amount)	0.022***	0.0016	0.012**	-0.011**	0.015***	0.012***
	(0.0055)	(0.0036)	(0.0042)	(0.0048)	(0.0040)	(0.0039)
is conforming	0.11***	0.10***	0.10***	0.086***	0.11***	0.10***
	(0.0097)	(0.0080)	(0.0067)	(0.011)	(0.0075)	(0.0067)
Loan-Level Controls	YES	YES	YES	YES	YES	YES
Holiday FE	YES	YES	YES	YES	YES	YES
Day-of-Week FE	YES	YES	YES	YES	YES	YES
Month-Year-County FE	YES	YES	YES	YES	YES	YES
Month-Year-Lender FE	YES	YES	YES	YES	YES	YES
$last - first$	0.090	0.056		0.050	0.077	
$p - value$	0.0000	0.0000		0.0000	0.0000	
$last - first\ (black)$	0.13	0.092		0.073	0.12	
$p - value\ (black)$	0.0000	0.0000		0.0000	0.0000	
$last - first\ (black - other)$	0.040	0.037		0.023	0.040	
$p - value\ (black - other)$	0.0000	0.0000		0.0004	0.0000	
$last - first\ (black)$			0.089			0.12
$p - value\ (black)$			0.0000			0.0000
$last - first\ (black, Z)$			0.096			0.10
$p - value\ (black, Z)$			0.0000			0.0000
$last - first\ (black, Z - noZ)$			0.0066			-0.018
$p - value\ (black, Z - noZ)$			0.15			0.022
N	1869937	2172022	4159023	1046528	3195579	4354784
r2	0.26	0.31	0.26	0.42	0.24	0.26

Table 8: The table reports individual loan-level regression estimates of abnormal approval rates in the last and first week of the month, for lenders with different characteristics (see equation 10). $lastweek$ and $firstweek$ are dummies equal to one, respectively, in the first and last week of the month. $black$ is a dummy equal to one for Black applicants. In columns (1) and (2) the sample is restricted, respectively, to Fintech and non-Fintech lenders, while in columns (4) and (5) the sample is restricted to shadow banks and non-shadow banks (deposit-taking institutions). The table also reports estimates of the difference between the coefficients for the dummies $lastweek$ and $firstweek$, and for the difference of the interaction coefficients for $black$ applicants across lender groups, along with their *p-values*. Standard errors are clustered by lender and year. Estimates are based on a 5% random sample of the HMDA data from 2014 to 2018.

	(1) approval High Top4 Sh.	(2) approval Low Top4 Sh.	(3) approval All	(4) approval High HHI	(5) approval Low HHI	(6) approval All
$lastweek$	0.042***	0.045***	0.045***	0.041***	0.045***	0.045***
	(0.0031)	(0.0031)	(0.0030)	(0.0031)	(0.0031)	(0.0030)
$firstweek$	-0.018***	-0.021***	-0.021***	-0.018***	-0.021***	-0.021***
	(0.0015)	(0.0019)	(0.0019)	(0.0015)	(0.0019)	(0.0019)
$black$	-0.074***	-0.063***	-0.063***	-0.074***	-0.063***	-0.063***
	(0.0044)	(0.0045)	(0.0046)	(0.0045)	(0.0045)	(0.0046)
$black \times lastweek$	0.027***	0.026***	0.026***	0.026***	0.026***	0.026***
	(0.0024)	(0.0022)	(0.0022)	(0.0023)	(0.0023)	(0.0023)
$black \times firstweek$	-0.0051**	-0.0076***	-0.0079***	-0.0059**	-0.0071***	-0.0074***
	(0.0021)	(0.0015)	(0.0015)	(0.0022)	(0.0015)	(0.0014)
$black \times Htop4$			-0.011***			
			(0.0033)			
$H(top4) \times lastweek$			-0.0035***			
			(0.0010)			
$H(top4) \times firstweek$			0.0034***			
			(0.00088)			
$black \times H(top4) \times lastweek$			0.0014			
			(0.0020)			
$black \times H(top4) \times firstweek$			0.0027			
			(0.0020)			
$black \times H(hhi)$						-0.012***
						(0.0033)
$H(hhi) \times lastweek$						-0.0040***
						(0.0010)
$H(hhi) \times firstweek$						0.0036***
						(0.00084)
$black \times H(hhi) \times lastweek$						0.00063
						(0.0019)
$black \times H(hhi) \times firstweek$						0.0016
						(0.0022)
log(income)	0.071***	0.069***	0.071***	0.072***	0.069***	0.071***
	(0.0040)	(0.0031)	(0.0035)	(0.0039)	(0.0032)	(0.0035)
log(loan amount)	0.0075***	0.0079***	0.0077***	0.0078***	0.0077***	0.0077***
	(0.0022)	(0.0025)	(0.0023)	(0.0022)	(0.0025)	(0.0023)
is conforming	0.090***	0.092***	0.091***	0.090***	0.091***	0.091***
	(0.0060)	(0.0053)	(0.0054)	(0.0060)	(0.0053)	(0.0054)
Loan-Level Controls	YES	YES	YES	YES	YES	YES
Holiday FE	YES	YES	YES	YES	YES	YES
Day-of-Week FE	YES	YES	YES	YES	YES	YES
Month-Year-County FE	YES	YES	YES	YES	YES	YES
Month-Year-Lender FE	YES	YES	YES	YES	YES	YES
$last - first$	0.060	0.066		0.059	0.066	
$p - value$	0.0000	0.0000		0.0000	0.0000	
$last - first\ (black)$	0.092	0.100		0.092	0.100	
$p - value\ (black)$	0.0000	0.0000		0.0000	0.0000	
$last - first\ (black - other)$	0.032	0.033		0.032	0.033	
$p - value\ (black - other)$	0.0000	0.0000		0.0000	0.0000	
$last - first\ (black)$			0.100			0.10
$p - value\ (black)$			0.0000			0.0000
$last - first\ (black, Z)$			0.099			0.099
$p - value\ (black, Z)$			0.0000			0.0000
$last - first\ (black, Z - noZ)$			-0.0013			-0.0010
$p - value\ (black, Z - noZ)$			0.63			0.71
N	8901836	8840521	17898971	8912233	8837435	17898971
r2	0.35	0.30	0.32	0.35	0.30	0.32

Table 9: The table reports individual loan-level regression estimates of abnormal approval rates in the last and first week of the month, for counties with different concentration of the local mortgage market (see equation 10). $lastweek$ and $firstweek$ are dummies equal to one, respectively, in the first and last week of the month. $black$ is a dummy equal to one for Black applicants. In columns (1) and (2) the sample is restricted, respectively, to counties in which the share of the top 4 originators is above and below median (across counties in the United States in the same year), while in columns (4) and (5) the sample is restricted to counties in which the HHI index based on lenders origination shares is above and below median (across counties in the United States in the same year) The table also reports estimates of the difference between the coefficients for the dummies $lastweek$ and $firstweek$, and for the difference of the interaction coefficients for $black$ applicants across lender groups, along with their *p-value*s. Standard errors are clustered by lender and year. Estimates are based on a 5% random sample of the HMDA data from 1994 to 2018.

