Artificial Intelligence and the Racial Gap in Mortgage Lending

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Abstract

We examine whether banks' adoption of artificial intelligence (AI) widens racial disparities in mortgage lending. Using 2022–2024 HMDA data merged with a bank-year AI adoption measure from job postings, we exploit within-bank variation with rich fixed effects. Higher AI adoption raises the denial-rate gap by 0.75 percentage points and the interest-rate gap by roughly 4 basis points. IV estimates exploiting banks' historical exposure to local AI labor supply support causality. The effects are concentrated in purchase loans, and are absent for GSE-backed loans and refinance loans. Our findings suggest that AI adoption amplifies racial disparities in mortgage lending, with implications for bank governance and financial regulation.

Keywords: Artificial Intelligence; Algorithmic Lending; Racial Gap; Mortgage Banking; Credit Allocation
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1 Introduction

Mortgage credit is the largest liability for most U.S. households and the primary gateway to wealth accumulation through homeownership. Racial disparities in mortgage approval and pricing therefore have first-order implications for wealth inequality: persistent gaps in access to credit and loan terms translate directly into gaps in housing equity and intergenerational wealth transfer (Munnell et al., 1996; Ambrose, Conklin, and Lopez, 2021; Frame et al., 2025). At the same time, mortgage origination has become increasingly technology-intensive. Lenders rely on automated underwriting systems, digital application channels, and algorithmic screening to reduce costs and scale originations (Fuster et al., 2019). The rapid diffusion of artificial intelligence (AI) and machine learning (ML) promises further gains in predictive accuracy and operational efficiency. When deployed thoughtfully, such tools could help broaden access to credit for underserved populations. Yet policymakers and industry leaders increasingly recognize that fairness in credit outcomes has become a critical and urgent policy concern. The 2025 FinRegLab AI Symposium highlighted that "fair outcomes to credit" and ensuring that vulnerable populations are not "affected most by" AI deployments with "the least amount of opportunity to affect that change" are central priorities for financial regulation going forward. Whether AI technologies narrow or widen racial disparities in credit access and pricing is thus both economically consequential and empirically open—a question with direct bearing on bank governance, fair-lending enforcement, and the design of financial regulation.

Well-founded theoretical perspectives yield sharply different predictions. On one hand, AI and ML may *reduce* racial disparities by displacing human discretion with objective, data-driven risk assessment—correcting systematic misclassification or bias in traditional underwriting (Berg et al., 2020; Kleinberg et al., 2018; Jagtiani and Lemieux, 2018; Howell et al., 2024). On the other hand, Fuster et al. (2022) identify two channels through which ML may *amplify* disparities. The *flexibility effect* arises because ML models exploit high-dimensional, nonlinear interactions among observables, generating finer individual-level risk estimates and greater dispersion in credit outcomes. This added precision can widen racial

gaps if the dispersion differentially affects minority borrowers—for example, if more flexible models uncover risk differentials or generate outcome distributions that disproportionately disadvantage certain groups. The *triangulation effect* arises because richer feature spaces allow models to proxy more effectively for excluded characteristics, including race, through correlated observables. Even when protected attributes are formally omitted from model inputs, ML can widen group-level disparities by exploiting correlates of race embedded in historical data. Calibrating to U.S. mortgage markets, Fuster et al. (2022) find that Black and Hispanic borrowers benefit less from ML adoption than White and Asian borrowers, with the former reclassified as lower risk at roughly half the rate of the latter. Experimental evidence further suggests that large language models reproduce racial biases in underwriting (Bowen et al., 2025). Whether banks' actual adoption of AI in practice improves or worsens outcomes for minority applicants therefore remains an empirical question with clear theoretical stakes.

The theoretical predictions in Fuster et al. (2022) carry a clear empirical implication: as banks adopt AI and ML technologies in their underwriting and screening processes, racial disparities in mortgage outcomes could widen. Importantly, this prediction holds even when lenders comply with fair-lending regulations by excluding race from model inputs, because the channel operates through correlated covariates that AI models are especially adept at exploiting. Complementary experimental evidence reinforces this concern (Bowen et al. 2025). Together, the theoretical framework of Fuster et al. (2022) and the experimental evidence from Bowen et al. (2025) motivate a prediction that AI adoption by mortgage lenders will amplify racial disparities in lending outcomes through both the statistical triangulation of protected characteristics and the reproduction of historically encoded biases.

This paper tests these predictions using nationwide mortgage application data from the Home Mortgage Disclosure Act (HMDA) for 2022–2024. We merge these applications with a bank-year measure of AI adoption derived from AI-skill intensity in job postings (Babina et al., 2024). This proxy captures banks' organizational investment in AI capabilities and varies both across banks and within banks over time. Our empirical design exploits within-bank variation while controlling for rich borrower and loan characteristics and a demanding

set of fixed effects, including bank×year, MSA, and census-tract×year. The bank×year fixed effects absorb all time-varying bank-level confounders—including changes in bank strategy, risk appetite, and lending standards—so that identification comes from the differential treatment of minority versus non-minority applicants within the same bank-year. The census-tract×year fixed effects control for local demand-side shocks and neighborhood compositional changes.

