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Temporal Focal Points and Economic Outcomes: Evidence from U.S. Mortgage Lending*

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Abstract

Temporal focal points shape high-stakes economic outcomes. We investigate this proposition in the U.S. mortgage market by documenting novel within-month patterns in lending. Using confidential Home Mortgage Disclosure Act (HMDA) data, we show that applications arrive smoothly throughout the month, yet approximately half of all originations occur in the final week. The Black approval gap, 2.4 percentage points unexplained at the start of the month, narrows to zero by month's end. Underperforming loan officers and high-turnover lending institutions amplify this convergence. Demand-side factors, such as borrower financial constraints, also increase end-of-month volume, but the sensitivity does not vary meaningfully by applicant group.

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1 Introduction

Schelling (1960) famously introduced the concept of focal points—salient cues that enable coordination when parties cannot communicate. He illustrated this with the intuitive example of two strangers selecting "noon at the information booth at Grand Central Station" as a meeting spot; its cultural prominence makes it an obvious default choice. In economic settings, focal points guide behavior in notable ways. For instance, Pope et al. (2015) show that house prices cluster at round numbers like multiples of $50,000, suggesting that certain numerals become natural anchoring spots in bargaining. These findings underscore a central behavioral insight: salient features, whether spatial or numeric, can anchor decision-making and guide high-stakes outcomes.

In this paper, we extend that insight to the temporal domain, showing that discrete calendar intervals function as powerful *temporal focal points*. Such focal points are pervasive in economic life. For example, federal budgets reset at calendar year-end, which leads to wasteful spending (Liebman and Mahoney, 2017). Fiscal year-end triggers seasonal fluctuations in corporate behavior (Oyer, 1998). Yet the influence of these temporal focal points remains surprisingly understudied in empirical settings where individuals make high-stakes financial decisions.

This paper provides evidence that temporal focal points can shape personal finance outcomes in ways that amplify or attenuate disparities across groups, particularly in contexts where discretion and incentives intersect. We turn to U.S. mortgage markets, a setting of immense economic importance for American households and the broader economy.[1] Mortgages represent more than $12 trillion in household debt and home equity accounts for over $35 trillion, making homeownership the single largest asset for most families. We show that discrete calendar boundaries—specifically, the end of the month—profoundly influence both borrower behavior and lender decision-making.

[1]Homeownership plays a vital role in household wealth accumulation (e.g., Kermani and Wong, 2021; Eldemire et al., 2022), affects health outcomes (Christensen et al., 2020), and transmits macroeconomic shocks into economic activity (Stroebel and Vavra, 2019).

Using high-frequency confidential HMDA data, we uncover a novel and consistent within-month pattern: roughly half of all mortgage originations occur in the final week of the month. This bunching arises despite mortgage applications arriving at a steady pace throughout the month. The timing aligns with coordination norms (a la Schelling, 1960), as housing transitions often coincide with the end of monthly lease cycles. Yet this concentration is not merely a benign reshuffling of originations across the calendar. Instead, we show that month-end bunching has economically meaningful consequences for the allocation of credit.

In particular, we document that the Black mortgage approval gap, which stands at 2.4 percentage points at the start of the month, converges to approximately zero by month's end. The economic magnitude is sizable: a 2.4 percentage point shift in approval rates is equivalent to improving applicants' FICO scores by approximately 25 points. Critically, this within-month convergence in approval rates is not driven by observable changes in borrower credit quality, automated underwriting recommendations, or lender-level fixed effects. Moreover, loans originated to Black applicants in the last week of the month are relatively *less likely* to default, suggesting a significant misallocation of credit within the month. These findings suggest that the timing of a loan application within a month materially influences outcomes, and that temporal focal points can mitigate disparities that otherwise persist.

The paper proceeds to test explanations for the month-end decline in the Black approval gap. The explanations can be broadly grouped into "supply-side" determinants relating to lending institutions and individual loan officers or "demand-side" determinants such as borrower preferences and financial constraints.

Supply-Side Responses to Month-End

Starting with supply-side mechanisms, our findings point towards loan officer employment incentives helping explain the month-end Black approval gap reduction. Though private employment contracts for loan officers are not widely available to researchers, it is generally well-known that loan officers—crucial gate-

keepers in the loan application process—often have compensation incentives and job retention hurdles that are evaluated at temporal focal points, such as calendar month ends.[2] Thus, loan officer employment contracts have calendar time nonlinearities that heighten employment pressures around focal points.

We develop empirical proxies for loan officer incentive pressure to explore the mechanism. First, loan officers with a low volume of originations in prior months have a heightened risk of employment termination if under-performance persists. The within-month decline in the Black approval gap is 25% to 35% larger (3 to 3.3 pp versus 2.4 pp) for loan officers in the bottom half of prior-month lending within their firm. These tests include loan officer fixed effects, suggesting that they capture a time-varying risk to loan officer employment rather than cross-sectional differences in their ability.

Second, we follow the approach of Jenter and Lewellen (2020) to measure lenders' performance-induced employee-turnover sensitivity. Essentially, firms less likely to retain underperforming loan officers are more likely to have binding employment incentives. The within-month decline in the Black approval gap is 25% to 35% larger (3pp to 3.3pp compared with the baseline 2.4pp) in firms that are in the top half of employee-turnover sensitivity, magnitudes similar to our tests on individual loan officer incentives. Notably, the Jenter and Lewellen (2020) firm-level measures and the preceding time-varying measure of loan officer underperformance are independent, but both point to the crucial role of employment incentives in mitigating the Black approval gap.

On the other hand, we find no evidence for other supply-side mechanisms, such as compliance with regulatory incentives. The results are not driven by time-varying bank examinations for the Community Reinvestment Act (CRA). Also, our results are robust to lender and loan officer fixed effects. Therefore, unobservable differences across institutions or time-invariant differences in loan officer ability

[2]Though it is not feasible for researchers to obtain a large sample of employment contracts from private lending institutions in the U.S., Section 4 describes the available anecdotal evidence and evidence from prior research on loan officer employment contracts.

cannot explain the month-end increase in lending that disproportionately benefits Black applicants.

Demand-Side Responses to Month-End

Next, we explore demand-side explanations for the increase in originations—particular to Black applicants—at the month-end focal point. First, mortgage loan demand does not exhibit within-month trends; the volume of applications and contractual agreements between borrowers and sellers are constant within the month, regardless of race. This suggests that application volumes cannot explain the within-month origination trends. It also indicates that the month-end increase in originations and reduced Black approval gap are explained by events occurring after sale terms are agreed upon and during the mortgage approval process.

Thus, the most plausible explanation that would stem from applicants' demand is that applicants delay closing until month-end to minimize closing costs. Closing costs can increase with the amount of pre-paid interest amortized over the partial month of ownership. Moreover, the explanation that applicants delay closing to month-end highlights a measurement shortcoming of the HMDA data; it contains closing dates but not the date of lenders' approval decisions, which occur before closing.

To address the channel of delayed closing, we estimate the maximum reduction in pre-paid interest from closing at month-end for each loan in our sample, using market interest rates and the mortgage loan terms. Indeed, applicants with larger expected pre-paid interest expenses are more likely to close at month-end, which helps explain why originations increase over the month. However, Black applicants are not more likely to close at month-end than other borrowers in response to pre-paid interest expenses, which suggests that Black applicants do not have stronger financial preferences to close at month-end. Therefore, though applicants' financial incentives help explain origination volume over the month, they struggle to explain the reduced Black approval gap.

To the extent that pre-paid interest expenses do not reflect all of the financial benefits of month-end closing, we also consider broader definitions of applicant

financial constraints. We find that different measures of financial constraints have opposing effects on the Black approval gap reduction, suggesting that financial constraints do not offer a compelling explanation. The Black approval gap reduction is larger for high loan-to-value applications, but smaller for subprime credit applicants and applicants with less income.

One more plausible effect of financial constraints is that new homeowners must simultaneously cover rent and mortgage payments or pay for transition housing. These applicants might time housing transitions at precisely month-end. Contrary to this explanation, the Black approval gap also reduces for refinancing applications, which do not involve a housing transition.

Estimating Magnitudes

Our findings suggest that loan officers' employment incentives are crucial to improving the Black approval gap at month-end focal points. And, that demand-side rationales, while helping explain month-end originations for all borrowers, struggle to explain the differential outcomes for Black applicants. Nonetheless, demand-side confounds could make it challenging to pinpoint the magnitude of the effect of loan officer employment incentives on Black applicants' approvals. Therefore, we estimate bounds on the share of the reduction in the Black approval gap that demand-side effects can explain.

Our first approach is to use the empirical bounding exercise proposed by Oster (2019). The approach calculates a lower bound on the point estimate of a coefficient in a regression model that hypothetically includes the universe of possible control variables, including variables that the researcher does not observe. The Oster (2019) approach allows us to estimate the size of the coefficient on the Black approval gap reduction if we could control for the universe of relevant demand variables.[3] We find that the estimate on the month-end Black interaction coefficient is highly stable under reasonable assumptions about the scope for omitted variables. The coefficient would reduce, in relative terms, by approximately

[3]The primary assumption in Oster (2019) is that the relation between unobservables and the treatment variable has to be proportional to the relation between observable controls and the treatment variable.

8% from our main regression estimates, far from being equal to zero. Even if we assume an exceptionally large scope for omitted variable bias, the lower bound on the coefficient is 1.3pp. This suggests that demand-side factors explain less than half of the 2.4pp within-month improvement in the Black approval gap, and the majority of the effect can be attributed to supply-side factors.

Our second approach to bounding the effects of supply-side factors is to isolate a subgroup of applicants who are insensitive to the financial incentives to close at month-end. Intuitively, the estimates of the Black approval gap represent a pure measure of supply-driven effects if only applicants who are indifferent to closing dates, namely financially unconstrained applicants, are included in the sample.

To bound the supply-driven effects of the month-end approval gap, we use the Specification Curve analysis of Simonsohn et al. (2020) to display a range of coefficient estimates for plausible definitions of financially unconstrained borrowers. The coefficient estimates in the specification curve span the feasible set of financial constraints. The month-end approval gap is never less than 1.8pp, suggesting that supply-driven effects can explain at least 1.8/2.4pp = 75% of the 2.4pp Black approval gap.

Together with the preceding Oster (2019) bounds, demand-driven factors explain less than half of the Black approval gap reduction and are likely closer to one-quarter. This leaves much scope for supply-side factors to contribute to the Black approval gap reduction.

Importance of Loan Officers and Origination Frictions

Because the volume of applications and contract agreement dates is constant within a month, the Black approval gap reduction is likely explained by occurrences while completing the approval process, with the month-end a crucial focal point for finalizing the loan origination. Loan officers help applicants navigate the approval process. And, loan officers who have binding employment incentives have heightened pressure to help borrowers get approved. We evaluate the

importance of loan officers for loan outcomes and the extent to which borrowers experience frictions during the approval process.

First, we evaluate the importance of loan officers in the approval process by estimating how much variation they explain in loan decisions. While our regressions employ loan officer fixed effects to account for unobserved differences in loan officer attributes, simply including loan officer fixed effects substantially increases the regression R^2 above that of controlling for underwriting variables. Moreover, loan officer fixed effects have roughly double the incremental explanatory power than lender fixed effects alone. This suggests that individual decision-makers within financial institutions are crucial to lending decisions. Second, Black applicants are more likely to be originated as loan officers' final loans within a month, regardless of calendar date. This highlights the fact that loans to Black applicants are more likely to be closed later than other loans within the pipelines of individual loan officers.

Furthermore, even though the HMDA data does not offer a detailed account of each step of the approval process from application to origination, we find anecdotal survey evidence from the National Survey of Mortgage Originations (NSMO) on the frictions that borrowers experience during origination. Indeed, Black applicants face substantially more issues and delays during the origination process, even after controlling for underwriting variables. Black applicants are more likely to need loan paperwork re-filed, to have property assessments revised, and to resolve credit errors. Because such problems require loan officers to exert additional effort (and the resolution of these issues is uncertain), this helps explain why Black applicants have better outcomes when loan officer employment incentives bind. As such, this survey evidence helps clarify the supply-side mechanism for the Black approval gap.

Black applicants are also more likely to face unexpected circumstances before closing. They are more likely to report that closing did not occur as expected, that they had to re-disclose their credit score and files on the day of closing, that there were unexpected terms, and that they had to file pre- or post-dated documents. These results show that Black applicants experience more barriers in the origina-

tion process that result in delays. Loan officers are needed to help resolve these issues, which could push closing dates to month-end and help explain the longer processing times for Black applicants (Wei and Zhao, 2022).

Related Literature

A useful organizing implication from the behavioral literature is that shared benchmarks, i.e., focal points, make certain outcomes salient and thereby coordinate beliefs and actions. A rich theoretical literature formalizes how such benchmarks operate in decision-making tasks of individual agents.[4] The empirical literature generally supports these theoretical models by documenting reference dependence in a range of tasks: bunching at focal numerals and signals in transactions (Beggs and Graddy, 2009), wage and effort responses around target pay (Mas, 2006), and goal-gradient behavior in settings such as competitive sports (Allen et al., 2017; Pope and Schweitzer, 2011). Related to our study, temporal landmarks operate as reference resets: "fresh start" moments (e.g., new weeks or months) spur aspirational actions, and engagement jumps at on-the-hour boundaries (see e.g., Dai et al., 2014; Huang et al., 2024). We build on this foundation by treating calendar time as a temporal focal point that shapes both demand and supply in a way that meaningfully affects economic outcomes.

This temporal perspective connects naturally to work on labor, deadlines, and task completion. Classic incentive models highlight how compensation timing, quota frequency, and reporting horizons shape intertemporal effort and the propensity to push tasks against period ends.[5] Empirically, present bias and procrastination generate demand for commitment and deadline-sensitive performance (Kaur et al., 2015), small timing nudges can unlock task adoption (Duflo et al., 2011), and output bunches around daily income goals and other salient targets.[6] In

[4]See e.g., Tversky and Kahneman, 1974; Kai-Ineman et al., 1979; Kőszegi and Rabin, 2007; Bordalo et al., 2019.

[5]See e.g., Basu et al., 1985; Holmstrom and Milgrom, 1987; Parsons and Van Wesep, 2013; Chung et al., 2021, 2025.

[6]See e.g., Camerer et al., 1997; Farber, 2008; Abeler et al., 2011.

our setting, month-end functions as a salient deadline that reallocates effort and throughput within the period.

Finally, we connect these deadline-driven reallocations to the literature showing that individual loan officers exercise economically meaningful discretion, so predictable calendar cutoffs can reallocate credit even absent changes in applicant mix. In the setting of credit allocation, prior work shows that individual loans exhibit heterogeneity in screening and approval beyond observables and lender fixed effects.[7] The literature documents how loan officer characteristics and social similarity affect lending outcomes.[8] Related research links market structure and technology to disparities—competition can attenuate discrimination across institutions (Buchak and Jørring, 2021; Butler et al., 2023), while policy tools and modern scoring do not fully eliminate discretionary gaps.[9] Our contribution bridges these strands by showing that predictable temporal focal points interact with discretion among individual agents to affect financial outcomes.

2 Data and Measurement

2.1 Loan Application Data

Our analysis uses data from HMDA, which contains the largest sample of mortgage applications available in the U.S. The data includes information on applicant characteristics—race, gender, reported income, and the property's location—and an identifier for the lender that received the application. Moreover, the data provides information on underwriting 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 data from HMDA covers the entire geography of the U.S., and the sample available to researchers begins in 1994.

[7] See e.g., Engelberg et al., 2012; Hanson et al., 2016; Chen et al., 2016; Cortés et al., 2016; Demiroglu et al., 2021.

[8] See e.g., Fisman et al., 2017, 2020; Beck et al., 2018; Montoya et al., 2020; Frame et al., 2025.

[9] See e.g., Bartlett et al., 2022; Fairlie et al., 2022; Howell et al., 2024; Chernenko and Scharfstein, 2024.

The HMDA data can be segmented into a "legacy" sample and a "new" sample starting in 2018. This new version of HMDA contains additional underwriting information for all loan applications, such as applicant FICO scores, LTVs, and debt-to-income ratios. For most loans, it includes the approval recommendation generated by the lender's Automated Underwriting System (AUS). These are automated processes that provide computer-generated approval recommendations. Several algorithms are used in the industry, developed by either private companies or government agencies, such as Fannie Mae's Automated Underwriting System. The new HMDA data also includes identifiers for the (anonymized) loan officer who handles each application.