	(1) approval Above Med Size	(2) approval Below Med Size	(3) approval All
$lastweek$	0.050***	0.036***	0.035***
	(0.0050)	(0.0018)	(0.0018)
$firstweek$	-0.022***	-0.016***	-0.016***
	(0.0026)	(0.0011)	(0.0011)
$black$	-0.070***	-0.064***	-0.064***
	(0.0058)	(0.0039)	(0.0040)
$black \times lastweek$	0.025***	0.029***	0.029***
	(0.0036)	(0.0016)	(0.0016)
$black \times firstweek$	-0.0057**	-0.0086***	-0.0090***
	(0.0025)	(0.0016)	(0.0015)
$black \times H(size)$			-0.0069
			(0.0066)
$H(size) \times lastweek$			0.015***
			(0.0052)
$H(size) \times firstweek$			-0.0065**
			(0.0024)
$black \times H(size) \times lastweek$			-0.0029
			(0.0040)
$black \times H(size) \times firstweek$			0.0034
			(0.0030)
log(income)	0.070***	0.070***	0.071***
	(0.0050)	(0.0028)	(0.0035)
log(loan amount)	0.0079*	0.0076***	0.0077***
	(0.0040)	(0.0023)	(0.0023)
is conforming	0.092***	0.088***	0.091***
	(0.0080)	(0.0039)	(0.0054)
Loan-Level Controls	YES	YES	YES
Holiday FE	YES	YES	YES
Day-of-Week FE	YES	YES	YES
Month-Year-County FE	YES	YES	YES
Month-Year-Lender FE	YES	YES	YES
$last - first$	0.072	0.052	
$p - value$	0.0000	0.0000	
$last - first\ (black)$	0.10	0.089	
$p - value\ (black)$	0.0000	0.0000	
$last - first\ (black - other)$	0.031	0.037	
$p - value\ (black - other)$	0.0000	0.0000	
$last - first\ (black)$			0.089
$p - value\ (black)$			0.0000
$last - first\ (black, Z)$			0.082
$p - value\ (black, Z)$			0.0000
$last - first\ (black, Z - noZ)$			-0.0064
$p - value\ (black, Z - noZ)$			0.27
N	9172101	8532602	17898971
r2	0.31	0.35	0.32

Table 10: The table reports individual loan-level regression estimates of abnormal approval rates in the last and first week of the month, for lenders with size (total originated mortgage amount) above and below median (see equation 10). $lastweek$ and $firstweek$ are dummies equal to one, respectively, in the first and last week of the month. $black$ is a dummy equal to one for Black applicants. In columns (1) and (2) the sample is restricted, respectively, to lenders with size above and below median. The table also reports estimates of the difference between the coefficients for the dummies $lastweek$ and $firstweek$, and for the difference of the interaction coefficients for $black$ applicants across lender groups, along with their *p-value*s. Standard errors are clustered by lender and year. Estimates are based on a 5% sample of the HMDA data from 1994 to 2018.

Appendix to:

Using High-Frequency Evaluations to Estimate Discrimination: Evidence from Mortgage Loan Officers

(intended for online publication)

A.I Identifying Time-varying Discrimination

We show how under the assumption in **Assumption Set (A)** approval probabilities for Whites and Blacks are different. The approval probability, conditional on race and other observable characteristics, is equal to:

$$P(a|R,X) = \frac{P(a,R|X)}{P(R|X)} = \frac{P(a,R,Z_H|X)+P(a,Z_L|X)}{P(R|X)} = \frac{P(a|R,Z_H,X)P(Z_H|R,X)P(R|X)+P(a|R,Z_L,X)P(Z_L|R,X)P(R|X)}{P(R|X)}$$

$$= P(a|Z_H,R|X)P(Z_H|R,X) + P(a|Z_L,R,X)P(Z_L|R,X)$$

where $Z \in \{Z_L, Z_H\}$ is a binary unobservable characteristic, X is a vector of observable characteristics and $R \in \{W, B\}$ is the applicants' race (white or black). Then, the difference in approval probabilities for Whites and Blacks is equal to:

$$P(a|W,X) - P(a|B,X) =$$

$$= [P(a|W,Z_H,X)P(Z_H|W,X) + P(a|W,Z_L,X)P(Z_L|W,X)] - [P(a|Z_H,B,X)P(Z_H|B,X) + P(a|Z_L,B,X)P(Z_L|B,X)]$$

$$= P(a|Z_H,X)[P(Z_H|W,X) - P(Z_H|B,X)] + P(a|Z_L,X)[P(Z_L|W,X) - P(Z_L|B,X)] > 0$$

where $P(a|Z_H,X) = P(a|W,Z_H,X) = P(a|B,Z_H,X)$ and $P(a|Z_L,X) = P(a|W,Z_L,X) = P(a|B,Z_L,X)$ from the assumption of no discrimination, and $P(Z_H|W,X) - P(Z_H|B,X) > 0$ and $P(Z_L|W,X) - P(Z_L|B,X) < 0$ due to the assumption of higher unobservable quality characteristics for Whites.

We now turn to the comparison of approval rates for Whites and Blacks at the beginning and the end of the month. The difference in the probability between Whites and Blacks is equal to:

$$P(a|W,X,T) - P(a|B,X,T) =$$

$$= P(a|Z_H,W,X,T)P(Z_H|W,X,T) + P(a|Z_L,W,X,T)P(Z_L|W,X,T) - P(a|Z_H,B,X,T)P(Z_H|B,X,T) - P(a|Z_L,B,X,T)P(Z_L|B,X,T)$$

$$= P(a|Z_H,W,X,T)[P(Z_H|W,X,T) - P(Z_H|B,X,T)] + P(a|Z_L,W,X,T)[P(Z_L|W,X,T) - P(Z_L|B,X,T)]$$

$$= P(a|Z_H,X,T)[P(Z_H|W,X,T) - P(Z_H|B,X,T)] + P(a|Z_L,X,T)[P(Z_L|W,X,T) - P(Z_L|B,X,T)]$$

where $T \in \{Start, End\}$. Exploiting the calculations above, we can then derive the properties of the change in difference between approval probabilities at the beginning and the end of the month:

$$[P(a|W,X,End) - P(a|B,X,End)] - [P(a|W,X,Start) - P(a|B,X,Start)] =$$

$$= P(a|Z_H,X,End)[P(Z_H|W,X,End) - P(Z_H|B,X,End)] + P(a|Z_L,X,End)[P(Z_L|W,X,End) - P(Z_L|B,X,End)]$$

$$-P(a|Z_H,X,Start)[P(Z_H|W,X,Start) - P(X_H|B,X,Start)] - P(a|Z_L,X,Start)[P(Z_L|W,X,Start) - P(Z_L|B,X,Start)]$$

$$= [P(a|Z_H, X, Start) - P(a|Z_H, X, Start)][P(Z_H|W, X) - P(Z_H|B, X)] + [P(a|Z_L, X, Start) - P(a|Z_L, X, Start)][P(Z_L|W, X) - P(Z_H|B, X)] = 0$$

where we set $P(Z_H|W, X, Start) = P(Z_H|W, X, End)$ based on the assumption that applications quality does not change over the month, while $P(a|Z_H, X, T) = P(a|W, Z_H, X, T) = P(a|B, Z_H, X, T)$ and $P(a|Z_L, X, T) = P(a|W, Z_L, X, T) = P(a|B, Z_L, X, T)$, based on the no discrimination assumption. Thus, the rejection the null that the counterpart of the equation above in the data is equal to zero, leads to a rejection of the no discrimination assumption, conditionally on not having changes in application quality between the beginning and the end of the month.