We find that higher AI adoption is associated with a statistically and economically significant widening of racial disparities in both underwriting and pricing. A one-standard-deviation increase in a bank's AI job-posting share (2.02 percentage points) is associated with a 0.75-percentage-point increase in the denial-rate gap between minority and non-minority applicants. Among approved loans, the same increase in AI adoption is associated with roughly a 4-basis-point increase in the interest-rate gap. These patterns persist after controlling for detailed observables and location-by-time shocks and are robust to alternative proxies for AI adoption.

To address endogeneity, we follow Babina et al. (2024) and instrument bank AI adoption with banks' *ex ante* exposure to the supply of AI graduates from universities. Using Revelio Lab data, we identify all employees at sample banks in 2008–2010 and their alma maters, then apply Babina et al. (2024)'s method to classify universities as AI strong. Our instrument, *AI Strong*, equals one if at least one employee in 2008–2010 graduated from an AI strong university, and zero otherwise.[1]

This instrument leverages banks' historical ties to universities with subsequent AI prominence. Conditional on our rich fixed effects, this supply-driven variation is highly unlikely to correlate with contemporaneous shocks to minority mortgage outcomes, thereby plausibly satisfying the exclusion restriction. We implement a two-stage least squares approach using this instrument to estimate the causal effect of bank AI adoption on the racial gap in mortgage lending. The first- and second-stage regression results are reported in Table 5.

We conduct several tests to rule out alternative explanations. AI adoption does not

[1]We do not use the share of employees from AI strong universities as the instrument because the dummy measure is empirically stronger, both in coefficient estimates and first-stage F-statistics.

significantly affect the share of minority loan officers or the composition of applicants, ruling out compositional channels. Minority applicants at banks with greater AI adoption appear, if anything, observably *less* risky along key dimensions (combined loan-to-value and loan-to-income), alleviating concerns that our results reflect risk-based sorting.

We further find that disparities concentrate in underwriting decisions rather than at the pre-application stage (withdrawals and incomplete applications), where AI involvement is minimal—consistent with AI affecting screening and pricing rather than application behavior. Robustness tests using McDash data, which provide credit scores and precise loan-to-value ratios not available in HMDA, confirm that our findings survive the inclusion of these critical underwriting variables.

We also examine heterogeneity across loans that differ in securitization status. We find that while the effect of AI adoption on the racial gap in denial is present for non-securitized loans and loans sold to non-GSE investors, the effect disappears for loans sold to GSEs. This result is consistent with the idea that GSEs' standardized underwriting guidelines and quality control processes may mitigate the amplification of racial disparities by lender AI.

We also separately examine the effect of AI adoption on the racial gap in mortgage lending for purchase and refinance loans. We find that the effect of AI adoption on the racial gap in denial is present for purchase loans, but not for refinance loans. Refinance loans, in contrast, are typically made to borrowers with an existing mortgage and an observable payment history, which may limit the flexibility and triangulation channels through which AI can amplify disparities. This pattern is consistent with the theoretical predictions in Fuster et al. (2022) that AI's amplification effects are more pronounced when models have greater flexibility and richer feature spaces to exploit, as is often the case in purchase lending where borrower risk is less directly observable.

As a contrast case, we examine FinTech lenders. In stark contrast to traditional banks, AI adoption does not amplify racial disparities among FinTech lenders, where fully automated underwriting with limited loan-officer discretion has been embedded from inception (Buchak et al., 2018; Fuster et al., 2019). This divergence underscores that the equity im-

plications of AI depend critically on institutional context: at traditional banks, AI appears to interact with legacy processes and human decision-making in ways that amplify historical disparities, whereas technology-native FinTech operations may insulate underwriting from such amplification.

This paper contributes to three three strands of the literature. First, we add to the literature on discrimination in mortgage and consumer lending. Foundational work on lending discrimination includes Munnell et al. (1996), Hunter (1996), and Yinger (1995), which documented systematic racial disparities in mortgage approval and pricing. More recent work documents persistent racial gaps in approval and pricing and relates them to intermediary characteristics and organizational practices (Ambrose, Conklin, and Lopez, 2021; Frame et al., 2025; Chu, 2025). Evidence from FinTech settings shows that algorithmic lending can coexist with disparate outcomes (Bartlett et al., 2022). Fuster et al. (2022) provide a theoretical framework predicting that ML widens racial disparities through flexibility and triangulation channels; Bowen et al. (2025) provide experimental evidence that LLMs reproduce racial biases. We provide the first large-sample empirical evidence that banks' actual AI adoption amplifies racial disparities in mortgage lending.

Second, we contribute to research on the role of AI and technology in financial markets. Prior work examines how automation reshapes origination processes and borrower–lender matching (Fuster et al., 2019; Buchak et al., 2018). We show that AI adoption has meaningful distributional consequences—effects that differ across borrower groups and across institutional contexts (traditional banks vs. FinTech). Understanding these distributional effects is essential for assessing the welfare implications of technological change in credit markets.