Our analysis primarily focuses on the new HMDA sample, which runs from 2018 to 2022, because it specifies the loan officer for each application. Nonetheless, our findings are similar when we use the legacy HMDA data. Table 1, columns (1) through (3), presents summary statistics for the different racial groups in the 2018-2022 HMDA data. Approximately 7% of applicants are Black and 70% are White. The remaining 23% of observations are included in the category "Other race," which includes all other race groups, as well as applications that do not specify race. The average Black applicant applies for a smaller loan, is more likely to have below-median income (63.3%, compared to 49.7% for White applicants and 48.9% for others), and is less likely to be approved (69.1%, compared to 83% for White applicants and 79.5% for other). White applicants receive 70.6% of approved loans, Black applicants receive 6%, and applicants of other races receive 23.4%.

Columns (4) to (6) report similar statistics for the longer HMDA sample (including the legacy data) from 1994 to 2022.

We also study the performance of *originated* loans. For this, we obtain additional information on the characteristics and performance of mortgages by merging HMDA with the Black Knight McDash (McDash) dataset. The McDash-HMDA merge is available to us for the legacy HMDA data (1994 to 2018). The merge follows the approach of Rosen (2011), in which individual observations 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 is approximately 60%.[10] McDash provides information on delinquencies, defaults, and future refinancings, along with additional information on loan characteristics, such as the mortgage interest rate, rate type (fixed or adjustable rate), the mortgage term, whether the loan is conforming, borrower FICO score, and the quality of the supporting documentation submitted by the borrower. Table 1 shows summary statistics for the merged sample (columns 7 to 9).

2.2 Measuring Approval Rates in HMDA

The confidential version of the HDMA data also includes the exact date the application was submitted and the date of the lender action, either a loan origination or denial. With the action dates, we define a daily approval rate as:

$$approval\ rate_t = \frac{originations_t}{originations_t + denials_t}, \tag{1}$$

where *originations* is the total number of mortgages that close on day t and *denials* are the total number of loan applications that are denied.[11] We define an *approval gap* as the difference between the *approval rate* for Black applicants and the *approval rate* for White applicants. Importantly, HMDA contains the origination date (i.e., the closing date) but not the date that an underwriter approved the mortgage, thereby clearing it for closing. Note that we use the mortgage origination date—set by the lender in agreement with the borrower—as a proxy for the loan approval date. This is an approximation, since mortgage approval occurs at an earlier date than mortgage origination. We discuss below the mortgage origination process in detail. We also develop in the later sections an extensive empirical analysis of the determinants of the gap between approval and origination dates, and of the potential implications for our main results.

[10] Lender and consumer identities were anonymized for the merged dataset used in this analysis. There are no within-month patterns in the match rates.

[11] We exclude applications withdrawn by the applicant because we do not know whether they would have been approved or denied.

The process of obtaining a mortgage begins with a loan application. The loan application includes the address of the intended purchase property (or the property that serves as collateral when the application is for refinancing). The application also includes the applicant(s) income, finances, and credit history. Typically, loan officers help prospective borrowers prepare the loan application package, to avoid issues that may arise in the later stages of the origination process.[12] Underwriters process applications after they are submitted. The underwriter verifies that the applicant qualifies for the loan. Concurrently, the property is appraised to verify that the purchase price, or the value used for refinancing, aligns with market valuations.

During this process, the underwriter can deny the application. The application can encounter issues with income verification or the appraisal of the house. The underwriter can determine that the loan does not meet underwriting standards, and then seek additional information or guarantees from the prospective borrower before proceeding with the loan.

Loan officers are vital to mortgage approvals. They mediate interactions between underwriters and borrowers and can help borrowers address such issues with their applications. As such, loan officers' choice of which applicants to work with is crucial to lenders' approval and denial decisions.

Finally, the lender issues a disclosure document that declares the borrower "cleared to close" after the loan clears underwriting. The document confirms the mortgage conditions and closing costs. At the lending institution, loan "closers" prepare the mortgage documentation in collaboration with the loan officer. They set a closing date, in agreement with the borrower, on which the loan documentation will be signed and the mortgage will be originated. However, the "clear to close" documentation is not a legal commitment to issue the loan. Before the closing date, lenders can re-verify applicants' credit history and other underwriting details. The loan can be denied, or require further investigation if applicants' underwriting characteristics have changed.

[12] See for example, article published on the Loan Officers HUB blog: *webpage link*.

The distinction between origination (closing) dates and cleared-to-close dates clarifies how our month-end patterns map to approval timing. In practice, "clear to close" typically arrives only a few days before closing—both because of the three-day disclosure rule and because rate locks, purchase contingencies, and officer evaluations create a common push to finalize quickly.[13] These features make month-end a temporal focal point that coordinates borrowers and loan officers on a shared deadline. While some applicants may delay to economize on pre-paid interest, such actions could occur on any day; the pronounced bunching just before month-end indicates that the calendar itself serves as the coordination anchor linking approval and origination.

3 The Black Approval Gap Within a Given Month

3.1 Main Facts

We begin the analysis by plotting the Black approval gap for days around the temporal focal point of month-end. Figure 1 presents the approval gap as the average Black approval rate minus the average White approval rate on each day t. The figure normalizes month-end calendar dates by counting backward from the month's last day (e.g., the 30th or 31st).

The figure shows that the approval gap reduces significantly over the month. It averages approximately 15pp in the first seven days of the month, but it steadily decreases over the last seven days and falls to around 8pp on the last day of the month. The reduction in the Black approval gap coincides with an increase in the total number of originations at month-end (Figure 2, panel a). Origination volume is roughly constant in the first seven days. It is approximately 15% larger than on the first day of the month, by the seventh day before month-end. It is 80% larger on

[13] The Consumer Financial Protection Bureau introduced the "Know Before You Owe" rule in October 2015. The rule imposed a minimum 3-day waiting period between receiving the closing disclosure document and the closing date. The rule was implemented so borrowers had enough time to review the documentation and seek legal counsel before committing to the mortgage, and because loans tended to be originated immediately after being cleared to close.

the last day. These findings on mortgage lending are robust back to the mid-1990s; the within-month patterns are similar in the legacy HMDA data (Appendix Figure A.I.1 and Figure A.I.2). Finally, the results are not driven by window-dressing around time-varying bank examinations for the Community Reinvestment Act (CRA) (see Table A.I.1 in the Appendix). The month-end lending patterns are similar for lenders that do not have an examination in the following month and those that do.

Though striking, the graphical findings on the reduction in Black approval gap do not account for differences in the underwriting characteristics of Black and White applicants. As such, we formally test for racial differences in application approvals in the following linear probability regression [14]:

$$Appr_j = \delta_{lw,Black}\left(I_{lw,j} \times I_{Black,j}\right) + \delta_{mw,Black}\left(I_{mw,j} \times I_{Black,j}\right) + \delta_{lw} I_{lw,j} + \\ + \delta_{mw} I_{mw,j} + \delta_{Black} I_{Black,j} + BX_j + a_{ym,county} + a_{ym,lender} + a_{dow} + a_{holiday} + u_j. \quad (2)$$

The unit of observation is a loan application, and the sample excludes withdrawn loan applications because we do not know whether they would have been approved or denied. The dependent variable $Appr_j$ equals one if the loan is originated, zero otherwise. The indicator variable $I_{mw,j}$ equals one if the loan is originated or denied in the middle weeks (from second to penultimate), while $I_{lw,j}$ is equal to one for the last week of the month. The omitted category consists of loans originated in the first week of the month. $I_{Black,j}$ is equal to one for Black applicants. The characteristics of mortgage application j are contained in the vector X_j. Year-month-county, year-month-lender, day of the week, and holiday fixed effects are $a_{ym,county}$, $a_{ym,lender}$, a_{dow}, and $a_{holiday}$, respectively. The coefficients of interest, $\delta_{mw,Black}$ and $\delta_{lw,Black}$, capture the average difference in the approval rate for Black applicants, compared with White applicants, relative to the month's first week.

Table 2 reports the regression results. They confirm the graphical evidence that the Black approval gap reduces markedly over the month. Column (1) esti-

[14] A formal discussion of identifying a decision gap is provided in the Online Appendix Section A.III.

mates equation 2 over the sample period 1994 to 2022, which combines both the legacy HMDA and the new HMDA sample periods. The control variables include mortgage contract characteristics that are available in both samples, namely the 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. The point estimate of δ_{Black} is equal to -0.077, which implies that the baseline start-of-month approval rate for Black applicants is nearly eight percentage points less than for White applicants. The coefficient estimate for $\delta_{lw,Black}$ equals 0.035, which means that the Black approval gap reduces in relative terms in the last week. In this regression, the Black approval gap is reduced by approximately half in the month's last week.

These results from the legacy HMDA sample show that the reduction in the Black approval gap around the month-end temporal focal point has been a persistent feature of U.S. mortgage lending for the past several decades. However, the new HMDA data, starting in 2018, contains significantly more information on underwriting characteristics and the loan application. Moreover, the new HMDA data includes Automated Underwriting System (AUS) loan origination recommendations, which purport to be a race-neutral evaluation of the loan based only on the application's risk characteristics. The data also contains identifiers for the loan officer who handles the application, which we incorporate in the regression analysis in Section 4. Thus, we use the new HMDA sample for the subsequent columns of Table 2 and in the paper's remaining empirical tests.

The month-end reduction in the Black approval gap survives the most rigorous regression specifications in the post-2018 HMDA data. Column (2) provides a baseline comparison between the legacy and new HMDA data. It uses the post-2018 sample but includes the same control variables as in column (1). We find that estimates of the Black approval gap and its within-month reduction are quantitatively similar to those in the 1994-2022 sample. Column (3) expands the set of control variables to include underwriting characteristics from the post-2018 HMDA. The regression controls for FICO scores, loan-to-value ratios, and debt-to-income

ratios. The findings on the month-end reduction in the Black approval gap are similar when including these controls.

Crucially, the month-end reduction of the Black approval gap is robust to controlling for the AUS recommendation for each loan. Columns (4) through (6) control for the AUS recommendations. With particular attention to column (6), which includes the most control variables and indicators for the type of AUS system used to evaluate the loan, the Black approval gap effectively converges to zero at month-end. The Black approval gap is 2.4pp in the first week and the interaction between Black and the indicator for last week equals 2.4pp, which completely negates the gap. The presence of an approval gap above the AUS recommendation in the first week of the month suggests that loan application decisions are partially driven by residual factors beyond the objective criteria used by the algorithm for evaluating loan applications.

3.2 Ex-Post Performance

As an alternative to "benchmarking tests," researchers often employ "outcome tests" whereby the success rates or outcomes of decisions help infer whether the decision-making process favors a particular group. In Appendix Table A.I.2, we test the ex-post performance of originated loans by using the HMDA-McDash merged sample. These regressions explore three different outcomes—90-day delinquencies, defaults, and loan terminations—over a five-year horizon. They also employ subsamples of observably riskier loans (low FICO score, high loan-to-value, and low documentation) in addition to the full sample of loans.

Across most of our tests, we find that mortgage originations to Black applicants in the last week of the month tend to have relatively better performance (i.e., lower rates of delinquency, default, and termination). This suggests that lenders could increase the risk threshold for their month-end originations to Black applicants for the loan performance across races to reach parity. This also indicates that our within-month benchmarking tests do not miss crucial unobservable risk factors that would explain changes in the approval gap.

3.3 Alternative Measurements

The decrease in the approval rate gap at the end of the month could be a byproduct of a general increase in approval rates at month-end. To illustrate this point, consider the following example: at the beginning of the month, lenders originate 800 loans (100 Black, 700 White) out of 1,000 applications, and thus deny 200 loans (60 Black, 140 White). The approval rate for Black applicants is 62.5% and the approval rate for White applicants is 83.3%. Then, the approval gap is 20.8 percentage points. Suppose that lenders originate 30% more loans than usual at month-end (holding constant the total number of denials), and do so by allocating the new originations proportionally across races, according to the same beginning-of-month shares. Lenders would approve 130 Black applicants and 910 White applicants, and the approval gap would shrink to 18.2 percentage points, even though the share of loans originated to Black applicants remained constant.

Our findings are not an artifact of an overall increased lending at month-end; they result from an increasing share of loans to Black applicants. Firstly, Appendix A.II presents regression results showing that, in relative terms, the share of loans originated to Black applicants is 5-7% higher in the last week of the month compared to the first week of the month. Secondly, the Appendix presents similar findings from logistic regression estimates of equation 2, allowing for non-linearity in approval probability.

4 Supply-Side Mechanisms

Our analysis reveals a reduction in the Black approval gap to close to zero before the month-end temporal focal point. This section examines potential supply-side explanations for the reduced approval gap. Of the various mechanisms considered, the most compelling evidence points to loan officers' employment incentives as a key factor driving the reduction in Black approval gap.

Section 2 describes loan officers as stewards of the origination process and a liaison between borrowers and banks' underwriters. Though loan officer em-

ployment contracts are held by private U.S.-based entities and a broad sample of contracts are not available to researchers, it is well understood that loan officer compensation includes commissions based on origination volume, and their job retention is evaluated based on their performance in driving volume. Such non-linear employment incentives are similar to what researchers document for salespeople in other professions (see e.g., Yang et al., 2019) and even government contracts (e.g., Liebman and Mahoney, 2017). U.S. regulations support the use of volume-based incentives and restrict alternative compensation schemes, such as commissions based on the terms and performance of individual loans.[15] Prior research also suggests that such employment incentives are widespread across lenders (e.g., Tzioumis and Gee, 2013). A cottage industry of compliance advisory firms helps lenders design their employment contracts, which include features such as non-linear commissions based on loan volume and minimum volume quotas that must be reached every month. Some of these consulting firms have made sample contracts publicly available.

A crucial feature of these employment contracts is that the incentives—commission payments and performance quotas— are resolved at fixed calendar focal points, such as the end of a month. For example, the sample contract in Appendix Figure A.I.4 states that a loan officer is expected to originate at least three loans or $600,000 in volume per month.[16] Therefore, the end of an evaluation period, the minimum of which is a month, is a focal point for securing loan originations. This is consistent with the increase in originations toward month-end, but borrower preferences for month-end closing dates might also matter. As such, the following tests explore the extent to which we can link loan officer employment incentives to the reduced Black approval gap.

[15] See, most recently, the dispositions of Regulation Z, implementing the Truth in Lending Act. The section on *Permissible Methods of Compensation* in Regulation Z describes compensation schemes and first outlines volume-based incentives (*webpage link.*)

[16] Another sample contract example is available at the following link: *webpage link*; calendar origination volume-based incentives are discussed at page 4 of the document.

4.1 Loan Officer Employment Incentives and the Black Approval Gap

We develop measures for loan officers' incentive pressure, which we connect to lending outcomes. We use the post-2018 HMDA data, which uniquely identifies individual loan officers and the lenders they are affiliated with.[17] Based on the sample employment contract structure, we hypothesize that loan officers experience heightened incentive pressure when their recent loan origination volume falls below expectations. Loan officers also experience heightened pressure when employed by lenders that terminate underperforming employees. Loan officers under such employment pressure are more likely to increase originations as they approach evaluation deadlines, particularly at month-end.

We construct two proxies to identify loan officers facing strong employment incentives. First, we identify loan officers whose previous month's origination volume fell in the bottom half relative to their peers at the same lender. The second proxy follows the approach of Jenter and Lewellen (2020) to measure lenders' performance-induced employee turnover sensitivity. The approach, which we detail in Appendix Section A.IV, estimates the propensity for the lowest-performing loan officers to exit from a given lender. Both proxies are associated with a larger month-end increase in originations (Appendix Figure A.I.5), consistent with encouraging lending that helps satisfy employment incentives.