A.II Additional Figures and Tables

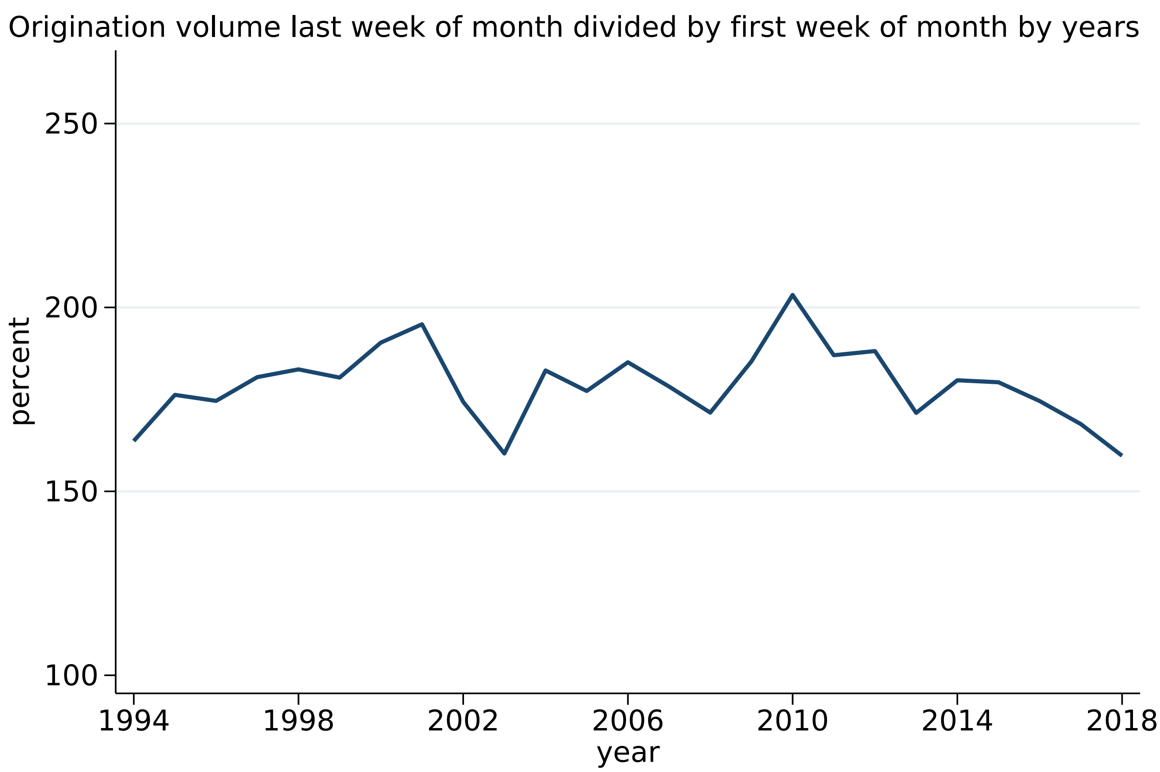


Figure A.1: The figure shows the percentage difference in average mortgage origination volume for the first and last week of the month, for each year over the period from 1994 to 2018. The evidence is based on the HMDA data from January 1994 to December 2018.

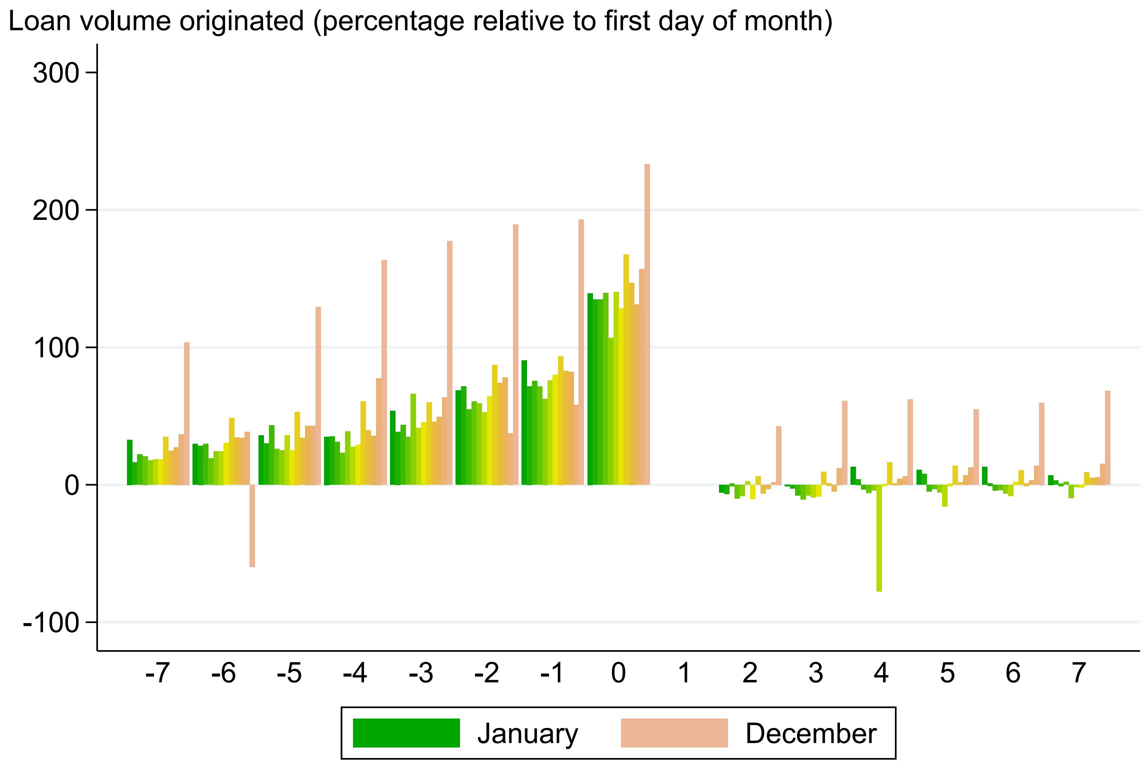


Figure A.2: The figure shows average percentage abnormal daily loan origination volume (measured as number of originations) in the U.S., for the last eight days of the month, and the first seven days of the following month, separately for each calendar month (January to December) over the sample period from January 1994 to December 2018. Abnormal volume is computed with respect to loan origination volume on the first day of the following month. The evidence is based on the HMDA data from January 1994 to December 2018.