Third, our analysis connects to research on algorithmic fairness and the distributional effects of predictive technologies (Dwork et al., 2012; Hardt, Price, and Srebro, 2016; Kleinberg et al., 2018). That literature emphasizes that improvements in predictive accuracy need not translate into equitable outcomes when protected characteristics are correlated with model inputs through historical and structural channels. We provide field evidence consistent with this concern: AI-assisted underwriting appears to change the mapping from applicant in-

formation to credit outcomes in ways that systematically disadvantage minority borrowers, even within narrowly defined geographic and time cells. These findings underscore the importance of model-risk management, bias testing, and transparency in AI deployment, as well as the need to evaluate not only average performance but also distributional impacts across demographic groups.

The remainder of the paper proceeds as follows. Section 2 describes the data and the construction of the bank-level AI adoption measure and mortgage outcomes. Section 3 presents the baseline results, instrumental-variables analysis, and heterogeneity tests. Section 4 rule out several alternative explanations. Cross-sectional analyses, robustness checks, and additional tests are reported in Section 5 and 6. Section 7 concludes.

2 Data and Sample

This section describes the data sources, sample construction, and variable construction used in the analysis.

2.1 Bank AI Adoption

Following the human-capital–based approach in Babina et al. (2024), we construct a bank-level measure of artificial intelligence (AI) adoption using job postings data. We obtain the job posting data from Revelio Labs, a global workforce intelligence provider that aggregates and harmonizes job postings and employee records from a wide range of public and proprietary sources, including online job boards, company career pages, and professional networking platforms. Revelio Labs standardizes employer identities, job titles, and skill taxonomies, enabling consistent measurement of skill demand across firms and over time. Such job-postings data are widely used in research to measure skill demand, technology diffusion, and firm behavior (Babina et al., 2024, 2023, 2025; Babina and Fedyk, 2025; Deming and Kahn, 2018; Alekseeva et al., 2021; Azar et al., 2018; Goldfarb, Taska, and Teodoridis, 2023; Blair and Deming, 2020).

The Revelio job-posting data are from two sources, LinkedIn and Indeed. The coverage of Indeed begins in 2016 and the coverage for LinkedIn begins in 2021. LinkedIn has better coverage of higher-skilled white-collar jobs, which is critical for measuring AI-related job postings. We therefore use the Revelio job postings from 2021–2023 to construct banks' AI adoption.

Specifically, for each bank-year, we compute the share of job postings that require AI-related skills relative to the bank's total number of job postings in that year. This share serves as our primary proxy for bank AI adoption. It captures the variation in banks' strategic emphasis on AI while mitigating concerns related to bank size or overall hiring activity. This AI adoption measure exhibits substantial cross-sectional heterogeneity. A large fraction of banks report zero AI-related job postings in a given year, while banks in the upper tail display meaningful and persistent AI hiring intensity. This distributional pattern is consistent with uneven and gradual adoption of AI technologies across banks, and mirrors the stylized facts documented for non-financial firms in Babina et al. (2024).

2.2 Mortgage Lending

We obtain mortgage application level data from the Home Mortgage Disclosure Act (HMDA) database covering the period 2022–2024 because our bank AI adoption measure is available for 2001–2023. Under HMDA reporting requirements, regulated financial institutions with assets exceeding $30 million, including commercial banks, credit unions, and mortgage companies, are required to disclose detailed information on their mortgage lending activities. The HMDA data include the lender's identity, the geographic location of the property, loan amount, application year, and application outcomes, indicating whether a loan is approved or denied. For approved applications, the dataset further reports pricing information, such as the contractual interest rate and the rate spread, the difference between the annual percentage rate (APR) and the average prime offering rate. In addition, HMDA provides detailed borrower characteristics, including reported income, race, ethnicity, and gender.

We restrict the sample to mortgage applications with complete information on borrower characteristics, loan attributes, and lender identifiers. The denial analysis is conducted on the full set of applications with non-missing denial outcomes. Analyses of interest rates and interest rate spreads are based on subsamples of approved loans with available pricing information, resulting in smaller sample sizes due to missing rate disclosures.

For our baseline testing sample, we focus on non-FinTech lenders because FinTech lenders have embedded algorithmic underwriting from inception, and their AI adoption may not reflect the same dynamics as traditional banks. We identify FinTech lenders using the list constructed by Buchak et al. (2018). The main sample thus consists of applications to traditional banks, while we conduct separate analyses for the FinTech subsample to examine heterogeneity.

Using the HMDA data, we construct a comprehensive set of loan-level outcome variables, borrower characteristics, and loan attributes. Mortgage lending outcomes include an indicator for loan denial, the contractual interest rate for approved loans, and the rate spread, defined as the difference between a loan's annual percentage rate (APR) and the average prime offering rate on similar mortgages. Borrower demographic characteristics—race, ethnicity, gender, and reported income—are obtained directly from HMDA filings. Loan attributes include the loan amount, loan maturity, combined loan-to-value (CLTV) ratio, the presence of a co-applicant, and debt-to-income information.

2.3 Sample Construction

We merge the mortgage lending data with the bank-level AI adoption measure. The Revelio Lab data provide the link between the Revelio company identifier (RCID) and the LEI, which is the HMDA lender identifier. We then merge the bank-year AI adoption measure with the HMDA data using the LEI and year identifiers. We restrict the sample to applications with non-missing values for key variables, including denial outcomes, interest rates, and borrower characteristics. We also exclude applications from FinTech lenders in our main analysis sample, while retaining them for separate heterogeneity analyses. The

final sample includes 13,915,800 loan applications for the denial regressions, with smaller samples for interest rate analyses due to missing pricing data for rejected loans.