4.2 Effects of Employment Incentives for Individual Loan Officers

To estimate the effects of loan officer employment incentives on the Black approval gap, we augment equation 2 to include interactions with our proxies. Specifically,

[17] Loan officer identifiers are included in the non-public version of the HMDA data.

we estimate the following regression equation:

$$
\begin{aligned}
Appr_j = {} & \delta_{lw,Black,p}\left(I_{lw,j} \times I_{Black,j} \times I_{pressure,j}\right) + \\
& + \delta_{mw,Black,p}\left(I_{mw,j} \times I_{Black,j} \times I_{pressure,j}\right) + \\
& + \delta_{lw,p}\left(I_{lw,j} \times I_{pressure,j}\right) + \delta_{mw,p}\left(I_{mw,j} \times I_{pressure,j}\right) + \\
& + \delta_{lw,Black}\left(I_{lw,j} \times I_{Black,j}\right) + \delta_{mw,Black}\left(I_{mw,j} \times I_{Black,j}\right) + \\
& + \delta_{Black,p}\left(I_{Black,j} \times I_{pressure,j}\right) + \delta_{lw} I_{lw,j} + \delta_{mw} I_{mw,j} + \\
& + \delta_{Black} I_{Black,j} + \delta_p I_{pressure,j} + BX_j + a_{LO} + a_{ym,county} + a_{ym,lender} + a_{dow} + a_{holiday} + u_j.
\end{aligned} \tag{3}
$$

In equation 3, the variables are the same as in equation 2 except that $I_{pressure,j}$ is an indicator for heightened incentive pressure. More specifically, $I_{pressure,j}$ is a dummy equal to one in month t if the loan officer processing loan j had origination volume in the bottom half of her institution in the previous month $(t-1)$. The regressions also include a_{LO}, which is a loan officer fixed effect.

We focus on the coefficient $\delta_{lw,Black,p}$, which captures the incremental within-month change in the approval gap for loan officers with heightened incentive pressure. A positive coefficient would imply a larger within-month reduction in the Black approval gap when loan officers' employment incentives bind. Crucially, $\delta_{lw,Black,p}$ does not merely capture cross-sectional heterogeneity in loan officer quality because the regressions include loan officer fixed effects. Instead, the regressions capture changes in the approval gap when an individual loan officer is underperforming relative to his or her peers. Indeed, loan officers' performance fluctuates over time; a loan officer in the bottom half of performance in month t has a 39% probability of moving out of the bottom half in the subsequent month. This allows us enough variation in $I_{pressure,j}$ to meaningfully estimate the time-varying component of heightened incentives.

Firstly, Table 3 shows that the reduction in the Black approval gap is robust to loan officer fixed effects. Column (1) reports estimates of equation 2, augmented with loan officer fixed effects. The estimate of the coefficient $\delta_{lw,Black}$ equals 0.026, similar to the coefficient estimates in Table 2. Next, the regressions in columns

(2) and (3) interact *midweek* and *lastweek* dummies with the incentive pressure dummy $I_{pressure,j}$. These regressions omit the *Black* dummy, but include the full set of controls. Column (2) omits loan officer fixed effects, while column (3) includes them. We find that, when including loan officer fixed effects, officers facing higher pressure have 1.2pp lower approval rates in the first week of the month (captured by the δ_p coefficient for the uninteracted pressure dummy). At the same time, when facing pressure, loan officers have abnormally high approvals at month-end of 0.9pp. Combined, the estimates imply that loan officers facing incentive pressure have a 2.1pp larger increase in approval rates over the month. These results are consistent with loan officers helping achieve originations before month-end and with employment incentives affecting month-end approval rates.

Lastly, heightened incentive pressure on loan officers further reduces the Black approval gap. Columns (4) and (5) estimate the full specification of equation 3. Column (4) excludes loan officer fixed effects and column (5) includes them. The estimates of $\delta_{lw,Black,p}$, capturing the impact of incentive pressure in the last week of the month, are equal to approximately 0.5pp and 1pp. Thus, relative to the Black approval gap at the start of the month—roughly 2.8pp to 3pp in these regressions—being in the top half of incentive pressure has an incremental effect of around 17% to 35%.

4.3 Effects of Employment Incentives Across Lending Institutions

Next, we study the effects of lending institutions that have more stringent performance incentives for employees to originate more volume. Though researchers do not have access to employment contracts for a broad sample of lending institutions, the post-2018 HMDA data allows us to measure loan officer turnover at individual firms. Thus, we develop measures for employee turnover due to performance that proxy for the stringency of lenders' employment contracts.

The first measure of performance-based turnover uses the Jenter and Lewellen (2020) methodology of employee turnover sensitivity, which captures employment separations due to loan officers' under-performance (Appendix A.IV contains

technical details of variable construction). Broadly, the measure disentangles a firm's employee turnover due to poor performance (i.e., firings) from turnover due to the nature of the labor market. Our second measure captures the sensitivity of loan officer tenure at a firm to their performance within the firm. We calculate each loan officer's tenure with a firm and how often the loan officer was in the bottom half of origination volume within the firm. Then, for each lender, we estimate the correlation between loan officer tenure and loan officers' low origination volume. Using this correlation, we classify firms as having strict employment incentives if poor-performing loan officers have shorter employment spells with the lender.

To estimate the effects of lenders' employment incentives on the Black approval gap, Table 4 presents a regression specification similar to equation 3. The regressions interact dummies for lenders with above-median employment incentive strictness with the interactions of Black and last-week (mid-week). Columns (1) - (3) estimate the effects of our firm-level measure of performance-induced turnover. Columns (4) - (6) assess the effects of our proxy for employment incentives based on the firm-level correlation between loan officer tenure and performance. The regressions include month-year by county, month-year by lender fixed effects, and loan officer fixed effects, along with the other controls in previous specifications.

We find that lenders with greater employment incentives have larger within-month reductions in the Black approval gap. Firms with above-median performance-induced turnover have approximately a 1pp larger reduction in the Black approval gap than firms below the median. The 1pp difference holds whether we estimate the regression using above- and below-median sub-samples (columns 1 and 2) or use a triple-interaction specification (column 3). Similarly, the Black approval gap reduction is approximately 0.6pp larger for firms with above-median sensitivity of loan officer tenure to their performance, whether we estimate effects using sub-samples (columns 4 and 5) or triple interaction terms (column 6).

5 Demand-Side Mechanisms

Next, we explore the role of demand-side factors—i.e., decisions made by the borrower—in explaining the reduction in the Black approval gap before the temporal focal point. Firstly, we explore whether demand for mortgage lending exhibits identifiable within-month patterns. Secondly, after the application has been submitted, borrowers can negotiate the closing date of the mortgage origination in collaboration with the loan officer. Thus, we investigate whether the reduced approval gap can be explained by Black borrowers' preference to close at month-end, with a particular focus on borrowers' financial constraints. Finally, to the extent that we cannot test for all demand-side explanations, we employ empirical methods to place bounds on the reduction in the Black approval gap that we can attribute to demand-side mechanisms.

5.1 Mortgage Applications Within the Month

We start by exploring the demand for mortgage lending around the month-end focal points. The application date reasonably reflects consumer demand for mortgages. Figure 2 shows that the number of applications is roughly constant around the last day of the month. This finding reveals that though originations grow steadily over the course of the month, with a marked increase in the last week, the volume of applications submitted to lenders is roughly constant. As such, loan officers clear much of their inventory of outstanding applications at month-end.[18]

We also explore the racial composition of applications over the month. Figure 3 plots the composition of new applicants on each day of the month. Panel (a) shows that Black applications constitute approximately 7% of total applications on a given day, and that the fraction stays constant over the course of the month. This confirms our identifying assumption that the racial composition of applicants is time-invariant.

[18]Figure A.I.2 in the Appendix shows the same pattern for application volume around month-end for the longer sample from 1994 to 2022.

Other characteristics of the applicant pool—characteristics that could correlate with race—are also constant over the course of the month. Panel (b) reports the fraction of applicants whose personal income is less than the median within the applicant's county and in the same year. Panel (c) shows the fraction of new originations for applicants with below-median incomes, by application day. In both panels, we sort the sample into applications submitted by Black and White applicants. The shares of low-income applicants are nearly constant regardless of race. Panel (d) plots outstanding applications—applications that have been submitted but have yet to be processed—in the lenders' inventory on each day. Again, we find that the racial composition of the applicant pool and application quality is constant over the course of the month.

Finally, panels (e) and (f) report the fraction of subprime (with FICO < 660) and high loan to value (with loan to value $> 80\%$) applicants by application day, separately for White and Black applicants. Similarly, the composition of these loan types are constant within the month. Among White applicants the fractions of subprime and high loan to value borrowers are approximately 12% and 48%, while among Black applicants the same fractions are 32% and 63%.[19]

5.2 Borrower Financial Constraints and the Black Approval Gap

Seeing as mortgage applications arrive at a constant rate over the month and there are no compositional differences in the rate of arrival, the month-end reduction in the Black approval gap must be the result of actions that occur between application and origination dates. One plausible demand-driven mechanism is that borrowers prefer to close at month-end, and thus negotiate month-end closing dates with the loan officer. For this to explain the reduction in the Black approval gap, Black borrowers must more strongly prefer month-end closing.

We proceed by exploring sensible rationales for borrowers to prefer month-end closing, namely financial constraints. First, home-buyers often need to pay accrued interest for the days between the origination date and the last day of the

[19]Figure A.I.3 in the Appendix shows that the stability of the applicant pool within the month is also a feature present in the longer sample from 1994 to 2022.

month. This is because the first mortgage payment is due at the end of the first complete month after the origination date, and thus the interest payment in the first installment only covers the first complete month of ownership. Second, borrowers who transition from renting to home ownership might have to pay rent on the overlapping days before moving if they cannot terminate the rental contract before the month's last day. However, on the other hand, the benefits to closing earlier include receiving the property more quickly, and for buyers who transition from another owned property, eliminating these days of interest payments on a previous mortgage.

To empirically investigate these mechanisms, Table 5 tests whether borrowers' closing dates are sensitive to the amount of pre-paid interest expenses that might be due at closing. For each loan, we approximate what would have been the incremental savings on accrued interest due at closing when a borrower delays closing until the last week of the month. Specifically, borrowers would owe approximately an extra month of interest payments at closing if they close on the month's first day instead of at month-end. Therefore, the accrued interest savings Z_j would be approximately equal to $L_j \times (r_t^M/12)$, where L_j is the loan amount and r_t^M is the market interest rate (APR) for month t. For context, the median savings equals around \$460 per loan, which is equal to roughly 0.9% of the down payment.

Then, we estimate borrowers' preference for month-end closing as a function of accrued interest payments in the following regression equation:

$$\begin{aligned} I_{j,lw} = \alpha_Z Z_j + \alpha_{Z,Black}\left(Z_j \times I_{Black,j}\right) + BX_j + \\ + a_{ym,county} + a_{ym,lender} + a_{dow} + a_{holiday} + u_j. \end{aligned} \tag{4}$$

The mortgage is originated in the last week of the month if the dummy variable $I_{j,lw}$ equals one. The coefficients of interest are α_Z, which captures the demand for month-end closing attributable to accrued interest payments and $\alpha_{Z,Black}$, which captures the differential effect for Black applicants. A positive estimate of α_Z implies that the accrued interest savings Z increases origination volume at month-

end and a positive estimate of $\alpha_{Z,Black}$ means that the effect is asymmetrically larger for Black applicants.

Estimates of α_Z are positive and statistically significant, which is consistent with higher accrued interest savings increasing origination volume at month-end. On the other hand, estimates of $\alpha_{Z,Black}$ (column 3) are statistically and economically insignificant. Thus, we cannot reject the null that the effect of accrued interest payments on the demand for month-end closing is not different for Black applicants relative to others. Therefore, the reduction in Black approval gap is unlikely to be mainly driven by borrowers closing at month-end to minimize closing costs.

While pre-paid interest expenses increase closing costs, we can also measure whether borrowers are financially constrained when they apply for a mortgage. Financially constrained borrowers would also seek to minimize upfront costs when taking out the mortgage, and could do so by pushing closing to month-end. As such, we explore whether borrower financial constraints contribute to the Black approval gap reduction.

In Table 6, we test for the effects of borrower financial constraints by augmenting equation 2 with interaction terms for the various measures of financial constraints. The regression equation with interaction terms is similar to the tests of supply-side employment incentives but also includes interactions between the characteristics of interest and all other controls (including the fixed effects). This allows for underwriting characteristics to differentially and flexibly affect different borrower groups. We assume borrowers are relatively financially constrained if they have less income or lower credit scores (FICO below 660), or if they take out a non-conventional mortgage or a mortgage with a high loan-to-value ratio, which we define as having an LTV greater than 70%. Applicants for a purchase mortgage are also more likely to be financially constrained than applicants for a refinance mortgage.

The regression results do not consistently support financial constraints as an explanation for the reduction in the Black approval gap. Lower-income applicants are more likely to originate in the last week, but Black borrowers are not differentially more likely to do so (column 1). Low-FICO Black applicants are

less likely than non-Black applicants to originate at month-end, countering the explanation that financial constraints differentially drive Black applicants to seek month-end closing dates (column 2). Black applicants are less likely to be approved for non-conventional mortgages, and the last week is not statistically different from other weeks for these mortgage types (column 3). Finally, the reduction in the Black approval gap is larger for high-LTV mortgages (column 4) and purchase mortgages (column 5). This result supports the financial constraints explanation; however, the reduction in the Black approval gap is still present for low-LTV mortgages, suggesting that other factors matter. Overall, these regressions present inconsistent evidence of financial constraints' role in reducing the Black approval gap.

Lastly, we test the effects of financial constraints that result from housing transition expenses. Specifically, we estimate whether the reduction in the Black approval gap persists when the sample is restricted to refinancing mortgage applications, because these applicants do not relocate to a new property. We find a large reduction in the Black approval gap for refinancing applications (column 5). The month-end reduction in the Black approval gap is 2.1pp for mortgage refinances. While the approval gap reduction for new purchases is larger than for refinancing applications, the incremental difference of 0.8pp is modest relative to the baseline reduction in the Black approval gap.

5.3 Bounding Unobserved Demand-Side Mechanisms

Though we find only mixed evidence supporting channels through which borrower preferences affect the reduction in the Black approval gap before a temporal focal point, some demand-side factors contribute to month-end originations for applicants of all races. Therefore, we are cautious not to rule out other demand-side explanations for the reduction in the Black approval gap, even those that are difficult to measure empirically. As such, we employ methodologies from the literature to estimate bounds on the effects of unobserved demand-side mechanisms for the Black approval gap reduction.

First, we use a methodology designed to empirically estimate the scope for unobservable bias, pioneered by Altonji et al. (2005) and Oster (2019). The approach allows us to assess the robustness of the regression estimates for the reduction in the Black approval gap to omitted variable bias. It also defines a lower bound on the coefficient estimates by uncovering the maximum scope for unobserved selection in the regression.

To employ this approach, using the terminology used in Oster (2019), we estimate regressions with both the complete set of observable controls (*long regression*, analogous to equation 2), and a restricted set of controls that excludes applicants' demand characteristics (*short regression*). For both regressions, we collect the coefficient estimates on the Black approval gap reduction ($\delta_{lw,Black}$) and the regression *R-square*. Using these estimated coefficients and the associated R-squares, we extrapolate the coefficient estimate as though it came from a regression specification that controls for the universe of relevant demand variables, including unobservable controls for demand. The extrapolation requires two assumptions: (1) the maximum achievable regression R-square, even when all controls are included, and (2) the relationship between the observable and the omitted control variables for a given increase in R-square.[20]

In our context, we estimate a lower bound on the reduction in Black approval gap $\delta_{lw,Black}$ to account for omitted demand-side factors. The *short* and *long* regressions both include the week-of-month dummy variables, the Black applicant dummy, and the interaction terms between these variables, as well as the complete set of fixed effects. The *short* regression excludes the demand-side controls (i.e., borrower underwriting variables). The derivation of the bounds (Oster, 2019) is based on the assumption that the relation between unobservable demand controls

[20]Oster (2019) shows that for a coefficient β of interest, given estimates β_L and β_S in the long and short regression, and the corresponding R-squares R_L and R_S, the bound is:

$$\beta^* \approx \beta_L + d(\beta_L - \beta_S)\frac{R_{max} - R_L}{R_L - R_S},$$

where β^* is the bound for the coefficient after accounting for the effects of unobservables, R_{max} is the maximum attainable R-square, and d is the sensitivity of the coefficient to the increase in R-square, due to the inclusion of unobservables. In our tests we set $d = 1$.

and the treatment variable (interaction between last week and Black applicant dummy) is proportional to the relation between observable demand controls and the treatment variable.