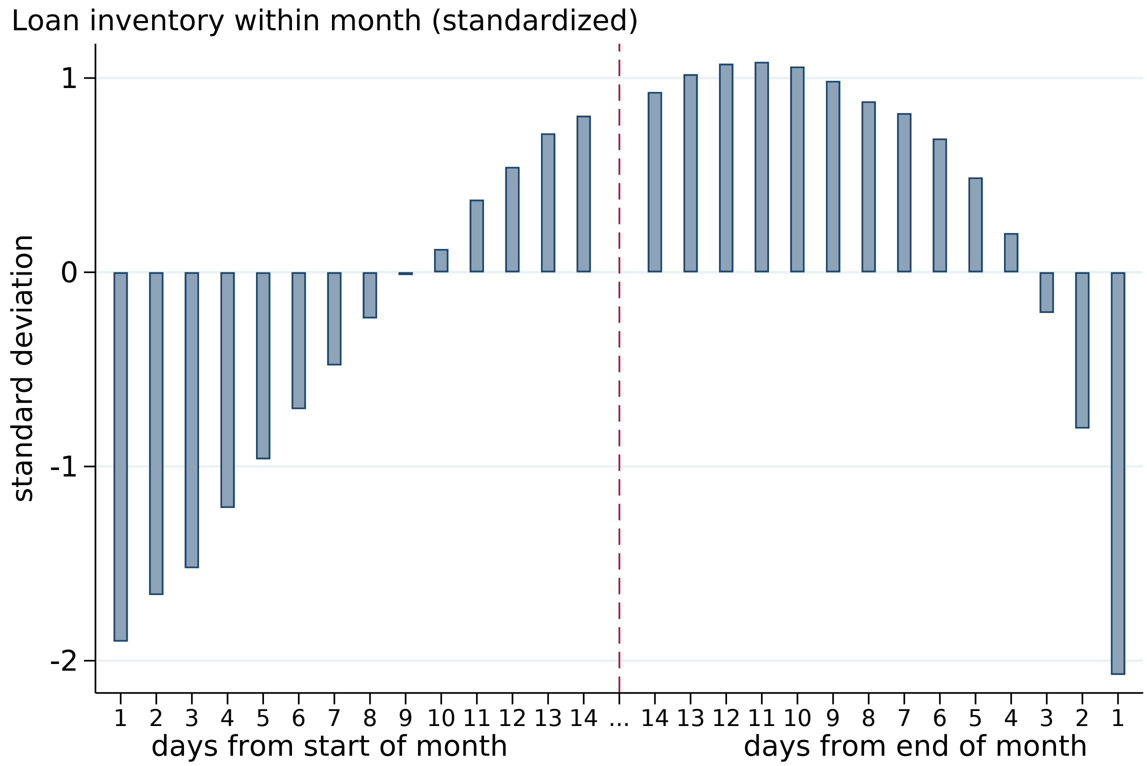
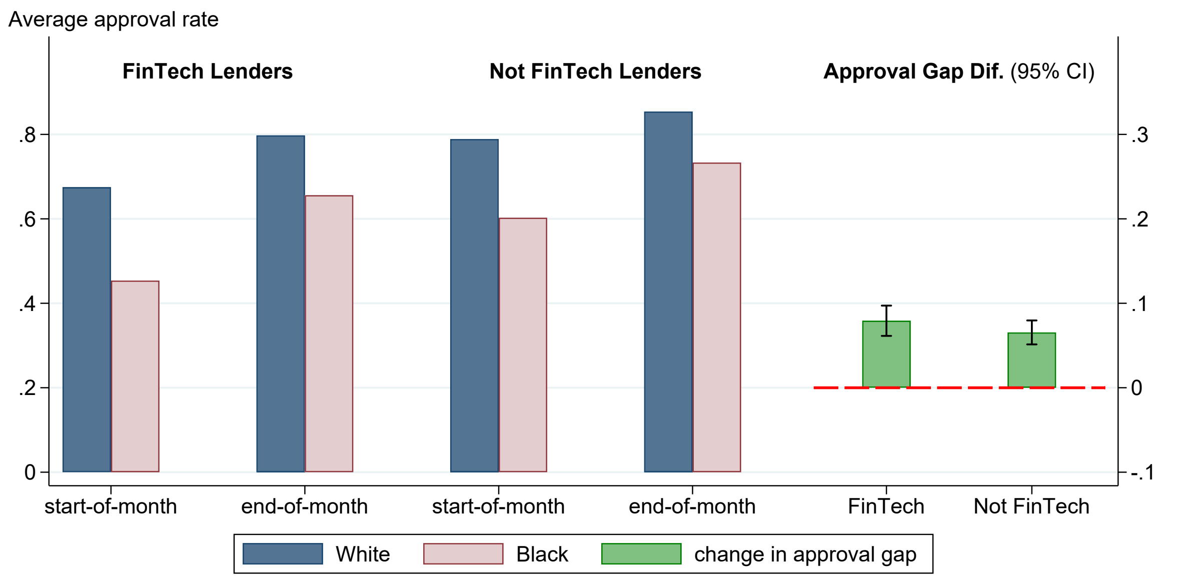
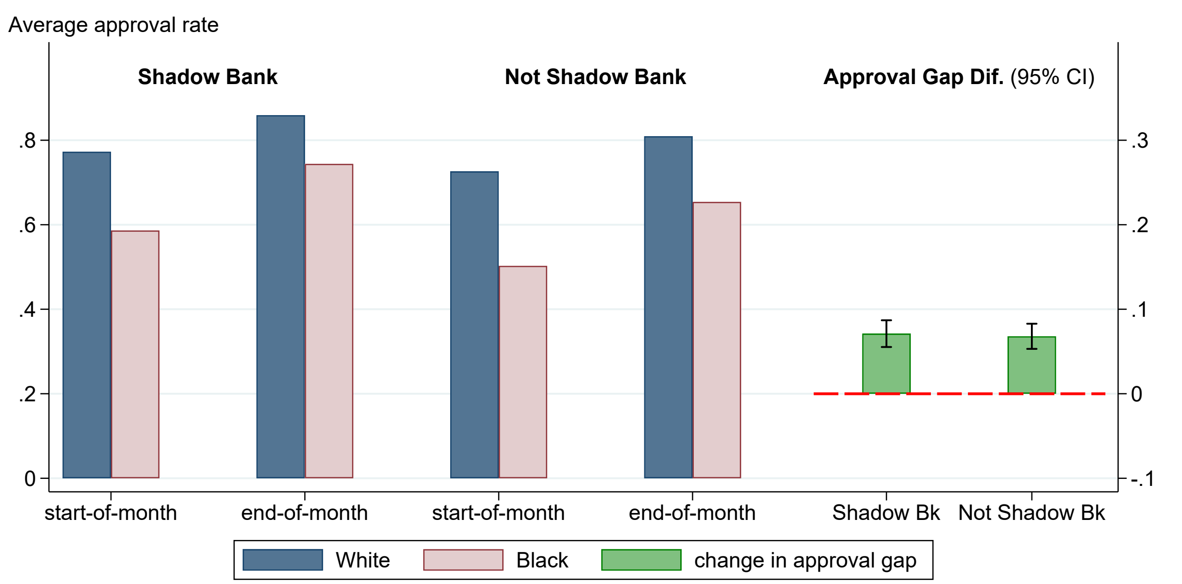


Figure A.3: This figure shows the within-month fluctuation, at the level of the entire United States, in the average number of loan applications in inventory (awaiting a decision by loan officers) by day of the month. Inventory size is standardized to have mean of zero and standard deviation of one. The evidence is based on the HMDA data from January 1994 to December 2018.