Table 1 reports summary statistics for the main variables used in the analysis. The sample includes 13.9 million mortgage applications spanning 2022–2024. The mean denial rate is 0.201, indicating that approximately 20.1% of applications are rejected, with a standard deviation of 0.400. Among the 11.1 million approved loans with available pricing information, the average contractual interest rate is 6.16 percent (standard deviation: 2.02%), ranging from 2.99% at the fifth percentile to 9.50% at the ninety-fifth percentile. The average rate spread—the difference between the loan's annual percentage rate and the average prime offering rate—is 0.465 percentage points (standard deviation: 1.374 percentage points), with substantial heterogeneity across borrowers (fifth percentile: −1.325%; ninety-fifth percentile: 2.750%).

Demographic characteristics reveal meaningful sample composition. Minority applicants (African American or Hispanic) account for 26.0% of the sample, and 37.0% of applicants are female. The borrower income distribution shows a mean log income of 4.627 with a standard deviation of 0.680, translating to a median income of approximately $99,000. Loan-to-income ratios average 2.236 (standard deviation: 1.562), indicating substantial variability in leverage across borrowers. Co-applicants are present in 41.3% of applications. The combined loan-to-value ratio averages around 0.73 (73.27%), reflecting typical down payment and equity positions.

The bank AI adoption measure exhibits considerable heterogeneity. The mean AI job-posting share is 1.14% (standard deviation: 2.02%), with a median of zero, reflecting that the majority of banks report minimal or no AI-related hiring in a given year. However, the distribution is highly right-skewed, with banks in the upper tail showing substantially higher AI intensity: the ninety-fifth percentile reaches 6.03%. This skewed distribution accurately captures the reality of uneven AI adoption across the banking sector, with most traditional lenders having limited AI investment while a subset of larger, technology-focused institutions report meaningful AI hiring intensity. The presence of substantial cross-sectional and time-

series variation in both AI adoption and lending outcomes provides rich identifying variation for our empirical design.

INSERT TABLE 1 HERE

3 Bank AI Adoption and the Racial Gap in Mortgage Lending

This section presents our baseline results on bank AI adoption and racial disparities in mortgage lending and then reports instrumental-variables results.

3.1 Research Design

We estimate the following specification:

$$Y_{i,b,m,c,t} = \beta_1 \left(Minority_i \times Bank\ AI_{b,t-1}\right) + \beta_2 Minority_i + \Gamma' X_i + \delta_{b\times t} + \delta_m + \delta_{c\times t} + \boldsymbol{\delta}' \mathbf{Z}_i + \varepsilon_{i,b,m,c,t}, \tag{1}$$

where $Y_{i,b,m,c,t}$ denotes lending outcomes for application i at bank b in year t for a borrower in MSA m and census tract c. We study two outcomes: an indicator for denial (*Denial*) and the contractual interest rate for approved loans (*Interest Rate*).

The independent variable of interest is $Minority_i \times Bank\ AI_{b,t-1}$, where $Minority_i$ equals one for African American or Hispanic applicants and zero otherwise, and $Bank\ AI_{b,t-1}$ is the bank's AI job-posting share in $t-1$. The vector X_i captures application and borrower characteristics, including co-applicant, loan-to-income, log income, loan term, CLTV, and a female indicator. $\mathbf{Z}_i$ collects fixed effects for debt-to-income bins, loan type, and applicant age. In particular, the debt-to-income ratios are sorted into less than 20%, 20%-29%, 30%-35%, 36%-40%, 41%-45%, 46%–49%, 50%–60%, and greater than 60%.[2]

[2]The HMDA data report actual debt-to-income ratios when the ratio is between 36% and 49%. Outside that range, we use the same bins as reported by HMDA. The results remain robust if we use alternative bins.

All regressions include bank×year fixed effects $\delta_{b\times t}$ to control for time-varying bank characteristics that could affect banks' underwriting standard. We also control for MSA fixed effects δ_m and census-tract×year fixed effects $\delta_{c\times t}$ to control for demand side factors, especially those potentially correlated with minority applicant characteristics. Standard errors are clustered at the bank level.

3.2 Application Denial

We present the results for application denial in Table 2. The coefficient estimate on *Bank AI*×*Minority* is positive and statistically significant at the 1% level, suggesting that AI adoption increases the denial rates of minority applications relative to non-minority applications. A one standard deviation increase in *AI Job Share* (2.02%) is associated with about 0.75 percentage-point increase in the denial gap between minority and non-minority applicants. The coefficient estimate on *Minority* remains positive and statistically significant, consistent with the vast literature documenting persistent racial gaps in mortgage approval (Munnell et al., 1996; Ambrose, Conklin, and Lopez, 2021; Bartlett et al., 2022; Lewis-Faupel and Tenev, 2024; Federal Reserve Bank of Minneapolis, 2024; Chu, Huang, and Zhang, 2025). In column (1), the coefficient estimate on *Bank AI* is negative and statistically significant, suggesting that higher AI adoption is associated with lower denial rates for non-minority applicants. This pattern is consistent with the theoretical predictions in Fuster et al. (2022) that AI adoption can lead to greater dispersion in credit outcomes, benefiting some borrowers while disadvantaging others.