Table 7 reports estimates of bounds on the demand-side effects for the reduction in the Black approval gap for a range of maximum R-squares. For robustness, we consider three different specifications of the *short* regression. In column (1), the specification omits borrower controls, as well as county and month-year fixed effects, but includes lender and seasonality fixed effects. In column (2), the specification also includes month-year fixed effects. Finally, column (3) adds county fixed effects. The results are robust across the three specifications of the short regression. We first set the maximum R-square equal to 47.5%, which is approximately 1.3 times the R-square in the full specification, which is the target maximum R-square proposed in Oster (2019). The bound on the estimate of $\delta^*_{lw,Black}$ approximately equals 2.4pp. Employing a higher threshold of unobservable selection, by roughly doubling the R-squared of the full specification to a maximum of 75%, results in a lower bound $\delta^*_{lw,Black}$ of 1.3pp.

With lower bounds on the coefficient between 1.3pp and 2.4pp, demand-side factors are doubtful to thoroughly explain the reduction in Black approval gap. In these regressions, the baseline Black approval gap at the start of the month is around 2.7pp. A month-end reduction of 2.4pp to 1.3pp would mitigate just 12% and, at most, 52% of the approval gap. This leaves substantial scope for supply-side mechanisms, such as employment incentives, to contribute to the Black approval gap reduction. As an alternative way to convey the possibility of omitted demand factors, the coefficient $\delta_{lw,Black}$ would need to be much more sensitive to omitted and unobservable controls for the Black approval gap reduction not to persist.

Secondly, we use a specification curve analysis to bound the demand-side effects on the reduction in the Black approval gap (Simonsohn et al., 2020). Specifically, the specification curve presents a range of plausible estimates for the reduction in the Black approval gap that is uncontaminated by demand-side factors. In the context of our empirical analysis, the goal is to capture the "pure" supply-side effects by isolating sub-samples of applicants that are indifferent to

the demand-side factors that would drive month-end closing. In the mortgage setting, financially unconstrained applicants would be indifferent to the financial motivations for closing at month-end.

The specification curve analysis presents a range of estimates for plausible definitions of financially unconstrained borrowers. Because the specification curve presents an extensive range of coefficient estimates drawn from different definitions of financially unconstrained borrowers, the estimates presented in the specification curve presumably span the feasible set of financially unconstrained borrowers. Therefore, the specification curve presents bounds on the Black approval gap reduction due to supply-side factors.

Figure 4 presents the specification curve, which is a range of coefficient estimates for the Black approval gap ($\hat{\delta}_{lw,Black}$ in equation 2) drawn from samples of unconstrained borrowers. The coefficient estimates come from regressions using sub-samples of applicants that are observably financially unconstrained. The sub-samples are selected based on the following restrictions, either one-by-one or in pairs: conventional loans only, refinancings only, loans with an LTV smaller than or equal to 70%, borrowers with prime FICO scores (above 660), borrowers with higher incomes, and borrowers who would have had less accrued interest due at closing (the Z_j measure calculated in the previous section).

The point estimates on the coefficient $\hat{\delta}_{lw,Black}$ range between 3pp and 1.8pp, and are always highly statistically significant. The range of coefficient estimates encompasses our estimate of the Black approval gap reduction in the full sample—approximately 2.4pp in previous tests. This suggests that supply-side effects are a crucial driver of the Black approval gap reduction in our main tests. The lowest estimate of 1.8pp implies that at least 75% (1.8pp/2.4pp) of the Black approval gap reduction can be explained by supply-side determinants, after accounting for possible demand-side incentives, similar to the lower bound from the approach in Oster (2019). As such, supply-side effects, such as loan officers' employment incentives, likely explain at least half of the reduction in the Black approval rate from roughly 2.4pp in the month's first week to approximately zero at month-end.

6 Importance of Loan Officers and Frictions During Origination

Given the constant volume of applications over the month, the Black approval gap reduction is likely due to incidents occurring during the approval process. A crucial premise of this mechanism is that loan officers actively guide applicants from application to origination. Loan officers with employment incentives tied to origination volume, evaluated at calendar time focal points, will be especially motivated to assist borrowers in securing approval. This section empirically examines the impact of loan officers on loan outcomes and assesses the frictions that Black borrowers may encounter throughout the approval process.

6.1 Loan Officers' Contribution to Mortgage Application Outcomes

Firstly, individual loan officers are empirically relevant to explaining application decisions, above the explanatory significance of applicants' underwriting characteristics and that of lending institutions. Table 8 presents regression R-squares for different specifications of equation 2. The R-squared is 0.29 when we include the fullest set of underwriting characteristics and a rich set of fixed effects, but exclude lender and loan officer fixed effects (column 1). Including lender fixed effects increases the R-squared to 0.34 (column 2). The R-squared is 0.39 when the regression includes loan officer fixed effects but excludes lender fixed effects (column 3). Thus, loan officer fixed effects increase the explanatory power of a regression model by roughly 35% (0.39/0.29) more than do underwriting variables and have roughly double the incremental explanatory power as lender fixed effects. Moreover, there is substantial heterogeneity in approval rates across different loan officers. The standard deviation of the loan officer fixed effect is 18pp. This is evidence of considerable variation in loan officers' baseline approval rates.

Next, we show that increased Black originations relate to loan officers' calendar-interval incentives rather than merely an artifact of month-end calendar dates. Figure A.I.6 orders loan officers' origination from first to last within a month and calculates the share to Black applicants. Loan officers' last origination in a given

month is more likely than their first origination to be to a Black applicant. Notably, the last origination can fall on any calendar day within the month.

6.2 Frictions During the Mortgage Origination Process

The previous sections show that the Black approval gap reduction relates to loan officers and their performance incentives. Concurrently, loan applications arrive at a constant rate over the month. Therefore, the Black approval gap reduction must result from frictions occurring during the origination process that delay Black applications relative to others. Loan officers, stewards of the origination process, can help applicants navigate the approval process and overcome the processing frictions they encounter. The following analysis finds that Black borrowers experience significantly more hurdles during the application process and are more likely to have their loan applications delayed.

The National Survey of Mortgage Originations (NSMO) allows us to study minority borrowers' experiences during the mortgage origination and closing process.[21] The data is a quarterly survey, which began in 2013, and is funded and managed by the Federal Housing Finance Agency (FHFA) and the Consumer Financial Protection Bureau (CFPB). It covers a representative sample of borrowers who originated closed-end first-lien residential mortgages, and details borrowers' demographics (e.g., race, income, and education). Moreover, survey questions are merged with extensive information on mortgage and underwriting characteristics. Unfortunately, the data does not include exact calendar dates, so its findings should be viewed as suggestive of mechanisms and complementary to the results from the confidential HMDA data.

We use regression analysis to study differences in mortgage experiences for Black applicants. The regression analysis helps control for other differences in the characteristics of Black applications, such as applicant credit risk and other demographic attributes. Specifically, we estimate the following regression equation

[21] The data are available at *webpage link*.

over answers to yes-no closed-ended questions:

$$I_{+,i} = \delta_{Black} I_{Black,i} + D\tilde{X}_i + d_y + d_{location} + u_i. \tag{5}$$

The dependent variable $I_{+,i}$ is a dummy equal to one for a positive response (*yes*) and zero for a negative response (*no*). The coefficient of interest is δ_{Black}, and I_{Black} is a dummy equal to one if the applicant is Black. The vector $\tilde{X}$ includes controls for education and income. It also contains controls for underwriting variables, including dummies for jumbo loans, GSE-securitized loans, loans originated by credit unions, and for DTI bins, LTV bins, FICO score bins, and loan amount bins. Year fixed effects are d_y, while $d_{location}$ are location fixed effects (based on whether the collateral is in a census tract within a metropolitan area and with low or moderate income, or it is in a metropolitan census tract with higher income, or it is not in a metropolitan area).

Table 9, panel A, presents a series of regression estimates of equation 5, based on answers to Question 20 of the survey. The question asks *"In the process of getting this mortgage from your mortgage lender/broker, did you..."* and proposes 8 sub-categories with answers *yes* and *no*. The regression results show that Black borrowers are more likely to have to resolve credit errors, have more than one appraisal, re-file paperwork, and have house value estimates revised. All these effects have large relative magnitudes, which range between a 20% and a 40% relative increase with respect to the mean. Most connected to our within-month findings from HMDA, Black applicants are 7pp or 35% more likely to have had their closing date delayed. This result is consistent with Black originations taking longer (Wei and Zhao, 2022) and potentially bunching toward month-end. The results also speak to the issues that Black applicants have with their applications, which leaves scope for loan officers to play an essential role in the origination process.

We also find that Black borrowers experience significantly more hold-ups during the closing process. Question 51 of the NSMO survey asks respondents: *"Did you face any of the following at your loan closing?"* Table 9, panel B, shows that

Black applicants are more likely to say that closing did not occur as scheduled, that they were asked for re-disclosure of credit characteristics after the 3-day compulsory waiting period between approval and origination, that there were unexpected terms, and that they were requested to sign pre- or post-dated documents. The difference for Black borrowers is substantial, ranging between a 50% and 150% increase above the baseline for each sub-question. These results highlight that Black applicants might have less control over the events at closing and have less say in the timing of closing dates. This leaves scope for loan officers to play an important role in the origination process by helping applicants finalize the loan origination before month-end focal points.

7 Conclusions

We show that calendar time itself acts as a shared focal point that coordinates behavior. In the setting of mortgage originations, applications arrive at a steady pace, yet originations bunch toward the end of each month and the Black approval gap shrinks within the month, converging by month-end.

In our setting, this temporal focal point interacts with discretion and incentives. Loan-officer employment pressure, especially among underperforming officers and at institutions with higher performance-induced turnover, coincides with larger month-end throughput and a pronounced narrowing of the Black approval gap. Loans originated to Black applicants late in the month are also less likely to default, indicating misallocation earlier in the cycle. Frictions that disproportionately affect Black applicants during processing and closing give loan officers scope to resolve issues as the deadline approaches, further amplifying the month-end convergence.

More broadly, our empirical approach applies wherever evaluators face recurring cutoffs. For example, future research can study the effects of monthly quotas on the propensity of highway patrol officers to issue speeding tickets or how firms make employment decisions around the end of evaluation periods, such as before public offerings. High-frequency views around these landmarks can

reveal within-cycle reallocations that period averages miss. Adjusting incentives and supervision at deadlines can improve consistency in screening and allocation, without requiring shifts in applicant mix.

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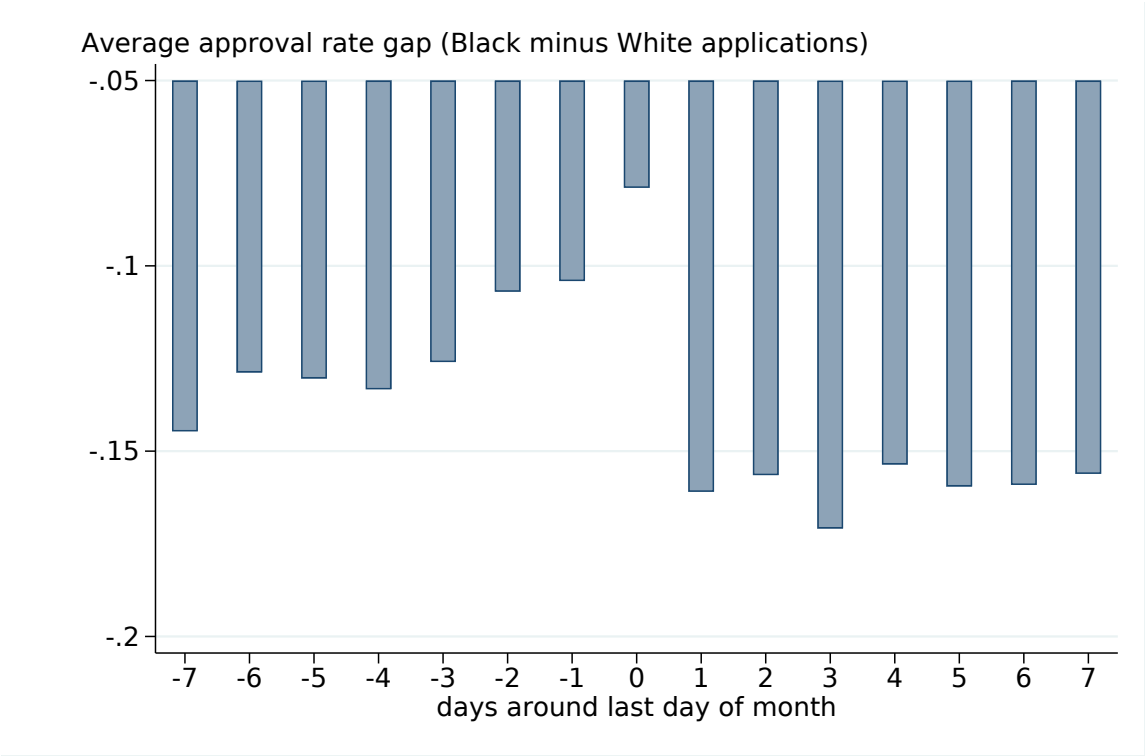
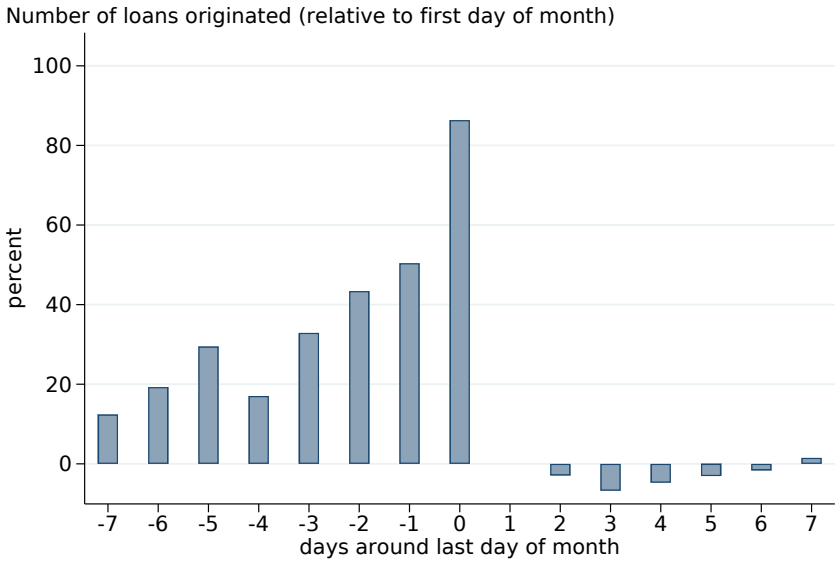
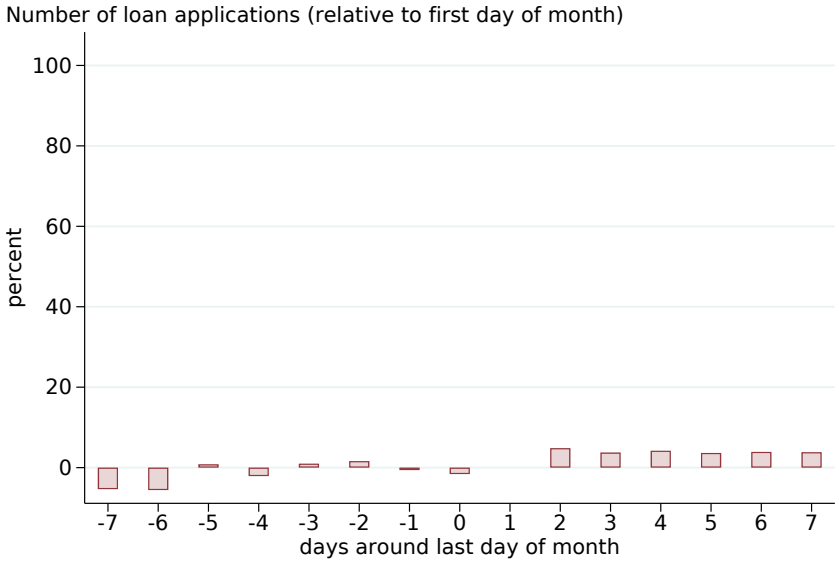


Figure 1: The figure uses a 5 percent sample from HMDA on U.S. mortgage applications that were originated or denied between January 2018 and December 2022 to calculate daily approval gaps between Black and White applicants, calculated as the difference in approval rates (equation 1) on each day. Negative values imply that approval rates are lower for Black applicants.