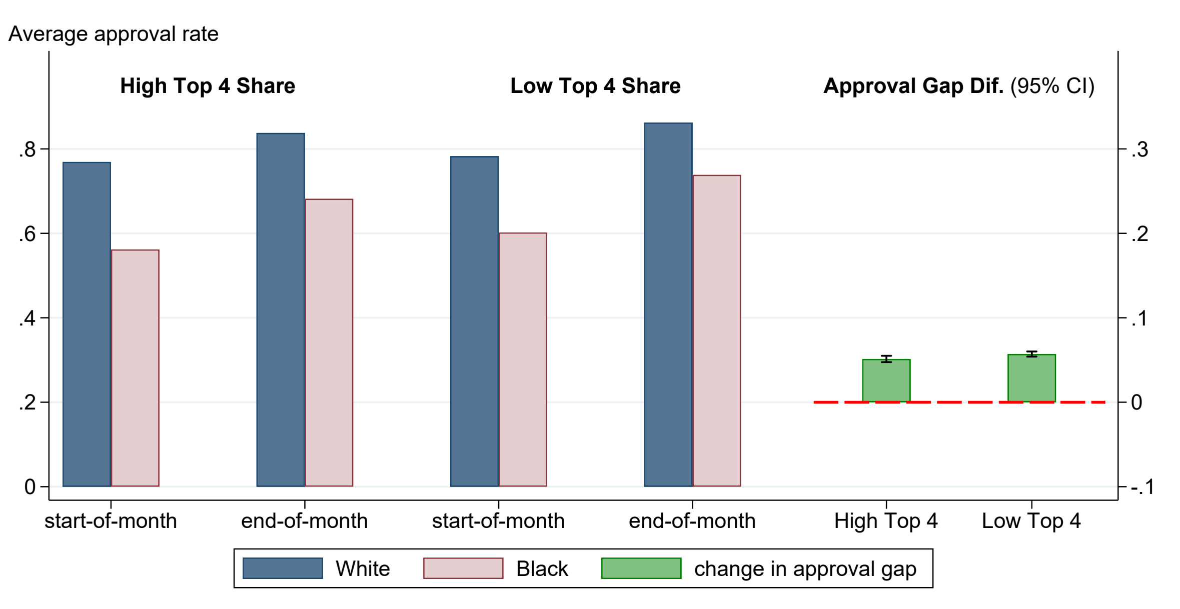


(a) Fintech

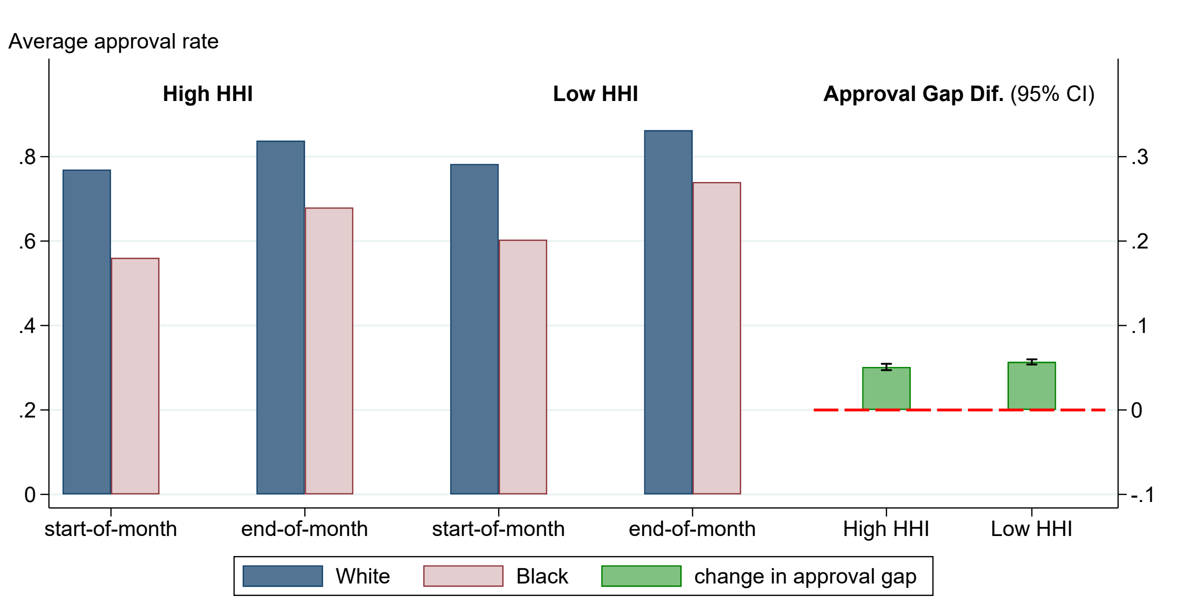


(b) Shadow banks

Figure A.4: Panel (a) of the figure shows on the left the approval rates for White and Black applicants, in the first and last week of the month. The rates are shown separately for Fintech and non-Fintech lenders. The right side of panel (a) show the change in the approval gap, defined as the difference between the approval rate for White applicants and the one for Black applicants, between the last and first week of the month, separately for Fintech and non-Fintech lenders. Panel (b) of the figure shows on the left the approval rates, and on the right the change in the approval gap, for shadow banks and non-shadow banks (depository institutions). Estimates in this figure are based on a 5% random sample of the HMDA data from 2014 to 2018.



(a) Top 4 Share



(b) HHI

Figure A.5: Panel (a) of the figure shows on the left the approval rates for White and Black applicants, in the first and last week of the month. The rates are shown separately for counties in which the share of the top 4 lenders is above and below the median (in the year). The right side of panel (a) shows the approval gap, defined as the difference between the approval rate for White applicants and the one for Black applicants, between the last and first week of the month, separately for counties with above and below median top 4 share. Panel (b) of the figure shows on the left the approval rates, and on the right the change in the approval gap, for counties with Herfindahl-Hirschman Index (HHI) above and below the median (in the year). Estimates in this figure are based on a 5% random sample of the HMDA data from 1994 to 2018.