The coefficient estimates on most controls align with standard underwriting patterns. Applications with co-applicants are less likely to be denied and, conditional on approval, tend to obtain more favorable pricing (Fetter et al., 2023; Goodman and Zhu, 2023). The negative coefficient estimates on *Loan to Income* are driven by the inclusion of the debt-to-income bucket fixed effects. By contrast, higher loan-to-income is associated with worse outcomes. The results are similar when we proxy AI adoption using the number (or log

number) of AI-related job postings[3].

INSERT TABLE 2 HERE

3.3 Mortgage Interest Rate

In Table 3, we present the results for mortgage interest rate. The coefficient estimate on *Bank AI*×*Minority* is again positive and statistically significant. A one-standard-deviation increase in *AI Job Share* increases the racial gap in mortgage interest rates by almost 4 basis points. However, the coefficient estimate on *Minority* itself is small and statistically insignificant. The difference between our results and those of Bartlett et al. (2022) could be driven by the different sample period we focus on. The coefficient estimates on most control variables e also consistent with the literature. Mortgage interest rates increase with the combined loan-to-value ratio, but decrease with the presence of co-applicants.

INSERT TABLE 3 HERE

3.4 Identification and the Instrumental Variable Results

Bank AI adoption could be correlated with unobserved changes in local demand, competition, or borrower composition, which could bias our OLS estimates. Our focus on the differential impact of AI adoption on minority versus non-minority borrowers allows us to control for time-varying supply-side factors with bank×year fixed effects and time-varying demand-side factors with census tract×year fixed effects, both of which could mitigate the endogeneity concern. However, it is still possible that bank AI adoption is correlated with banks' changing attitudes toward minorities or changing characteristics of minority borrowers relative to non-minority borrowers, which could bias our OLS estimates. For example, banks trying to mitigate human-caused racial bias may decide to adopt AI, under which the OLS estimates could underestimate the true effect of AI adoption on the racial gap. On the other hand, banks may find that minority borrowers in the absence of AI have higher *ex post*

[3]The results are not reported here

default risk, and decide to employ AI to better capture minority borrower credit risk in the underwriting process. In this case, our OLS estimates could overestimate the effect of AI adoption on the racial gap.

To mitigate this concern, we follow Babina et al. (2024) and instrument bank AI adoption with banks' *ex ante* exposure to the supply of AI graduates from universities. Using Revelio Lab data, we identify all employees at sample banks in 2008–2010 and their alma maters, then apply Babina et al. (2024)'s method to classify universities as AI strong. Our instrument, *AI Strong*, equals one if at least one employee in 2008–2010 graduated from an AI strong university, and zero otherwise.[4] This instrument leverages banks' historical ties to universities with subsequent AI prominence. Conditional on our rich fixed effects, this supply-driven variation is highly unlikely to correlate with contemporaneous shocks to minority mortgage outcomes, thereby plausibly satisfying the exclusion restriction.

To further support the validity of the instrument, we examine whether the instrument affects the racial gap in mortgage lending before 2008. If the instrument affects the racial gap in mortgage lending before 2008, it would suggest that the instrument is correlated with other factors that affect the racial gap, violating the exclusion restriction. For example, if banks with historical ties to AI strong universities are more likely to adopt other technologies that could affect the racial gap, then the exclusion restriction may be violated. Or more generally, if executives in banks with historical ties to AI strong universities are different than those without the ties, and these different characteristics affect the racial gap, then the exclusion restriction may be violated.

To test this, we regress mortgage denial decisions on the interaction between the minority dummy and the instrument, using mortgage applications from 2005–2007. We cannot perform the same test for mortgage interest rates because the interest rate data are available only starting from 2018. We use a three-year sample because our baseline results are also based on a three-year sample. We first present the results for each year separately in columns (1)–(3), and for the full sample in column (4) of Table 4. The coefficient estimates on *AI*

[4]We do not use the share of employees from AI strong universities as the instrument because the dummy measure is empirically stronger, both in coefficient estimates and F-statistics of the first stage regression.

Strong×*Minority* are all small and statistically insignificant, suggesting that the instrument does not affect the racial gap in mortgage lending before 2008. This evidence supports the validity of our instrument.

INSERT TABLE 4 HERE

We then implement a two-stage least squares approach using this instrument to estimate the causal effect of bank AI adoption on the racial gap in mortgage lending. The first- and second-stage regression results are reported in Table 5. In the first stage, we regress the interaction term *Bank AI*×*Minority* on the interaction between the instrument, Historical AI hiring (*AI Strong*), and the minority dummy, *Minority*, and other control variables. The results are presented in Table 5. The coefficient estimate on *AI Strong*×*Minority* is positive and statistically significant, suggesting that the instrument likely satisfies the relevance condition. Furthermore, the first-stage F-statistic is 10.26, suggesting that the instrument is strong.