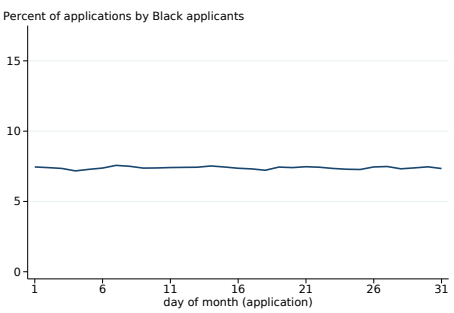


(a) Origination Volume around End of Month

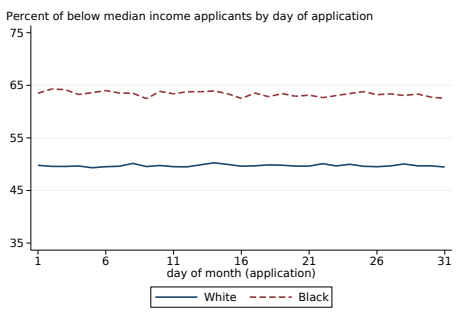


(b) Application Volume around End of Month

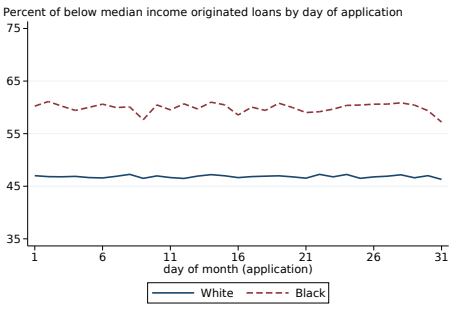
Figure 2: The figure uses data from HMDA on U.S. mortgage applications submitted between January 2018 and December 2022. Panel (a) reports the percentage differences between the average daily origination volume on each day in the first and last week of the month, and the first day of any given month. Panel (b) presents the same calculations for average daily application volume.



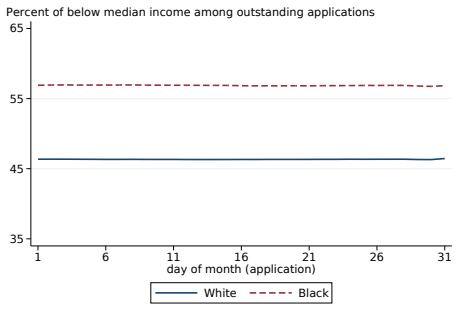
(a) Racial Composition by Application Day



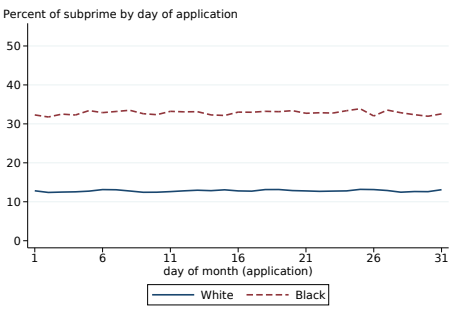
(b) Income by Application Day



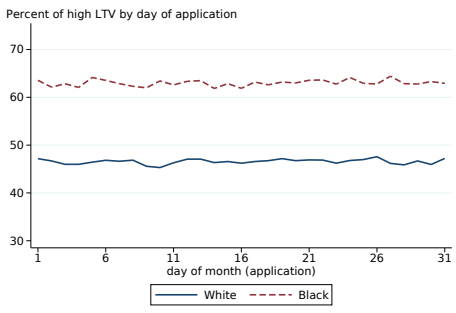
(c) Originated by Application Day



(d) Outstanding Applications by Day



(e) Subprime by Application Day



(f) High Loan-To-Value by Application Day

Figure 3: The figure uses data from HMDA on U.S. mortgage applications between January 2018 and December 2022. Panel (a) shows the average fraction of applications submitted by Black applicants, by application day. Panel (b) shows the fraction of applicants, among Black and White applicants, whose income is less than their county's median income in that year, by application day. Panel (c) shows the fraction of loans originated to applicants whose income is less than their county's median income in that year, by application day. Panel (d) shows the fraction of outstanding applications (not yet originated or denied), on each day, submitted by applicants whose income is less than their county's median income in the year. Panel (e) shows the fraction of subprime loan applications (FICO below 660) by application day, and panel (f) shows the fraction of applications with high loan-to-value (loan-to-value greater than 80%).

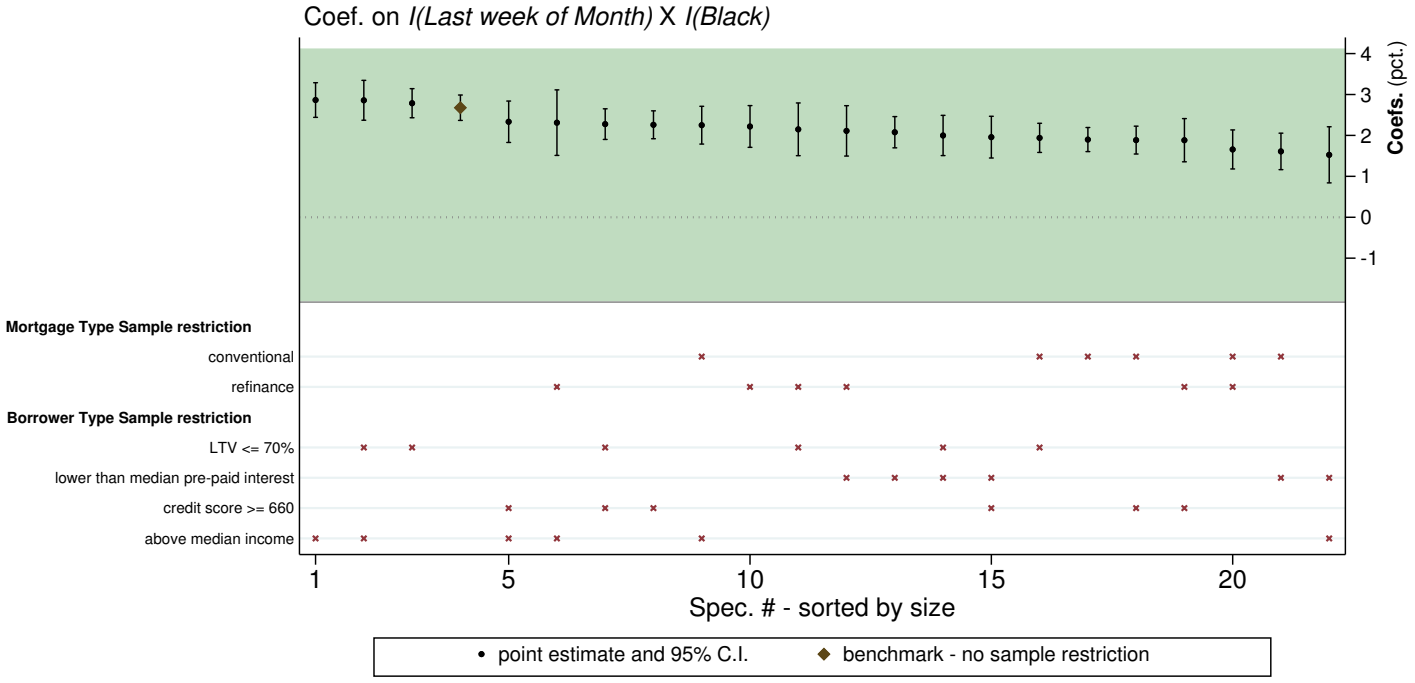


Figure 4: The figure reports a Specification Curve for $\delta_{lw,Black}$, the coefficient for the interaction term between a dummy equal to one for mortgages originated or denied in the last week of the month, and a dummy equal to one for mortgages to Black applicants. The estimates are based on the specification in equation 2. The fourth dot from the left (diamond marker) represents the estimate based on the full sample of loans. The other dots represent estimates based on subsamples of the data, which select borrowers who are less likely to face financing constraints at month-end. The subsamples are constructed using the following restrictions, either one-by-one or in pairs: conventional mortgages only, refinancing mortgages only, mortgages with LTVs smaller than or equal to 70%, mortgages with below median pre-paid interest, mortgages with FICO scores above 660, and applicants with above median income in their county. The combination of restrictions imposed on the sample used for each estimate (dot) are highlighted by the red crosses at the bottom of the figure. The estimates reported in the figure present a range of magnitudes for the month-end reduction in the Black approval gap for unconstrained borrowers. The results are based on 20% samples from the new HMDA data set for 2018-2022.

Tables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	New HMDA 2018-2022 Main Sample			HMDA 1994-2022 Longer Sample (Includes Legacy)			HMDA-McDash 1994-2018		
	White	Black	Other Race	White	Black	Other Race	White	Black	Other Race
Observations	3,131,266	340,663	1,551,680	18,374,407	2,070,065	7,619,694	29,909,913	2,556,790	7,128,756
Share of Applications	70.37%	6.62%	23.02%	65.47%	7.37%	27.15%	-	-	-
Approval Rate	82.99%	69.13%	79.46%	82.99%	69.13%	79.22%	-	-	-
Average Loan Amount ($ 1,000)	254.29	221.78	359.38	175.55	141.69	212.85	198.34	162.88	231.67
Share Low Income Apps	49.72%	63.32%	48.86%	48.60%	63.66%	52.33%	49.46%	64.73%	50.27%
Share Conforming	91.07%	94.13%	88.69%	90.64%	92.35%	89.40%	94.58%	97.15%	91.65%
Share Primary Residence	92.53%	94.20%	87.81%	91.38%	91.80%	90.00%	91.77%	92.49%	90.54%
Share New Purchases	39.94%	45.59%	42.19%	41.40%	42.89%	34.62%	48.36%	54.34%	44.87%
Share of Originated Loans	70.63%	6.00%	23.37%	72.63%	5.91%	21.46%	75.54%	6.46%	18.00%

Table 1: Summary statistics, across different race groups, for the new HMDA data (2018-2022), for the longer sample including the legacy HMDA data (1994-2022), and for the merged sample of originated loans from HMDA and McDash (1994-2018). All are based on a 5% random sample. *Share of Applications* is the share of applications belonging to each group out of the total, *Approval Rate* is the fraction of approved loans (within each group), *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 Purchases* is the fraction of loans for new house purchase (within each group), and *Share of Originated Loans* is the fraction of originated loans belonging to each group of applicants, out of the total.

	(1) approval 1994-2022	(2) approval 2018-2022	(3) approval 2018-2022	(4) approval 2018-2022	(5) approval 2018-2022	(6) approval 2018-2022
midweek	0.019***	0.014***	0.011***	0.011***	0.0095**	0.0096**
	(0.0006)	(0.0023)	(0.0019)	(0.0022)	(0.0021)	(0.0022)
lastweek	0.059***	0.036***	0.027***	0.028***	0.024***	0.024***
	(0.0013)	(0.0052)	(0.0044)	(0.0049)	(0.0047)	(0.0048)
black	-0.077***	-0.089***	-0.030***	-0.047***	-0.025***	-0.024***
	(0.0019)	(0.0069)	(0.0029)	(0.0058)	(0.0026)	(0.0025)
midweek × *black*	0.0081**	0.011**	0.0079**	0.0099**	0.0084**	0.0082**
	(0.0010)	(0.0025)	(0.0025)	(0.0025)	(0.0022)	(0.0022)
lastweek × *black*	0.035***	0.034***	0.027***	0.026***	0.024***	0.024***
	(0.0015)	(0.0045)	(0.0039)	(0.0038)	(0.0033)	(0.0033)
AUS Approved				0.46***	0.35***	0.41***
				(0.033)	(0.033)	(0.027)
Historic Loan-Level Controls	YES	YES	YES	YES	YES	YES
New Loan-Level Controls (2018-2022 HMDA)	NO	NO	YES	NO	YES	YES
AUS Type Controls	NO	NO	NO	NO	NO	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
N	20567020	12851435	10951888	9273150	8404733	8404733
r2	0.31	0.25	0.37	0.28	0.33	0.34

Table 2: The table reports individual loan-level regression estimates of differences in approval rates across races and within the month (see equation 2), based on legacy and new HMDA data. *Historic Loan-Level Controls* stands for the set of controls available both in the legacy (old) HMDA sample covering the years from 1994 to 2018 and in the new sample from 2018 to 2022. *New Loan-Level Controls* stands for the new controls available for the 2018-2022 sample. In particular, we include dummies for quintiles of the applicants' debt-to-income ratios, FICO scores, and loan-to-value ratios. In columns (3), (4), and (5) we include a dummy equal to one when we observe that the Automated Underwriting System (AUS) used by the lender recommended approval of the loan. *AUS Type Controls* is a set of dummies selecting the different types of AUS models used for each loan. The dependent variable for all regressions is a dummy that takes a value of one if a loan application is originated and zero if it is denied. *midweek* and *lastweek* are dummies equal to one, respectively, if the action on the application is taken in the middle weeks (not the first or the last 7 days of a month) and last week of the month. *black* is a dummy equal to one for Black applicants. Standard errors are clustered by lender and year. Estimates in column (1) are based on a 5% random sample of the historical and new HMDA data, while estimates in columns (2) to (6) are based on a 20% random sample of the new HMDA data.

	(1) approval 2018-2022	(2) approval 2018-2022	(3) approval 2018-2022	(4) approval 2018-2022	(5) approval 2018-2022
midweek	0.0099***	0.011***	0.010***	0.010***	0.0095***
	(0.00091)	(0.00098)	(0.00093)	(0.00096)	(0.00090)
lastweek	0.025***	0.028***	0.026***	0.026***	0.024***
	(0.0014)	(0.0016)	(0.0015)	(0.0015)	(0.0014)
black	-0.028***			-0.030***	-0.028***
	(0.0012)			(0.0015)	(0.0013)
pressure		-0.029***	-0.012***	-0.027***	-0.012***
		(0.00096)	(0.00059)	(0.00094)	(0.00057)
midweek × *black*	0.0090***			0.0092***	0.0087***
	(0.00095)			(0.0010)	(0.00098)
lastweek × *black*	0.026***			0.028***	0.025***
	(0.0012)			(0.0014)	(0.0013)
midweek × *pressure*		0.0050***	0.0042***	0.0046***	0.0039***
		(0.00066)	(0.00057)	(0.00069)	(0.00058)
lastweek × *pressure*		0.011***	0.0092***	0.0099***	0.0084***
		(0.00086)	(0.00077)	(0.00085)	(0.00077)
pressure × *black*				-0.014***	-0.0031*
				(0.0020)	(0.0016)
midweek × *pressure* × *black*				0.0036**	0.0019
				(0.0018)	(0.0018)
lastweek × *pressure* × *black*				0.0097***	0.0051***
				(0.0022)	(0.0019)
Historic Loan-Level Controls	YES	YES	YES	YES	YES
New Loan-Level Controls (2018-2022 HMDA)	YES	YES	YES	YES	YES
Holiday FE	YES	YES	YES	YES	YES
Day-of-Week FE	YES	YES	YES	YES	YES
Month-Year-County FE	YES	YES	YES	YES	YES
Month-Year-Lender FE	YES	YES	YES	YES	YES
Loan Officer FE	YES	NO	YES	NO	YES
N	54347527	54403341	54347527	54403341	54347527
R-sq	0.376	0.336	0.376	0.336	0.376

Table 3: The table reports individual loan-level regression estimates of differences in approval rates across races and within the month, augmented with interactions with individual loan officers' incentive pressure (see equation 3). We include the same set of controls as in column (3) of Table 2. Columns (1), (3), and (5) also include loan officer fixed effects. The dependent variable for all regressions is a dummy that takes a value of one if a loan application is originated and zero if it is denied. *midweek* and *lastweek* are dummies equal to one, respectively, if the action on the application is taken in the middle weeks (not the first or the last 7 days of a month) and last week of the month. *black* is a dummy equal to one for Black applicants. *pressure* is a dummy equal to one if the loan officer had origination volume in the bottom half within her institution in the previous month. Standard errors are clustered by lender and year. Estimates are based on the full sample of the new HMDA data from 2018 to 2022.