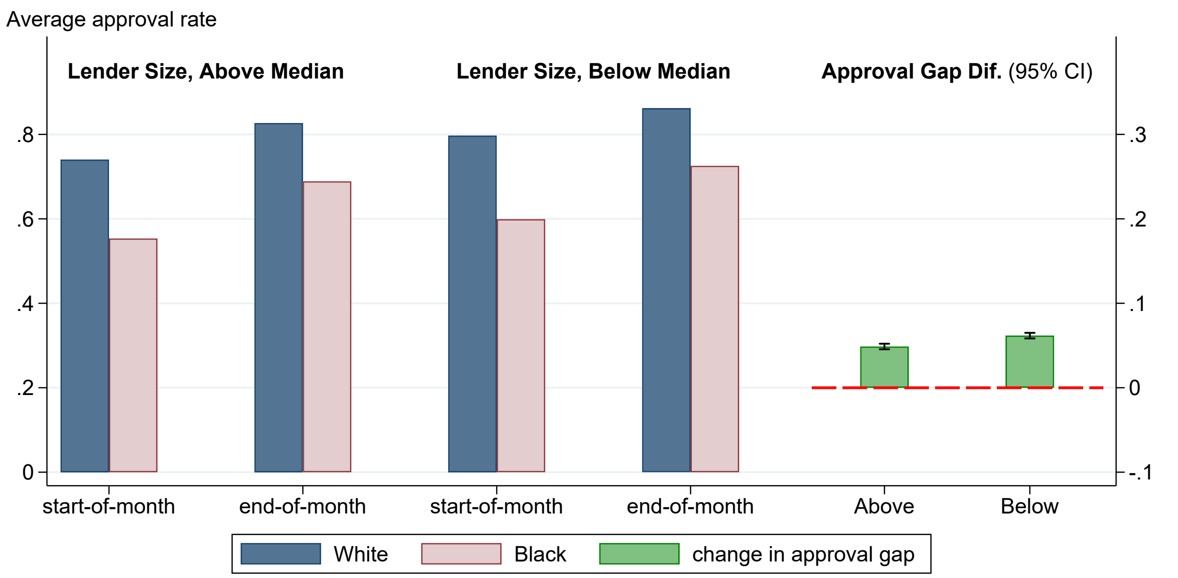


Figure A.6: The figure shows on the left the approval rates for White and Black applicants, in the first and last week of the month. The rates are shown separately for lenders above and below median size (for each year across the United States), measured as the total volume of loans originated per year. The right side of the figure shows the change in the approval gap, defined as the difference between the approval rate for White applicants and the one for Black applicants, between the last and first week of the month, separately for lenders above and below median size. Estimates in this figure are based on a 5% random sample of the HMDA data from 1994 to 2018.

	U.S.-Level														
	(1) White	(2) Black	(3) Other	(4) White Inc Q1	(5) White Inc Q2	(6) White Inc Q3	(7) White Inc Q4	(8) Black Inc Q1	(9) Black Inc Q2	(10) Black Inc Q3	(11) Black Inc Q4	(12) Other Inc Q1	(13) Other Inc Q2	(14) Other Inc Q3	(15) Other Inc Q4
$lastweek$	0.30***	0.38***	0.31***	0.31***	0.31***	0.29***	0.26***	0.35***	0.38***	0.37***	0.33***	0.31***	0.32***	0.30***	0.27***
	(0.012)	(0.013)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)	(0.013)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
$firstweek$	-0.15***	-0.19***	-0.15***	-0.15***	-0.16***	-0.16***	-0.13***	-0.16***	-0.18***	-0.17***	-0.16***	-0.16***	-0.17***	-0.16***	-0.13***
	(0.012)	(0.013)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)	(0.013)	(0.013)	(0.012)	(0.012)	(0.012)	(0.012)
Holiday FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Day-of-Week FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Month-Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
$last - first$	0.45	0.56	0.46	0.46	0.47	0.45	0.39	0.51	0.55	0.54	0.48	0.47	0.48	0.46	0.40
$p - value$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
N	9131	9131	9131	9131	9131	9131	9131	9131	9131	9131	9131	9131	9131	9131	9131
r2	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.94	0.94	0.94	0.94	0.95	0.95	0.95	0.95

Table A.1: The table reports regression estimates of the abnormal loan originations volume in the last and first week of the month (see equation 6) for borrowers of different race and income level. The first three columns report results for White, Black and other race applicants, while the remaining columns show, within each of the three ethnicity groups, breakdown based on income: first, second, third and fourth quartile of income within the county of the loan application (*Inc Q1*, *Inc Q2*, *Inc Q3* and *Inc Q4*). $lastweek$ and $firstweek$ are dummies equal to one, respectively, in the first and last week of the month. The dependent variable is the log of the number of originations for each group, at the U.S. level. Standard errors are clustered by lender and year. Estimates are based on the sample of HMDA mortgage originations from 1994 to 2018.