INSERT TABLE 5 HERE

In column (2) of Table 5, we present the second-stage regression results for denial. The coefficient estimate on *Bank AI*×*Minority* remains positive and statistically significant. The magnitude of the IV estimate is more than double that of the OLS estimate in Table 2, suggesting that the OLS estimate is likely biased downward. This could happen if the banks try different strategies to mitigate human bias in mortgage lending, and adopting AI is one such strategy. While other strategies work as intended to reduce the racial gap, AI adoption exacerbates the bias.

In column (3) of Table 5, we present the second-stage regression results for interest rate. The coefficient estimate on *Bank AI*×*Minority* is again positive and statistically significant, and the magnitude is more than double that of the OLS estimate in Table 3. Overall, the 2SLS results suggest that the effect of bank AI adoption on the increased racial gap in mortgage lending is likely to be causal.

4 Alternative Explanations

This section rules out several potential alternative explanations, thereby clarifying that our results are driven by banks' adoption of AI.

4.1 The Composition of Loan Officers

We argue that the impact of AI on the racial gap is driven by AI's flexibility to uncover structural relationships or its triangulation of excluded characteristics, such as race. However, the effect documented above could also be driven by the changing racial composition of the mortgage lenders induced by the adoption of AI. For example, if banks' AI adoption disproportionately replaces minority loan officers, the decreased presence of minority loan officers could then lead to an increased racial gap (Frame et al. 2025). To see whether this is the case, we regress the percentage of minority loan officers on *Bank AI* in a lender-year regression. We report the results in column (1) of Table 6. The coefficient estimate on *Bank AI* is small and statistically insignificant, suggesting that AI adoption does not affect the share of minority loan officers at the lender.

INSERT TABLE 6 HERE

4.2 The Composition of Loan Applications

Alternatively, the adoption of AI and the associated announcement could affect borrowers' choices. For example, minority borrowers may think that the bank AI adoption could mitigate human bias and then choose to borrow from banks that use more AI. More applications in general or more applications from minority applicants may affect banks' underwriting or pricing decisions. To see whether this is the case, we first examine how bank AI adoption affects the total number of applications using the fixed-effects Poisson model. The result is presented in column (2) of Table 6. The coefficient estimate on *Bank AI* is again statistically insignificant. However, the estimate is positive, suggesting that AI adoption may increase the total number of applications. We then focus on the percentage of

minority applications to see if AI adoption disproportionately attracts minority applicants. The result is presented in column (3) of Table 6. The coefficient estimate is again small and statistically insignificant, suggesting that AI adoption does not disproportionately increase minority applications.

4.3 Bank AI Adoption and Applicant Risk

An alternative concern is that banks adopt AI when the riskiness of their applicant pool changes, which could mechanically affect approval and pricing outcomes. Table 7 addresses this concern by testing whether bank AI adoption is associated with observable measures of applicant risk, focusing on the combined loan-to-value ratio (CLTV) and the loan-to-income ratio. Columns (1) and (2) examine the average relationship between lagged bank AI adoption and these two risk proxies. Columns (3) and (4) include the interaction term *Bank AI*×*Minority* to test whether AI adoption is associated with differential changes in these risk measures for minority applicants.

INSERT TABLE 7 HERE

The results suggest that AI adoption does not increase applicant risk, and in particular does not increase the risk of minority applications. In Columns (1) and (2), the coefficients on *Bank AI* are negative and statistically insignificant for both CLTV and loan-to-income, indicating no meaningful change in these risk proxies as banks adopt AI. In Columns (3) and (4), the interaction term *Bank AI*×*Minority* is negative and statistically significant, implying that, if anything, minority applicants at banks with greater AI adoption appear observably less risky along these dimensions. Taken together, these findings alleviate concerns that our main results are driven by banks attracting riskier applicants (especially riskier minority applicants) when adopting AI, and instead support an interpretation in which AI adoption affects underwriting decisions and pricing rather than the risk composition of loan applications.

5 Cross-sectional Heterogeneity

5.1 Securitization Status

The impact of AI adoption on racial disparities in mortgage lending may vary across different segments of the market. One important dimension of heterogeneity is the securitization status of loans. Securitized loans are those that are bundled and sold to investors as mortgage-backed securities, while non-securitized loans are held on banks' balance sheets. In particular, a substantial share of mortgages are sold to government-sponsored enterprises (GSEs), including Fannie Mae, Freddie Mac, and Ginnie Mae. These GSEs have their own underwriting and pricing algorithms, and hence the lenders' adoption of AI may have limited effect on these loans. For originated loans, the HMDA data report whether a loan is sold during the reporting year, and if it is sold, to whom it is sold. We use this information to split the sample of approved loans into three samples: not sold during the reporting year, sold to GSEs during the reporting year, and sold to other entities during the reporting year.

We then examine the effect of Bank AI adoption on racial disparities in interest rate in each of the three loan segments. The results are presented in Table 8. In column (1), for loans that are not sold during the reporting year, the coefficient estimate on *Bank AI*×*Minority* is positive and statistically significant. In contrast, in column (2) for loans sold to GSEs, the coefficient estimate is much smaller and statistically insignificant, suggesting that AI adoption does not significantly affect racial disparities in this segment. In column (3) for loans sold to other entities, the coefficient estimate is again positive and statistically significant, although the magnitude is smaller than that for non-securitized loans. These patterns are consistent with the institutional features of these segments: non-securitized loans are more likely to be influenced by lenders' underwriting and pricing decisions, while GSE-sold loans are subject to standardized underwriting criteria that may limit the scope for AI-driven disparities. Loans sold to other entities may fall somewhere in between, depending on the nature of the buyers and their own underwriting practices.