	(1) approval 2018-2022 $LP(PerfTurn)$	(2) approval 2018-2022 $HP(PerfTurn)$	(3) approval 2018-2022	(4) approval 2018-2022 $LTenSens$	(5) approval 2018-2022 $HTenSens$	(6) approval 2018-2022
midweek	0.0060***	0.016***	0.0062***	0.0083***	0.0098***	0.0083***
	(0.0011)	(0.0012)	(0.0011)	(0.0013)	(0.00080)	(0.0012)
lastweek	0.018***	0.036***	0.019***	0.023***	0.025***	0.023***
	(0.0016)	(0.0019)	(0.0016)	(0.0019)	(0.0013)	(0.0019)
black	-0.028***	-0.033***	-0.032***	-0.028***	-0.030***	-0.032***
	(0.0016)	(0.0013)	(0.0017)	(0.0017)	(0.0012)	(0.0018)
$midweek \times black$	0.0076***	0.014***	0.0077***	0.0065***	0.012***	0.0065***
	(0.0014)	(0.0012)	(0.0014)	(0.0013)	(0.0011)	(0.0013)
$lastweek \times black$	0.024***	0.035***	0.024***	0.024***	0.030***	0.024***
	(0.0014)	(0.0020)	(0.0014)	(0.0015)	(0.0016)	(0.0015)
$midweek \times HighP(PerfTurn)$			0.0091***			
			(0.00094)			
$lastweek \times HighP(PerfTurn)$			0.016***			
			(0.0014)			
$black \times HighP(PerfTurn)$			0.0066***			
			(0.0016)			
$midweek \times black \times HighP(PerfTurn)$			0.0056***			
			(0.0013)			
$lastweek \times black \times HighP(PerfTurn)$			0.0099***			
			(0.0017)			
$midweek \times HighTenSens$						0.0015*
						(0.00086)
$lastweek \times HighTenSens$						0.0024**
						(0.0012)
$black \times HighTenSens$						0.0045***
						(0.0016)
$midweek \times black \times HighTenSens$						0.0051***
						(0.0012)
$lastweek \times black \times HighTenSens$						0.0062***
						(0.0016)
Historic Loan-Level Controls	YES	YES	YES	YES	YES	YES
New Loan-Level Controls (2018-2022 HMDA)	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
Loan Officer FE	YES	YES	YES	YES	YES	YES
N	23050245	13795456	36879798	20193457	26534716	46766675
R-sq	0.319	0.353	0.323	0.336	0.392	0.360

Table 4: The table reports individual loan-level regression estimates of differences in approval rates across races and within the month, augmented with interactions with lender-level incentive pressure (see Section 4.3). We include the same set of controls as in column (3) of Table 2 with the addition of loan officer fixed effects. The dependent variable for all regressions is a dummy that takes a value of one if a loan application is originated and zero if it is denied. *midweek* and *lastweek* are dummies equal to one, respectively, if the action on the application is taken in the middle weeks (not the first or the last 7 days of a month) and last week of the month. *black* is a dummy equal to one for Black applicants. $HighP(PerfTurn)$ is a dummy equal to one for lenders with probability of performance-induced loan officer turnover above the median. *HighTenSens* is a dummy equal to one for lenders with correlation between loan officer tenure and performance above the median. Columns (1) and (4) (2 and 5) report estimates based on subsamples restricted to lenders with low (high) incentive pressure, defined as incentive pressure below (above) median. Standard errors are clustered by lender and year. Estimates are based on the entire sample of the new HMDA data from 2018 to 2022.

	(1) last-week origination New Purchase 2018-2022	(2) last-week origination New Purchase 2018-2022	(3) last-week origination New Purchase 2018-2022
Accr	0.0030*	0.0048**	0.0049**
	(0.0017)	(0.0022)	(0.0022)
black			0.013***
			(0.0022)
Accr × *black*			-0.00028
			(0.00040)
Historic Loan-Level Controls	NO	YES	YES
New Loan-Level Controls (2018-2022 HMDA)	NO	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
N	3554233	3091137	3091137
R-sq	0.085	0.090	0.090

Table 5: The table reports individual loan-level regression estimates of how the likelihood of a loan closing at month-end is influenced by the saved accrued interest payment with respect to originating in the first week of the month (see equation 4). The sample is restricted to originated loans only. We include the same set of controls as in Table 2. The dependent variable for all regressions is a dummy that takes a value of one if a loan is originated in the last week of the month, and zero if it is originated in any other week. *Accr* is the estimate of the accrued interest savings from closing at month-end. *black* is a dummy equal to one for Black applicants. Standard errors are clustered by lender and year. Estimates are based on a 20 percent sample of the new HMDA data from 2018 to 2022.

	(1) approval 2018-2022	(2) approval 2018-2022	(3) approval 2018-2022	(4) approval 2018-2022	(5) approval 2018-2022
black	-0.033***	-0.025***	-0.028***	-0.032***	-0.033***
	(0.0020)	(0.0018)	(0.0019)	(0.0032)	(0.0028)
midweek	0.0083***	0.0088***	0.0085***	0.0095***	0.014***
	(0.00094)	(0.00091)	(0.00087)	(0.0010)	(0.0014)
lastweek	0.021***	0.022***	0.021***	0.021***	0.029***
	(0.0015)	(0.0014)	(0.0013)	(0.0014)	(0.0022)
black × *midweek*	0.0064***	0.0068***	0.0089***	0.0069***	0.0073***
	(0.0019)	(0.0015)	(0.0015)	(0.0022)	(0.0022)
black × *lastweek*	0.028***	0.022***	0.018***	0.017***	0.021***
	(0.0021)	(0.0017)	(0.0015)	(0.0027)	(0.0026)
black × *LowInc*	0.0067***				
	(0.0021)				
midweek × *LowInc*	0.0037***				
	(0.00062)				
lastweek × *LowInc*	0.0083***				
	(0.00078)				
black × *midweek* × *LowInc*	-0.0026				
	(0.0020)				
black × *lastweek* × *LowInc*	-0.0046				
	(0.0028)				
black × *nonprime*		-0.0091***			
		(0.0032)			
midweek × *nonprime*		0.012***			
		(0.0011)			
lastweek × *nonprime*		0.033***			
		(0.0014)			
black × *midweek* × *nonprime*		-0.0012			
		(0.0033)			
black × *lastweek* × *nonprime*		-0.0084**			
		(0.0039)			
black × *nonconv*			-0.0056**		
			(0.0027)		
midweek × *nonconv*			0.010***		
			(0.0011)		
lastweek × *nonconv*			0.027***		
			(0.0016)		
black × *midweek* × *nonconv*			-0.00036		
			(0.0025)		
black × *lastweek* × *nonconv*			0.0029		
			(0.0027)		
black × *HighLTV*				0.00098	
				(0.0031)	
midweek × *HighLTV*				0.0015**	
				(0.00064)	
lastweek × *HighLTV*				0.0073***	
				(0.00093)	
black × *midweek* × *HighLTV*				0.0011	
				(0.0027)	
black × *lastweek* × *HighLTV*				0.012***	
				(0.0035)	
black × *purchase*					-0.0018
					(0.0030)
midweek × *purchase*					-0.0066***
					(0.0011)
lastweek × *purchase*					-0.0033*
					(0.0017)
black × *midweek* × *purchase*					0.0025
					(0.0028)
black × *lastweek* × *purchase*					0.0081**
					(0.0033)
All Controls, FEs, and Interactions	YES	YES	YES	YES	YES
N	10775618	10764907	10784387	10772997	9263691
R-sq	0.38	0.40	0.41	0.39	0.35

Table 6: The table reports individual loan-level regression estimates of differences in approval rates across races and within the month, augmented with interactions with financial constraints variables. We include the same set of controls as in column (3) of Table 2, as well as interactions between financial constraint variables and both loan-level controls and fixed effects. The dependent variable for all regressions is a dummy that takes a value of one if a loan is originated in the last week of the month, and zero if it is originated in any other week. *midweek* and *lastweek* are dummies equal to one, respectively, if the action on the application is taken in the middle weeks (not the first or last 7 days of a month) and last week of the month. *black* is a dummy equal to one for Black applicants. The financial constraints variables are: *LowInc*, which is a dummy equal to one for applicants with income below the median in their county; *nonprime*, which is a dummy equal to one for applicants with FICO scores lower than 660; *nonconv*, which is a dummy equal to one for non-conventional mortgages; *HighLTV*, which is a dummy equal to one for loans that have loan-to-value (LTV) ratio greater than or equal to 70%; *purchase*, which is a dummy equal to one for home purchase mortgages. Standard errors are clustered by lender and year. Estimates are based on a 20 percent sample of the new HMDA data from 2018 to 2022.

	Oster Bounds		
	(1) approval 2018-2022	(2) approval 2018-2022	(3) approval 2018-2022
lastweek × *black*, *Short Regression*	0.0382	0.0382	0.0380
lastweek × *black*, *Long Regression*	0.0268	0.0268	0.0268
	Estimated Coefficient Lower Bounds		
lastweek × *black* Bound, $R_{max} = 47.5\%$	0.0247	0.0245	0.0234
lastweek × *black* Bound, $R_{max} = 75.0\%$	0.0136	0.0130	0.0131
	Short Regression Controls		
Lender FE	YES	YES	YES
County FE	NO	NO	YES
Month-Year FE	NO	YES	YES
Month-Year-County FE	NO	NO	NO
Month-Year-Lender FE	NO	NO	NO
Holiday FE	YES	YES	YES
Day-of-Week FE	YES	YES	YES
Month-Year FE	YES	YES	YES
Historic Loan-Level Controls	NO	NO	NO
New Loan-Level Controls (2018-2022 HMDA)	NO	NO	NO
midweek	YES	YES	YES
lastweek	YES	YES	YES
black	YES	YES	YES
midweek × *black*	YES	YES	YES

Table 7: The table reports lower bounds for estimates of the month-end decrease in the approval gap ($\delta_{lw,Black}$ in equation 2), based on the methodology in Oster (2019). *Long Regression* corresponds to Column (3) of Table 2; it includes all seasonality fixed effects, lender by year-month and county by year-month fixed effects. The *Short Regressions* are characterized by the sets of controls selected in the different columns of the table. The bounds are based on maximum attainable R-squares of 47.5% (the R-square in the *Long Regression* multiplied by 1.3, as suggested by Oster, 2019) and 75% (twice the R-square in the *Long Regression*). Estimates are based on a 20% random sample of new HMDA data from 2018 to 2022.

	(1) approval 2018-2022	(2) approval 2018-2022	(3) approval 2018-2022
R-square	0.29	0.34	0.39
Loan Officer FE Std	-	-	0.18
Loan Officer FE Q25	-	-	-0.069
Loan Officer FE Q75	-	-	0.100
Loan Officer FE	NO	NO	YES
Historic Loan-Level Controls	YES	YES	YES
New Loan-Level Controls (2018-2022 HMDA)	YES	YES	YES
Holiday FE	YES	YES	YES
Day-of-Week FE	YES	YES	YES
Month-Year-County FE	YES	YES	YES
Lender FE	NO	YES	NO
N	8103689	8103689	8103689

Table 8: The table reports R-squares for different specifications of equation 2, with varying sets of fixed effects. Estimates are based on a 20% random sample of the new HMDA data from 2018 to 2022.

	Panel A: Question 20 of the National Survey of Mortgage Originations							
	(1) Had to Add Cosigner	(2) Resolved Credit Errors	(3) Income-Asset Follow-Up	(4) Had More Appraisals	(5) Refiled Paperwork	(6) Delayed Closing Date	(7) Had Estimate Revised	(8) Checked On Other Sources
black	-0.021**	0.048***	-0.021	0.028***	0.037**	0.070***	0.066***	0.041**
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
jumbo	0.020	-0.014	0.071***	0.030**	0.029	0.040*	0.009	0.035
	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
gse	-0.001	0.001	0.016*	0.004	-0.014**	-0.018**	0.005	0.014
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
credit union	0.018*	-0.021**	-0.067***	-0.007	-0.002	-0.009	0.007	0.005
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
R-Square adj	0.013	0.087	0.034	0.018	0.015	0.027	0.015	0.013
N	18279	18279	18279	18279	18279	18279	18279	18279
μ Dep. Var.	0.080	0.120	0.572	0.054	0.142	0.201	0.267	0.293

	Panel B: Question 51 of the National Survey of Mortgage Originations								
	(1) Loan Docs Not Ready	(2) Not Occur as Scheduled	(3) 3-Day Rule Redisclosure	(4) Unexpected Terms	(5) More Cash Needed	(6) Less Cash Needed	(7) Sign Blank Doc	(8) Sign Pre-Post Dated Docs	(9) Felt Rushed
black	0.016	0.034**	0.065***	0.027***	0.007	0.014*	0.012	0.015*	0.012
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
jumbo	0.005	0.002	0.025*	-0.002	-0.009	-0.009	-0.015	-0.005	0.016
	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
gse	-0.008	-0.012	0.007	-0.000	-0.003	-0.003	-0.002	-0.002	0.005
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)
credit union	-0.014	0.006	-0.006	-0.005	-0.012	0.006	-0.008	-0.003	0.022*
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
R-Square adj	0.009	0.015	0.020	0.007	0.010	0.004	0.007	0.005	0.017
N	18279	18279	18279	18279	18279	18279	18279	18279	18279
μ Dep. Var.	0.031	0.074	0.043	0.016	0.028	0.017	0.023	0.012	0.044
DTI Bins FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
LTV Bins FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
FICO Bins FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Loan Type FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Loan Amount Bins FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Location FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Education FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Income Bins FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table 9: The table reports estimates of equation 5, based on data from answers to the sub-categories of Question 20 (panel A) and Question 51 (panel B) in the National Survey of Mortgage Originations (NSMO). The dependent variable is a dummy equal to one if the respondent selects "yes" and zero if she selects "no." *black* is a dummy equal to one for Black borrowers, *jumbo* is a dummy equal to one for jumbo loans, *gse* is a dummy equal to one for loans securitized by the GSEs, and *credit union* is a dummy equal to one for loans originated by credit unions. We report robust standard errors in parentheses. The sample consists of waves 19 to 34 of the survey, covering the period from 2018 to 2021.