	(1) All Approvals	(2) Male	(3) White	(4) AFA	(5) Other Race	(6) Income > Med	(7) Income $\leq$ Med	(8) Income Q1	(9) Income Q2	(10) Income Q3	(11) Income Q4	(12) Loan > Med	(13) Loan $\leq$ Med
$lastweek$	0.024***	0.023***	0.021***	0.049***	0.023***	0.019***	0.030***	0.035***	0.028***	0.022***	0.018***	0.026***	0.022***
	(0.0012)	(0.0012)	(0.0012)	(0.0020)	(0.0011)	(0.0012)	(0.0014)	(0.0016)	(0.0014)	(0.0012)	(0.0012)	(0.0015)	(0.0012)
$firstweek$	-0.013***	-0.013***	-0.013***	-0.020***	-0.013***	-0.011***	-0.017***	-0.018***	-0.016***	-0.014***	-0.010***	-0.015***	-0.013***
	(0.0012)	(0.0013)	(0.0013)	(0.0023)	(0.0012)	(0.0012)	(0.0014)	(0.0016)	(0.0015)	(0.0012)	(0.0012)	(0.0012)	(0.0014)
CRA month	-0.0012	-0.00069	-0.000057	0.0023	-0.0014	-0.0012	-0.00036	-0.000051	-0.00031	-0.00090	-0.000022	-0.00070	-0.0016
	(0.0011)	(0.00093)	(0.00081)	(0.0022)	(0.0011)	(0.0012)	(0.0017)	(0.0020)	(0.0015)	(0.0014)	(0.0010)	(0.00068)	(0.0015)
CRA month(+1)	-0.00032	-0.00043	0.00056	0.0032	-0.00028	-0.00014	-0.000019	0.000085	-0.00029	-0.00022	0.00020	0.00014	-0.00059
	(0.0013)	(0.0011)	(0.00095)	(0.0023)	(0.0014)	(0.0010)	(0.0013)	(0.0016)	(0.0014)	(0.0014)	(0.0010)	(0.0013)	(0.0013)
CRA month(+2)	-0.00049	-0.00042	-0.00050	-0.0013	-0.00079	-0.00018	-0.00098	-0.0019	-0.00020	-0.00090	-0.00034	0.000098	-0.0014
	(0.0013)	(0.0012)	(0.0012)	(0.0028)	(0.0012)	(0.0014)	(0.0016)	(0.0019)	(0.0014)	(0.0020)	(0.0012)	(0.0010)	(0.0017)
CRA month(+3)	-0.0023*	-0.0021	-0.0018	0.00039	-0.0020	-0.0018*	-0.0017	0.0011	-0.0030	-0.00064	-0.0011**	-0.00067	-0.0016
	(0.0013)	(0.0013)	(0.0011)	(0.0024)	(0.0013)	(0.0010)	(0.0020)	(0.0024)	(0.0018)	(0.0017)	(0.00049)	(0.0011)	(0.0019)
CRA month(-1)	-0.0020**	-0.0016	-0.0012*	-0.0022	-0.0017**	-0.0013	-0.0020*	-0.0019	-0.0019	-0.0014	-0.0015**	-0.0018*	-0.0020*
	(0.00071)	(0.00098)	(0.00057)	(0.0028)	(0.00069)	(0.00080)	(0.0010)	(0.0014)	(0.0018)	(0.0011)	(0.00064)	(0.00098)	(0.00096)
CRA month(-2)	-0.0011	-0.0015*	-0.00075	0.0021	-0.0010	-0.00099	-0.00059	0.00074	-0.0015	-0.00092	-0.00030	-0.00068	-0.0015
	(0.00088)	(0.00083)	(0.00081)	(0.0028)	(0.00090)	(0.00100)	(0.0014)	(0.0017)	(0.0019)	(0.0013)	(0.0010)	(0.0011)	(0.0013)
CRA month(-3)	-0.00074	-0.0010	-0.00076	-0.0013	-0.00063	-0.00065	-0.00088	-0.00062	-0.0021	-0.0019	0.00040	0.00027	-0.0014
	(0.0010)	(0.00098)	(0.00091)	(0.0025)	(0.0011)	(0.00085)	(0.0016)	(0.0017)	(0.0018)	(0.0012)	(0.0011)	(0.00065)	(0.0012)
Holiday FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Day-of-Week FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Month-Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Lender FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
N	2216169	2116758	2122995	823391	2205077	2020223	1976495	1711880	1694957	1717338	1779768	1878114	2049297
r2	0.25	0.22	0.22	0.16	0.25	0.22	0.21	0.19	0.19	0.19	0.20	0.22	0.22

Table A.2: Table reports regression estimates of abnormal approval rates in the last and first week of the month. The dependent variable is the approval rate (approval decisions over approval and denial decisions) per day and lender. Column (1) reports results for all applicants, while the other columns report results for subgroup of applicants based on sex, race, income and loan amount. *Income* $\leq$ *Med* and *Loan* $\leq$ *Med* are income and loan amount smaller or equal than the median in the county and year. *Income Q1*, *Income Q2*, *Income Q3* and *Income Q4* are quartiles of the income distribution in each county and year. $lastweek$ and $firstweek$ are dummies equal to one, respectively, in the first and last week of the month. We include controls accounting for whether the lender is subject to a CRA examination in the current month, or the previous or next three months. Estimates are based on the sample of HMDA mortgage applications and originations from 1994 to 2018.

	(1) approval All	(2) approval All	(3) approval New Purchases	(4) approval Refinancing	(5) approval Conforming	(6) approval All	(7) approval
$lastweek$	0.043***	0.043***	0.035***	0.051***	0.043***	0.043***	
	(0.0030)	(0.0030)	(0.0021)	(0.0049)	(0.0032)	(0.0031)	
$firstweek$	-0.020***	-0.020***	-0.014***	-0.025***	-0.020***	-0.019***	
	(0.0017)	(0.0017)	(0.0011)	(0.0026)	(0.0018)	(0.0017)	
$black$		-0.067***	-0.070***	-0.056***	-0.067***	-0.068***	-0.064***
		(0.0043)	(0.0036)	(0.0059)	(0.0043)	(0.0044)	(0.0043)
$black \times lastweek$	0.027***	0.027***	0.028***	0.025***	0.026***	0.028***	
	(0.0021)	(0.0021)	(0.0018)	(0.0041)	(0.0022)	(0.0021)	
$black \times firstweek$	-0.0074***	-0.0073***	-0.0063***	-0.0096***	-0.0067***	-0.0072***	
	(0.0015)	(0.0015)	(0.0015)	(0.0024)	(0.0015)	(0.0015)	
$female$		-0.017***					
		(0.0025)					
$lastday$							0.081***
							(0.0068)
$firstday$							-0.020***
							(0.0031)
$black \times lastday$							0.046***
							(0.0039)
$black \times firstday$							-0.0069**
							(0.0033)
log(income)	0.071***	0.069***	0.058***	0.068***	0.071***	0.071***	0.071***
	(0.0035)	(0.0034)	(0.0038)	(0.0038)	(0.0034)	(0.0036)	(0.0036)
log(loan amount)	0.0076***	0.0073***	0.0031	-0.010*	0.0089***	0.0077***	0.0079***
	(0.0023)	(0.0023)	(0.0021)	(0.0050)	(0.0024)	(0.0023)	(0.0023)
is conforming	0.090***	0.090***	0.058***	0.084***		0.091***	0.091***
	(0.0054)	(0.0054)	(0.0038)	(0.0056)		(0.0055)	(0.0055)
$black$-Year	YES	NO	NO	NO	NO	NO	NO
Loan-Level Controls	YES	YES	YES	YES	YES	YES	YES
Holiday FE	YES	YES	YES	YES	YES	YES	YES
Day-of-Week FE	YES	YES	YES	YES	YES	YES	YES
Lender FE	YES	YES	YES	YES	YES	YES	YES
Month-Year-County	YES	YES	YES	YES	YES	YES	YES
Month-Year-Lender	YES	YES	YES	YES	YES	YES	YES
$last - first$	0.063	0.063	0.049	0.076	0.063	0.062	0.10
$p - value$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
$last - first\ (black)$	0.097	0.097	0.084	0.11	0.096	0.097	0.15
$p - value\ (black)$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
$last - first\ (black - other)$	0.034	0.034	0.035	0.034	0.033	0.035	0.053
$p - value\ (black - other)$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
N	17898971	17898971	7046904	8705784	16392963	17893870	17893870
r2	0.32	0.32	0.33	0.35	0.32	0.32	0.32

Table A.3: The table reports individual loan-level regression estimates of abnormal approval rates in the last and first week of the month (see equation 9). The dependent variable is a dummy that takes value 1 if a loan application is approved and 0 if it is denied. For all columns the regression specification includes all the controls used in column 6 of Table 4. In column (3) the sample is restricting to new mortgages issued for home purchases, in column (4) it is restricted to refinanced mortgages, and in column (5) to conforming mortgages. Columns (6) and (7) redefine month fixed effects so that a month breaks at the 15th day. This helps comparing differences in approval rates in weeks or days immediately adjacent to the calendar month cutoff. $lastweek$ and $firstweek$ are dummies equal to one, respectively, if the decision on the application is taken in the first and last week of the month, while $lastday$ and $firstday$ are dummies equal to one, respectively, if the decision on the application is taken in the first and last day of the month. $black$ is a dummy equal to one for Black applicants and $female$ is a dummy equal to one for female applicants. The table also reports estimates of the difference between the coefficients for the dummies $lastweek$ and $firstweek$ ($lastday$ and $firstday$), and for the difference of the interaction coefficients for $black$ applicants, along with the *p-value* of tests of the null that each difference is equal to 0. Standard errors are clustered by lender and year. Estimates are based on a 5% random sample of the HMDA data from 1994 to 2018.