INSERT TABLE 8 HERE

5.2 Purchase versus Refinance Loans

Table 9 reports results separately for purchase and refinance loans. For purchase mortgages, the key interaction term, *Bank AI*×*Minority*, is positive and statistically significant in both the denial and interest-rate regressions, indicating that AI adoption is associated with a larger racial gap in underwriting and pricing for home-purchase credit. By contrast, the corresponding estimates for refinance loans are much smaller and statistically insignificant.

INSERT TABLE 9 HERE

These differences are consistent with institutional features of the two markets. Purchase loans are often originated to households facing tighter cash-flow constraints and greater information frictions, and the underwriting decision must incorporate property-level details and down-payment constraints. As a result, screening intensity is high and model-based decision tools can have a large marginal effect on approval and pricing. If AI models exploit variables that proxy for protected characteristics through historical and structural channels, the resulting screening rules can widen minority gaps most strongly in the purchase segment.

Refinance loans, in contrast, are typically made to borrowers with an existing mortgage and an observable payment history, implying positive selection on unobserved credit quality and richer lender-observable information. In addition, refinancing is heavily driven by interest-rate incentives and often processed through more standardized, eligibility-based workflows. These features reduce the scope for incremental AI-driven screening to differentially affect minority versus non-minority applicants. Consistent with this interpretation, Table 9 shows that the differential effect of AI adoption is concentrated in purchase loans.

5.3 FinTech Lenders

FinTech lenders represent a distinct segment of the mortgage market characterized by technology-intensive business models, algorithmic underwriting platforms, and digital-first customer acquisition (Buchak et al., 2018; Fuster et al., 2019). These lenders have embedded automated decision-making into their core operations from inception, rather than retrofitting

AI into legacy processes. This structural difference raises the question of whether AI adoption has similar effects on racial disparities in FinTech versus traditional banking contexts.

Table 10 presents results for the FinTech subsample. In stark contrast to our main findings for traditional banks, the coefficient on *Bank AI*×*Minority* is negative and statistically insignificant across all specifications for both denial and interest rate outcomes. For denial, the point estimates range from -0.274 to -0.351 and are never significant at conventional levels. Similarly, for interest rates, the estimates are imprecise and do not indicate that AI adoption widens racial gaps among FinTech lenders.

INSERT TABLE 10 HERE

Several institutional features may explain why AI adoption does not amplify racial disparities in the FinTech segment. First, FinTech lenders typically rely on fully automated underwriting systems with limited loan officer discretion throughout the lending process. Because human judgment plays a minimal role, the marginal impact of adopting additional AI capabilities may be smaller—these firms already operate in a high-automation environment where incremental AI investments affect operational scale rather than fundamentally altering decision rules. Second, FinTech lenders often employ newer data sources and alternative credit scoring models that were developed in the post-fair-lending regulatory environment and may incorporate fairness constraints or bias-mitigation techniques more systematically than legacy models at traditional banks. Third, FinTech business models emphasize standardization and scale, which may reduce the scope for heterogeneous treatment effects across borrower subgroups that can emerge when AI tools are layered onto discretionary human processes.

The divergence between FinTech and traditional bank results suggests that the institutional context in which AI is deployed matters critically for its distributional consequences. At traditional banks, AI adoption appears to interact with existing organizational structures, legacy data, and human decision-making in ways that disadvantage minority applicants. In contrast, FinTech lenders' technology-native operations may better insulate underwriting

decisions from the amplification of historical disparities. These findings underscore that the equity implications of AI in lending depend not only on the technology itself but also on the organizational and operational environment in which it is embedded.

6 Robustness and Additional Tests

6.1 Pre-application versus Underwriting Stage

To better understand where differential treatment arises in the lending process, we decompose mortgage outcomes by stage. The HMDA mortgage application data not only include completed applications that are submitted for underwriting, but also incomplete applications that are either withdrawn or closed because of incomplete information. In the analysis above, we also treat these applications as being denied. However, these outcomes occur before underwriting, and distinguishing these outcomes from underwriting decisions could provide more information on the source of the effect of AI on mortgage lending. In particular, application withdrawn and closed for incomplete information happen in the pre-application information collection stage, in which AI is less likely to be involved. In contrast, AI is more likely to be used in the underwriting stage to conduct in-depth analysis of the risk of the applications. We therefore expect the effect to concentrate in the underwriting stage if the effect is truly driven by AI adoption.

We therefore first examine how bank AI adoption affects whether an application is more or less likely to be withdrawn or closed for incomplete information. The results are presented in column (1) of Table 11. The coefficient estimate on *Bank AI*×*Minority* is positive but statistically insignificant, suggesting that the impact of AI adoption on the racial gap does not occur in the pre-application stage. We then focus on completed applications that are submitted for underwriting. The results are presented in column (2) of Table 11. The coefficient estimate on *Bank AI*×*Minority* is positive and statistically significant, suggesting that the impact of AI on mortgage lending does occur at the underwriting stage.