Online Appendix:

Temporal Focal Points and Economic Outcomes: Evidence from U.S. Mortgage Lending

(intended for online publication)

A.I Additional Figures and Tables

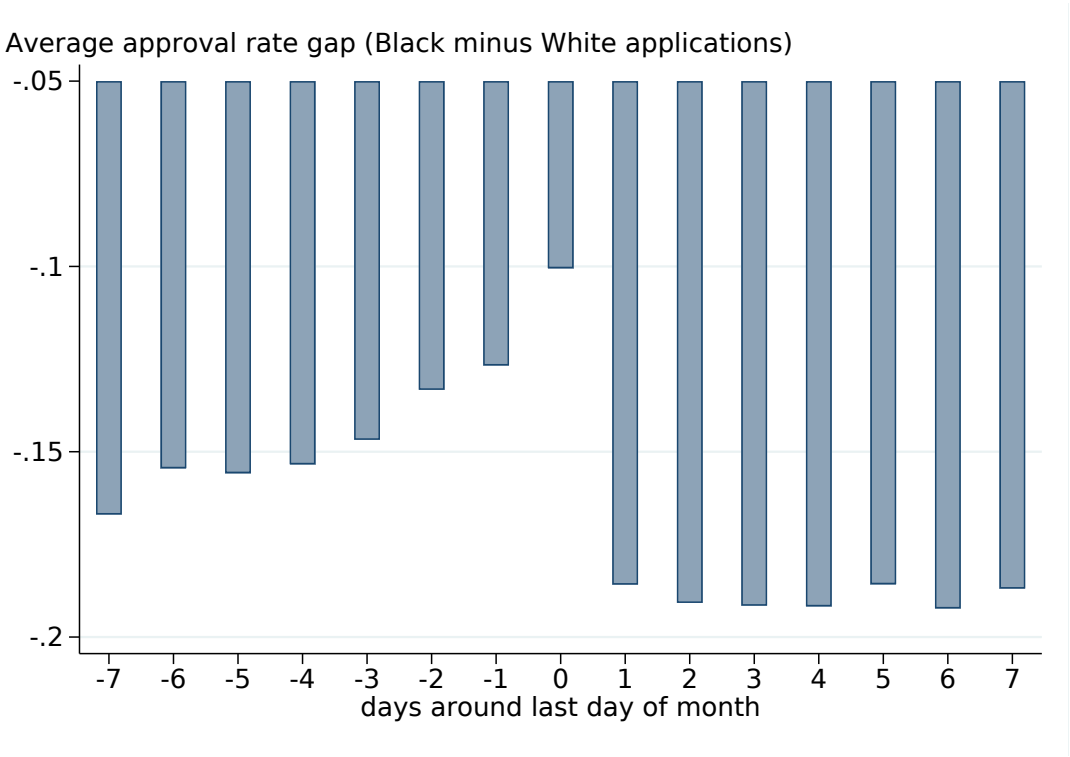
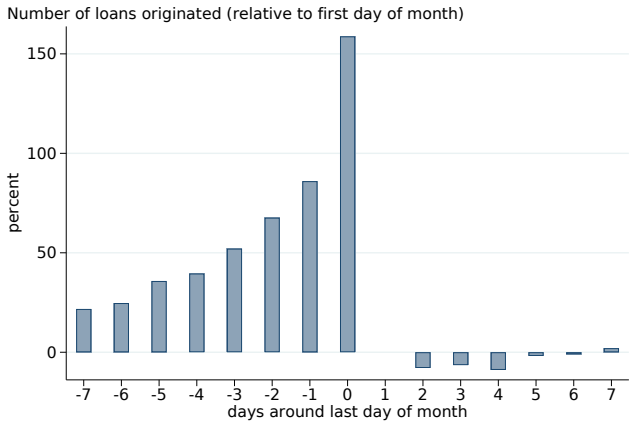
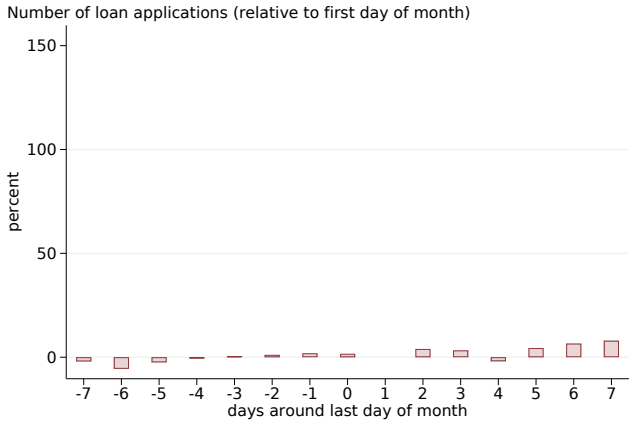


Figure A.I.1: The figure uses data from HMDA on U.S. mortgage applications between January 1994 and December 2022 to calculate daily approval gaps between Black and White applicants, calculated as the difference in approval rates (equation 1 in the paper) on each day. Negative values imply that approval rates are lower for Black applicants.

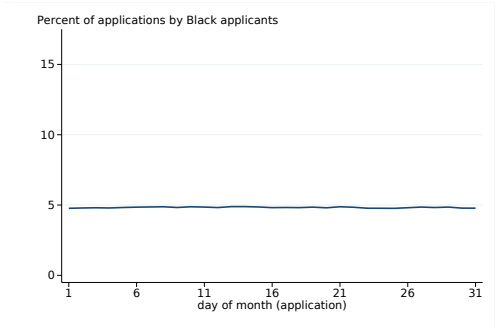


(a) Origination Volume around End of Month

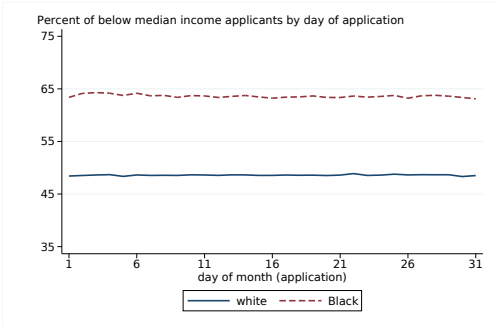


(b) Application Volume around End of Month

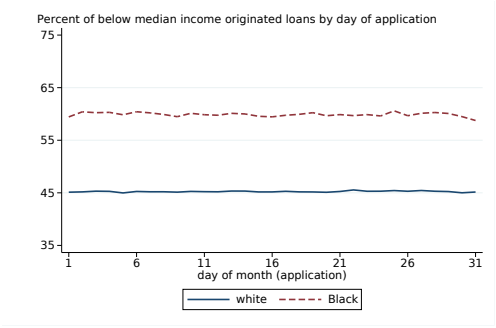
Figure A.I.2: The figure uses data from HMDA on U.S. mortgage applications submitted between January 1994 and December 2022. Panel (a) reports the percentage differences between the average daily origination volume on each day in the first and last week of the month, and the first day of any given month. Panel (b) presents the same calculations for average daily application volume.



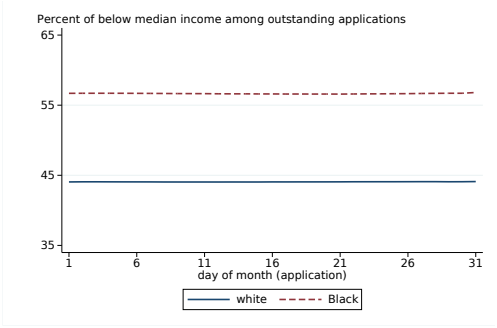
(a) Racial Composition by Application Day



(b) Income by Application Day



(c) Originated by Application Day



(d) Outstanding Applications by Day

Figure A.I.3: The figure uses data from HMDA on U.S. mortgage applications submitted between January 1994 and December 2022. Panel (a) shows the average fraction of applications submitted by Black applicants, by application day. Panel (b) shows the fraction of applicants, among Black and White applicants, whose income is less than their county's median income in that year, by application day. Panel (c) shows the fraction of loans originated to applicants whose income is less than their county's median income in that year, by application day. Panel (d) shows the fraction of outstanding applications (not yet originated or denied), on each day, submitted by applicants whose income is less than their county's median income in the year.

Sample Commission Schedule

Commissions are based on Loan Volume ONLY. Commissions are calculated as follows:

1. At the end of each period, LO assembles a "commissions due" report including all loans which have funded for the period. In addition, the LO provides a complete Pipeline Report, indicating loans in process, loans with appraisals received and loans with Firm Approval.
2. For the purpose of calculating commissions we base commissions on loan volume. In order to reward higher production volume, as loan volume increases, the commission on the volume which exceeds the incentive threshold is calculated at a higher level.
3. Company Name will approve the Commissions Due report, and note any corrections. The commissions will be paid in the following regular pay period.

Commission Rates are incremental, not cumulative. Volume adjustments are applied to the closed volume above each threshold.

Closed Loan Volume for Month	Commission Rate
Up to $499,999	85 bps
From $500,000 to $999,999	85 bps + 5 bps on balance
Over $1,000,000	85 bps + 5 bps on balance over $500,000 + 10 bps on balance over $1,000,000

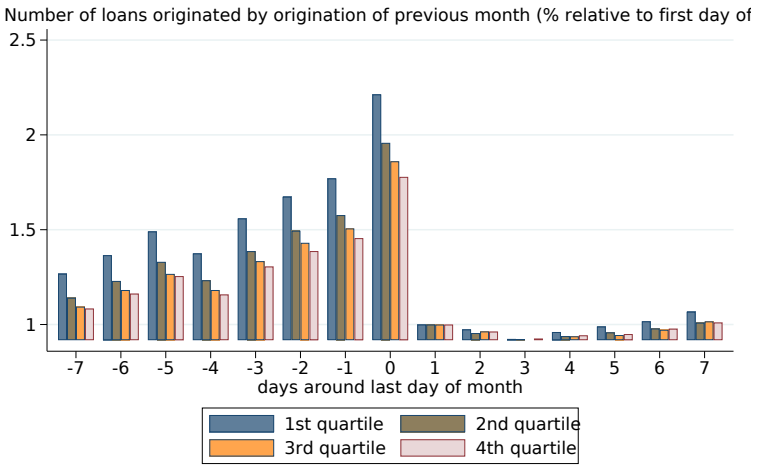
Loan Volume Performance Expectations

On a monthly basis Company Name expects LO to close :

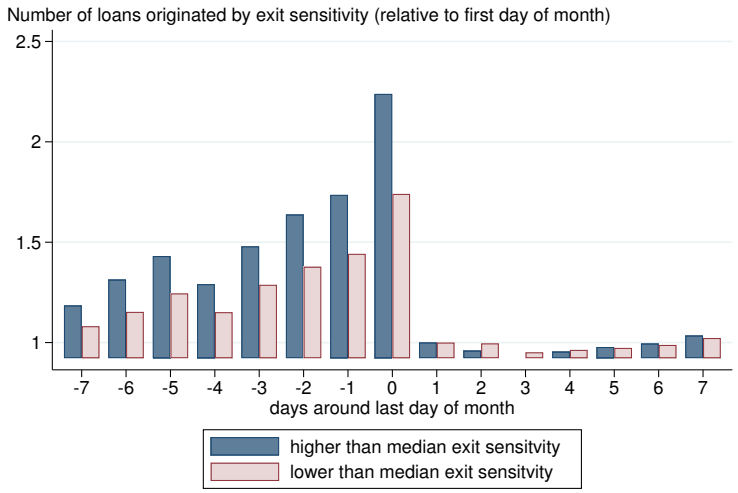
3 loans per month and/or
$600,000 in total volume

Company Name Manager will evaluate LO pipeline to determine necessary corrective action.

Figure A.I.4: Commission schedule from a sample loan officer contract available from *Mortgage Manuals* (a compliance advisory firm specializing in banking). The schedule highlights two different forms of monthly volume-based incentives: a commission rate marginally increasing in origination volume, and a minimum loan volume threshold, below which the loan officer may be subject to disciplinary action.



(a) Month-End Loan Originations by Loan Officer-Level Pressure



(b) Month-End Loan Originations by Lender-Level Pressure

Figure A.I.5: The figure shows percentage differences in daily origination volume, around month-end and relative to the first day of the month, for groups of loan officers that experience different degrees of performance pressure. The results are based on data from the new HMDA dataset for 2018-2022. In the top panel, we report volume for four groups, based on whether loan officers in the previous month ($t-1$) were in the first (bottom), second, third, and fourth (top) quartile of mortgage origination volume within their lender (see Section 4.2). In the bottom panel, we allocate loan officers to two groups, based on whether they are employed by lenders that are above or below the median likelihood of performance-induced turnover, according to the Jenter and Lewellen (2020) measure (see Section 4.3).

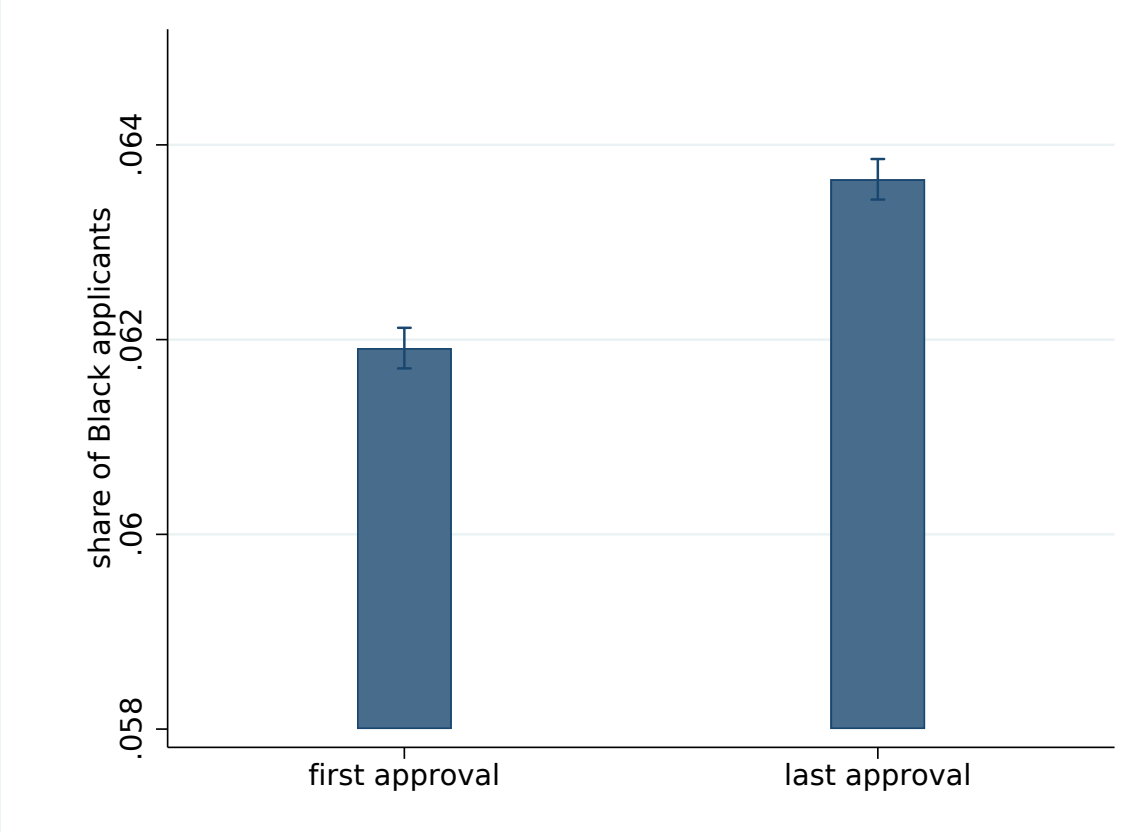


Figure A.I.6: The figure reports the average share of originations to Black applicants, for the first and last origination by loan officers in a month. The sample is restricted to loan officers with 3 or more loans originated in a month. The results are based on the new HMDA data set for 2018-2022.

	U.S.-Level					
	(1)	(2)	(3)	(4)	(5)	(6)
	log(Num Loans)	log(Num Loans)	log(Num Loans)	log($ Amount)	log(Num Loans) non-CRA	log(Num Loans) CRA
midweek	0.24**	0.16***	0.16***	0.15***	0.15***	0.15***
	(0.11)	(0.038)	(0.029)	(0.056)	(0.027)	(0.030)
lastweek	0.27**	0.25***	0.25***	0.22***	0.22***	0.26***
	(0.14)	(0.045)	(0.035)	(0.066)	(0.032)	(0.035)
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
N	1826	1826	1826	1826	1826	1826
r2	0.0030	0.89	0.94	0.83	0.95	0.93

Table A.I.1: The table reports regression estimates of differences in loan origination volume within the month, at the U.S.-level. In columns (1) to (3) the dependent variable is the log of the number of originations per day in the U.S. In column (4), the dependent variable is the total dollar amount of loan originations per day. In column (5), the dependent variable is the log number of originations for lenders not undergoing CRA examination, and in column (6) it is the log number of originations for lenders undergoing CRA examination. *midweek* and *lastweek* are dummies equal to one, respectively, in the middle (from second to second-to-last week) and last week of the month. Estimates are based on a 5 percent sample of HMDA mortgage originations from 2018 to 2022.