	(1) Time to Origination	(2) Time to Origination	(3) Time to Denial	(4) Time to Action
$lastweek$	-0.49***			
	(0.15)			
$firstweek$	-0.55***			
	(0.13)			
$black$		3.08***	-0.85***	0.76**
		(0.39)	(0.16)	(0.29)
$lastweek$		-0.51***	0.72***	0.13
		(0.15)	(0.12)	(0.24)
$firstweek$		-0.54***	0.73***	0.53
		(0.13)	(0.16)	(0.49)
$black \times lastweek$		0.26*	0.13	0.82***
		(0.13)	(0.13)	(0.14)
$black \times firstweek$		-0.26**	-0.063	-0.052
		(0.11)	(0.15)	(0.100)
log(income)	-1.01***	-0.94***	1.35***	0.95***
	(0.17)	(0.17)	(0.12)	(0.15)
log(loan amount)	5.38***	5.41***	3.16***	4.56***
	(0.31)	(0.32)	(0.37)	(0.31)
is conforming	1.08**	1.10**	1.74***	1.54***
	(0.40)	(0.41)	(0.32)	(0.35)
$last - first$	0.0590	0.0240	-0.0083	-0.4000
$p - value$	0.7900	0.9100	0.9700	0.3300
$last - first\ (black)$		0.5400	0.1800	0.4800
$p - value\ (black)$		0.02800	0.2900	0.3000
$last - first\ (black - other)$		0.5200	0.1900	0.8800
$p - value\ (black - other)$		0.0031	0.2500	0.0000
N	11924971	11924971	3915189	20683438
r2	0.29	0.29	0.40	0.25

Table A.4: The table reports individual loan-level regression estimates of abnormal mortgage processing time in the last and first week of the month. We use the same specification as in equation 9. In column (1), the sample is restricted only to applications from Black applicants, while in all other columns the sample includes all applicants. In columns (1) and (2), the sample is restricted to originated loans, and the dependent variable is the time to origination, defined as the number of days between the application date and the origination date. In column (3), the sample is restricted to denied applications, and the dependent variable is the time to denial. In column (4), the sample includes both approved and denied loans, and the dependent variable is time to action (time to approval). The dependent variable is a dummy that takes value 1 if a loan application is approved and 0 if it is denied. $lastweek$ and $firstweek$ are dummies equal to one, respectively, if the decision on the application is taken in the first and last week of the month. $black$ is a dummy equal to one for Black applicants. The table also reports estimates of the difference between the coefficients for the dummies $lastweek$ and $firstweek$, and for the difference of the interaction coefficients for $black$ applicants, along with the *p-value* of tests of the null that each difference is equal to 0. Standard errors are clustered by lender and year. Estimates are based on a 5% random sample of the HMDA data from 1994 to 2018.

	(1) 5-Year Termination	(2) 5-Year Termination FICO $<$ 660	(3) 5-Year Termination LTV $>$ 80%	(4) 5-Year Termination Low Docs
$lastweek$	-0.0026	-0.00060	-0.0041*	0.0023
	(0.0022)	(0.0012)	(0.0020)	(0.0038)
$firstweek$	0.0010	0.00032	0.0018	-0.00028
	(0.0014)	(0.0020)	(0.0016)	(0.0017)
$black$	-0.054***	-0.038***	-0.061***	-0.044***
	(0.0083)	(0.0063)	(0.0091)	(0.0086)
$black \times lastweek$	-0.0024*	-0.0043***	-0.0014	-0.0088**
	(0.0014)	(0.0012)	(0.0015)	(0.0039)
$black \times firstweek$	0.0018	0.0013	0.0033	0.0036**
	(0.0018)	(0.0019)	(0.0021)	(0.0014)
LTV	-0.0015***	-0.0011***	-0.0029***	-0.0016***
	(0.00043)	(0.00031)	(0.00061)	(0.00050)
log(income)	0.025***	0.0018	0.028***	0.023**
	(0.0073)	(0.011)	(0.0080)	(0.0086)
log(loan amount)	0.096***	0.068***	0.12***	0.11***
	(0.018)	(0.010)	(0.016)	(0.021)
is conforming	0.087***	0.080***	0.090***	0.13***
	(0.027)	(0.011)	(0.018)	(0.035)
FICO 620:659	0.016	0.024*	0.011	0.0042
	(0.013)	(0.012)	(0.012)	(0.0059)
FICO 660:719	0.028		0.030	0.010
	(0.020)		(0.020)	(0.0080)
FICO 720:759	0.039		0.044*	0.034**
	(0.025)		(0.024)	(0.012)
FICO 760:799	0.048		0.051*	0.067***
	(0.031)		(0.028)	(0.017)
FICO $\geq$ 800	0.032		0.029	0.066***
	(0.032)		(0.029)	(0.018)
$last - first$	-0.0036	-0.00092	-0.0059	0.0026
$p - value$	0.2900	0.7700	0.0780	0.6200
$last - first\ (black)$	-0.0078	-0.0066	-0.0110	-0.0099
$p - value\ (black)$	0.1100	0.0440	0.0067	0.1200
$last - first\ (black - other)$	-0.0042	-0.0057	-0.0047	-0.0120
$p - value\ (black - other)$	0.1200	0.0410	0.1000	0.0047
N	20732913	3729582	6606008	5617655
r2	0.22	0.28	0.25	0.32

Table A.5: The table reports regression estimates of the difference in performance between mortgages originated in the last and first week of the month. The dependent variable is a dummy equal to one for mortgage that were terminated (due to default or refinancing) within 5 years after origination. In column (2), the sample is restricted to subprime loans (FICO < 660). In column (3) the sample is restricted to high loan-to-value loans (LTV$> 80\%$), and in column (4) to loans with low documentation. $lastweek$ and $firstweek$ are dummies equal to one in the first and last week of the month. $black$ is a dummy equal to one for Black applicants. The table also reports estimates of the difference between the coefficients for the dummies $lastweek$ and $firstweek$, and for the difference of the interaction coefficients for $black$ applicants, along with their *p-value*s. Standard errors are clustered by lender and year. Estimates are based on the merged sample of HMDA and Black Knight McDash data from 1994 to 2018.