	Panel A: 5-Year Delinquency			
	(1)	(2)	(3)	(4)
		FICO $<$ 660	LTV $>$ 80%	Low Docs
midweek	-0.00098	-0.0022	-0.0022**	-0.0014
	(0.00072)	(0.0015)	(0.0010)	(0.00099)
lastweek	-0.00086	0.0000079	-0.0023	-0.0018
	(0.0013)	(0.0024)	(0.0018)	(0.0016)
black	0.050***	0.060***	0.056***	0.055***
	(0.0055)	(0.0045)	(0.0037)	(0.0089)
black $\times$ *midweek*	-0.0052***	-0.0047	-0.0047**	-0.0078**
	(0.0018)	(0.0032)	(0.0022)	(0.0029)
black $\times$ *lastweek*	-0.0037	-0.00078	-0.0044	-0.015**
	(0.0028)	(0.0037)	(0.0027)	(0.0062)
N	18797106	3065611	5870489	5278008
r2	0.26	0.25	0.26	0.34
	Panel B: 5-Year Default			
	(1)	(2)	(3)	(4)
		FICO $<$ 660	LTV $>$ 80%	Low Docs
midweek	-0.00044	-0.0011	-0.00097*	-0.00049
	(0.00027)	(0.00063)	(0.00053)	(0.00041)
lastweek	-0.00055	-0.0012	-0.0013	-0.000069
	(0.00049)	(0.0010)	(0.00083)	(0.00095)
black	0.0053***	0.0022	0.0042*	0.011***
	(0.0016)	(0.0017)	(0.0020)	(0.0028)
black $\times$ *midweek*	-0.0020***	-0.0011	-0.0025**	-0.0033***
	(0.00059)	(0.00095)	(0.00093)	(0.0011)
black $\times$ *lastweek*	-0.0033***	-0.0031**	-0.0047***	-0.0072***
	(0.00074)	(0.0013)	(0.0012)	(0.0019)
N	20732940	3729582	6606020	5617662
r2	0.12	0.16	0.15	0.22
	Panel C: 5-Year Termination			
	(1)	(2)	(3)	(4)
		FICO $<$ 660	LTV $>$ 80%	Low Docs
midweek	-0.0010	-0.00032	-0.0018	0.00028
	(0.0014)	(0.0020)	(0.0016)	(0.0016)
lastweek	-0.0036	-0.00092	-0.0058*	0.0026
	(0.0033)	(0.0030)	(0.0031)	(0.0050)
black	-0.052***	-0.037***	-0.058***	-0.040***
	(0.0076)	(0.0063)	(0.0091)	(0.0085)
black $\times$ *midweek*	-0.0018	-0.0013	-0.0033	-0.0037**
	(0.0016)	(0.0018)	(0.0020)	(0.0013)
black $\times$ *lastweek*	-0.0042*	-0.0057**	-0.0047*	-0.012***
	(0.0024)	(0.0025)	(0.0026)	(0.0039)
N	20732940	3729582	6606020	5617662
r2	0.22	0.28	0.25	0.32
All Loan-Level Controls	YES	YES	YES	YES
Holiday FE	YES	YES	YES	YES
Day-of-Week FE	YES	YES	YES	YES
Month-Year-County	YES	YES	YES	YES
Month-Year-Lender	YES	YES	YES	YES

Table A.I.2: The table reports regression estimates of the difference in ex-post performance for mortgages originated in different weeks within the month. The dependent variable is either a dummy equal to one for mortgages that experience a 90-day delinquency within 5 years after origination (panel A), a dummy equal to one for mortgages that default within 5 years after origination (panel B), or a dummy equal to one for mortgages that are terminated (due to default, refinancing, or loan payoff) within 5 years after origination (panel C). 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. *All Loan-Level Controls* stands for the set of controls for application characteristics used in column (1) of Table 2, augmented with FICO and LTV quintile bins. *lastweek* and *midweek* are dummies equal to one in the last and intermediate (not the first or last 7 days of a month) weeks of the month. *black* is a dummy equal to one for Black applicants. 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.

A.II Alternative Dependent Variables

In this section, we test for changes to the share of new originations to Black applicants within the month. We estimate the following regression specification:

$$I_{Black,j} = \delta_{lw,Orig}\left(I_{lw,j} \times Orig_j\right) + \delta_{mw,Orig}\left(I_{mw,j} \times Orig_j\right) + \delta_{lw} I_{lw,j} + \tag{A.II.1}$$
$$+ \delta_{mw} I_{mw,j} + \delta_{Orig} Orig_j + BX_j + a_{ym,county} + a_{ym,lender} + a_{dow} + a_{holiday} + v_j,$$

where $I_{Black,j}$ equals one for applications submitted by Black borrowers, while $Orig_j$ equals one for originated loans (and zero for denied loans). The other variables are the same as in equation (2) in the main body of the paper. The coefficient on the interaction term between the last week of the month and the indicator for originations—$\delta_{lw,Orig}$—should not be statistically different from zero under the null that the share of loans originated to Black applicants is constant within the month.

Table A.II.1 presents estimates of the main coefficients of interest in equation (A.II.1). Across all different specifications and samples we reject the null that $\delta_{lw,Orig}$ is equal to zero and find instead positive and statistically significant estimates.

Column 1 reports OLS estimates (linear probability model) for the extended sample from 1994 to 2022. We find that the likelihood of observing a loan originated to a Black rather than a White applicant in the last week of the month is 0.18 percentage points higher in the last rather than in the first week of the month. Since loans originated to Black applicants are only approximately 6% of originations, this is a 3% relative increase in origination volume. In columns 2 and 3 we restrict the analysis to the period in which the new HMDA data are available, consisting of the years from 2018 to 2022. We find that in this sample the increase in likelihood of observing a loan originated to a Black applicant is even larger. When including all controls available from new HMDA data, we find an increase of 3.3 percentage points, which corresponds to a relative increase in the share of origination to Black applicants of 6.3%. Columns 5 and 6 report logit estimates of equation (A.II.1), for the extended sample (1994-2022) and the shorter sample (2018-2022), respectively. In these specifications, estimates of the coefficient $\delta_{lw,Orig}$ directly measure the increase in the likelihood of observing a loan originated to a Black applicant in the last week of the month. We find highly significant and positive estimates of approximately 7%.

	(1) OLS 1994-2022	(2) OLS 2018-2022	(3) OLS 2018-2022	(4) Logit 1994-2022	(5) Logit 2018-2022
Orig	-0.050***	-0.056***	-0.025***	-0.75***	-0.39***
	(0.0022)	(0.0026)	(0.0019)	(0.011)	(0.013)
midweek	0.00022	0.00049	-0.00049	0.0023	-0.0045
	(0.00052)	(0.0014)	(0.0016)	(0.011)	(0.013)
lastweek	-0.00048	0.00021	-0.00055	0.0048	0.0027
	(0.00060)	(0.0014)	(0.0016)	(0.013)	(0.015)
Orig × *midweek*	-0.00030	0.00072	0.0016	0.020	0.024
	(0.00055)	(0.0014)	(0.0015)	(0.013)	(0.015)
Orig × *lastweek*	0.0018***	0.0033**	0.0038**	0.073***	0.066***
	(0.00067)	(0.0015)	(0.0017)	(0.015)	(0.018)
Historic Loan-Level Controls	YES	YES	YES	YES	YES
New Loan-Level Controls (2018-2022 HMDA)	NO	NO	YES	NO	YES
Holiday FE	YES	YES	YES	YES	YES
Day-of-Week FE	YES	YES	YES	YES	YES
Month-Year-County FE	YES	YES	YES	YES	YES
Month-Year-Lender FE	YES	YES	YES	YES	YES
N	15496115	2411040	2049113	2496057	2109210
r2	0.254	0.226	0.237	-	-

Table A.II.1: The table reports individual loan-level regression estimates of the likelihood that an originated (or denied) loan is from a Black applicant. In columns (1), (2), and (3) we estimate a linear probability model with dependent variable equal to a dummy for Black applicants. The variable *Orig* is a dummy equal to one for originated loans, *lastweek* and *midweek* are dummies equal to one for loans originated or denied in the last and middle (not the first or the last 7 days of a month) weeks of the month. In columns (4) and (5), we estimate logit models. For all columns, estimates are based on a 5% random sample of the HMDA data. In columns (1) and (4) the sample consists of all years from 1994 to 2022, while in all other columns it is restricted to the years from 2018 to 2022.

A.III The Framework for Identifying a Decision Gap

This section presents a formal discussion of our empirical setup. Existing frameworks for identifying a decision gap face important challenges when dealing with differences in unobserved characteristics across subject groups. Our approach is to "filter out" these unobserved differences using high-frequency data and to exploit changes to decision-makers' incentives.

Our approach extends conventional tests for decision gaps, called either benchmarking or audit. These tests compare the conditional likelihood that a subject group receives favorable treatment relative to another group, after controlling for observable subject characteristics. For instance, assume that the decision-maker considers whether to approve loan applications. The researcher claims to have uncovered a decision gap when he rejects the null of no difference in the conditional likelihood of favorable decisions between groups (for example, Black and White). Specifically, the researcher claims a decision gap against Black subjects when he finds that:

$$P(Y|W,X) > P(Y|B,X), \tag{A.III.2}$$

where $P(Y|R,X)$ is the probability of receiving a favorable decision, conditional on race $R \in \{W,B\}$ (White or Black) and a vector of characteristics X observed by the researcher. However, this approach is exposed to the criticism that the difference in the estimated conditional probability between White and Black subject groups might be driven by unobserved characteristics that are relevant to the decision-maker's assessment but are not included in the vector of controls X observed by the researcher. To illustrate, assume that there is a binary variable, unobserved by the researcher, $Z \in \{Z_L, Z_H\}$, such that the following assumptions are satisfied:

Assumptions Set (A)

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

The inequality in favorable decisions formalized by equation (A.III.2) holds under the above assumption set when omitting the variable Z, even though *there is no decision gap when all of the characteristics are accounted for* (see Online Appendix A.III.1). The differences in the observed conditional probability of favorable decisions between groups simply capture the differences in the unobserved characteristic. In

the mortgage-lending setting, Black and White applicants have substantially different observable characteristics (see Table 1). Such differences raise concern that there might also be meaningful differences in unobservables.

Our goal is to refine existing approaches to address the identification problems due to the systematic differences in unobservables across subject groups. Rather than testing only for the differences in the likelihood of a favorable decision between racial groups, we use high-frequency data to test whether those differences vary over a short period of time. Under the null of no decision gap, and if applicant characteristics remain constant over time, there shall be no change in the probability of favorable decisions between groups over time. On the other hand, a change in the relative favorable decision probability over time suggests a decision gap when there is no change in applicant characteristics 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 a time-varying decision gap we expect to find:

$$P(Y|W, X, End) - P(Y|B, X, End) < P(Y|W, X, Start) - P(Y|B, X, Start), \qquad \text{(A.III.3)}$$

where $P(Y|., X, .)$ is the probability of receiving a favorable decision, 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 (A.III.3). Consider the following set of assumptions that characterize a situation in which there is no decision gap:

Assumptions Set (B)

No decision gap:	$P(Y\|W, Z_k, X, T) = P(Y\|B, Z_k, X, T)$ for $k \in \{H, L\}$
Higher quality predicts higher favorable decision probability:	$P(Y\|Z_H, X, T) > P(Y\|Z_L, X, T)$
On average White applicants have better unobservables:	$P(Z_H\|W, X, T) > P(Z_H\|B, X, T)$
No time pattern in subject group quality:	$P(Z_H\|R, X, Start) = P(Z_H\|R, X, End)$
Stable Decision Criteria:	$P(Y\|Z_H, X, T) - P(Y\|Z_L, X, T) = \lambda$

The first three assumptions are the same as in **Assumptions Set (A)**, while the last two assumptions state that the unobserved characteristics of the applicants, for both White and Black, are constant over time, and that their effect on decision making is constant over time. Jointly, these assumptions imply (see Online Appendix A.III.1):

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

Thus, the condition in equation (A.III.3) indeed amounts to a rejection of the null of no decision gap.

A.III.1 Identifying a Time-Varying Decision Gap

We show how under the assumptions in **Assumption Set (A)**, favorable decision probabilities for White and Black applicants are different. The probability, conditional on race and other observable characteristics, is equal to:

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

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

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 favorable decision probabilities for White and Black is equal to:

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

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

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

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

where we use $P(Y|Z_H,X) = P(Y|W,Z_H,X) = P(Y|B,Z_H,X)$ and $P(Y|Z_L,X) = P(Y|W,Z_L,X) = P(Y|B,Z_L,X)$ from the assumption of no decision gap, and $P(Z_H|R,X) = 1 - P(Z_L|R,X)$. Then, $P(Z_H|W,X) - P(Z_H|B,X) > 0$ from the assumption of higher unobservable quality characteristics for White applicants, and $P(Y|Z_H,X) - P(Y|Z_L,X) > 0$.

We now turn to the comparison of the favorable decision probabilities for White and Black applicants at the beginning and the end of the month, under **Assumption Set (B)**. The difference in the probability between White and Black applicants is equal to:

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

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

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

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

where $T \in \{Start, End\}$, and we use the assumption of no decision gap: $P(Y|Z, W, X, T) = P(Y|Z, B, X, T) = P(Y|Z, X, T)$. Exploiting the calculations above, we can then derive the properties of the change in the difference between favorable decision probabilities at the beginning and the end of the month:

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

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

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

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

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

where we use $P(Z_H|R, X, Start) = P(Z_H|R, X, End) = P(Z_H|R, X)$, and $P(Z_L|R, X, Start) = P(Z_L|R, X, End) = P(Z_L|R, X)$, based on the assumption that application quality does not change over the month, and $P(Z_H|R, X) = 1 - P(Z_L|R, X)$. The condition is equal to zero since $P(Y|Z_H, X, End) - P(Y|Z_L, X, End) = \lambda$ and $P(Y|Z_H, X, Start) - P(Y|Z_L, X, Start) = \lambda$, due to the stable decision criteria assumption. Thus, the rejection of the null that the empirical counterpart of the condition above is equal to zero in the data leads to a rejection of **Assumption Set (B)**.

A.IV Proxies for Lender-Level Performance Incentives

Our main proxy for lender-level performance incentives is constructed using the methodology developed by Jenter and Lewellen (2020) to measure CEO performance-induced turnover. For each lender, we estimate the following logit regression:

$$\log\left(\frac{\hat{P}_{turn}(x_{i,t})}{1-\hat{P}_{turn}(x_{i,t})}\right) = \hat{\alpha} + \sum_{k=1}^{4} \hat{\beta}_k I(x_{i,t} \in Q_{k,t}), \tag{A.IV.1}$$

where $x_{i,t}$ indicates the loan origination volumes for loan officer i in the current and past quarters and $Q_{k,t}$ is a group of performance measures within lender, with $Q_{1,t}$ being the bottom group, and $Q_{4,t}$ the top group. The bottom group consists of loan officers meeting the following two conditions: (1) have lower than median performance two months in a row; (2) have loan origination volumes in the lowest quartile within a lender for at least one of those two calendar quarters. The top group consists of loan officers being in the highest quartile in originations two months in a row. $\hat{P}_{turn}(x_{i,t})$ is the estimated probability that loan officer i leaves the lender in the following quarter $(t+1)$. Following Jenter and Lewellen (2020), we assume that events that lead to loan officer turnover for other (non-performance induced-reasons) are independent from performance-induced turnover. This implies that turnover probability, given origination volume $x_{i,t}$, can be written as:

$$\hat{P}_{turn}(x_{i,t}) = \hat{P}_{other} + \hat{P}_{perf}(x_{i,t}) + \hat{P}_{other}\hat{P}_{perf}(x_{i,t}), \tag{A.IV.2}$$

where $\hat{P}_{turn}(x_{i,t})$ is estimated turnover probability given performance $x_{i,t}$, $\hat{P}_{other}$ is turnover probability for reasons unrelated to $x_{i,t}$, and $\hat{P}_{perf}(x_{i,t})$ is the probability of performance-induced turnover, which is our key variable of interest.

By rearranging the equation above we obtain:

$$\hat{P}_{perf}(x_{i,t}) = \frac{\hat{P}_{turn}(x_{i,t}) - \hat{P}_{other}}{1-\hat{P}_{other}}. \tag{A.IV.3}$$

Following again Jenter and Lewellen (2020), we assume that in the top performance group the probability of performance-induced turnover is zero, which implies that in this quartile turnover is equal to turnover for non-performance reasons: $\hat{P}_{turn}(x_{i,t} \in Q_{4,t}) = \hat{P}_{other}$. Then, we can use estimated turnover in the top group as our estimate of turnover for other reasons, and find turnover in the

bottom group of performance by substituting in the equation above:

$$\hat{P}_{perf}(x_{i,t} \in Q_{1,t}) = \frac{\hat{P}_{turn}(x_{i,t} \in Q_{1,t}) - \hat{P}_{turn}(x_{i,t} \in Q_{4,t})}{1 - \hat{P}_{turn}(x_{i,t} \in Q_{4,t})}. \tag{A.IV.4}$$

We construct estimates of $\hat{P}_{perf}(x_{i,t} \in Q_{1,t})$ for each lender in our sample. This is a proxy for the likelihood that loan officers who are in the lowest group of performance are forced to separate from the lender. We then divide lenders into two groups: high and low performance-based turnover. Lenders are assigned to each group based on whether the probability of performance-induced turnover in the bottom quartile is above or below the median across all lenders.