INSERT TABLE 11 HERE

6.2 Origination Fees

We also examine whether AI adoption affects the racial gap in origination fees, which are upfront fees charged to borrowers at loan closing. Origination fees are an important component of the total cost of credit and can reflect differences in underwriting risk assessment and pricing strategies. Bhutta and Hizmo (2021) show that ignoring origination fees could bias the estimates of the racial gap in mortgage pricing. The HMDA data provide the following information on origination fees: the total loan cost, the sum of borrower paid origination charges and borrower paid third party charges, such as appraisal fees and title insurance; the origination charges, the total fees charged by lenders for originating the loan, including discount points paid by the borrower; and the discount points, the total amount spent on discount points, including those paid by the borrower and those paid by the others. We scale these fees by the loan amount to construct the origination fee rate. We then regress the origination fee rate on the same set of controls as in the interest rate regression, and focus on the coefficient estimate on *Bank AI*×*Minority* to see whether AI adoption is associated with a larger racial gap in origination fees.

The results are presented in columns (1)-(3) in Table 12. The coefficient estimates on *Bank AI*×*Minority* are all small and statistically insignificant, suggesting that Bank AI adoption does not affect the racial gap in origination fees. This pattern contrasts with the significant effect of AI adoption on the racial gap in interest rates, and suggests that the impact of AI on mortgage pricing is primarily reflected in the contractual interest rate rather than upfront fees. This finding is consistent with the interpretation that AI adoption affects risk assessment and pricing decisions embedded in the interest rate setting process, rather than fee structures that may be more standardized or subject to regulatory constraints.

INSERT TABLE 12 HERE

The HMDA data also report the rate spread, the annual percentage rate (APR) minus

the average prime offer rate (APOR) for a comparable mortgage. The rate spread captures the total cost of credit relative to market benchmarks and can reflect both interest rate and fee components. We also regress the rate spread on the same set of controls, and focus on the coefficient estimate on *Bank AI*×*Minority* to see whether AI adoption is associated with a larger racial gap in overall pricing. The results are presented in column (4) of Table 12. The coefficient estimate on *Bank AI*×*Minority* is positive and statistically significant, suggesting that AI adoption is associated with a larger racial gap in overall mortgage pricing as measured by the rate spread. This pattern reinforces our findings for contractual interest rates.

6.3 Additional Evidence from McDash Data

The HMDA data miss one important underwriting variable, the credit score. Additionally, the HMDA data provide the combined loan-to-value ratio rather than the loan-to-value ratio. Both of these could raise concerns about omitted variable bias. To mitigate this concern, we augment the HMDA data with the McDash data. McDash provides comprehensive loan-level records with detailed credit characteristics not available in HMDA, including borrower credit scores and precise loan-to-value ratios. This additional information allows us to more thoroughly control for applicant creditworthiness and test whether our results are robust to the inclusion of these key underwriting variables. We follow the literature and merge the two datasets using variables common to both, including year of origination, location (census tract in HMDA and zip code in McDash), loan amount, loan term, property value, interest rate, the debt-to-income ratio, loan type (FHA, VA, or Conventional), loan purpose (refinance or purchase). We retain only unique matches and achieve a match rate of about 20%.[5]

Table 13 presents results for mortgage interest rates using the McDash sample. Column (1) replicates our baseline interest-rate specification from Table 3 in the matched data.

[5]Our match rate is lower than the match rate between confidential HMDA and McDash because confidential HMDA reports origination date instead of just origination year.

The coefficient estimate on *Bank AI*×*Minority* is 0.845 and statistically significant at the 1% level, indicating that AI adoption is associated with higher interest rates for minority applicants relative to non-minority applicants. This estimate is smaller in magnitude than the corresponding estimates in Table 3.

INSERT TABLE 13 HERE

Column (2) adds two critical underwriting variables: the loan-to-value ratio and the borrower's credit score. Both variables enter with expected signs: higher LTV increases the mortgage interest rate, while higher credit scores reduce the interest rate. Both coefficient estimates are statistically significant at the 1% level. Importantly, the inclusion of these additional risk controls leaves the coefficient on *Bank AI*×*Minority* virtually unchanged at 0.885, suggesting that our main results are not driven by omitted measures of applicant credit quality that happen to correlate with both AI adoption and minority status.

Columns (3) and (4) address concerns about time-varying compositional shifts across different mortgage market segments. We construct securitization buckets that classify loans by their conforming status and government guarantee eligibility, as these categories face different underwriting standards and competitive dynamics (Bartlett et al. 2022). Column (3) includes bucket×year fixed effects to control for annual shifts in lending standards within each market segment, while column (4) employs bucket×year-month fixed effects to capture even more granular temporal variation. The coefficient on *Bank AI*×*Minority* remains positive and statistically significant in both specifications (0.848 and 0.632, respectively), though the magnitude attenuates somewhat with the most demanding fixed effects structure.

The robustness of our findings in the McDash data is particularly reassuring given this dataset's advantages for mortgage research. The availability of credit scores, arguably the single most important predictor in automated underwriting systems, allows us to verify that AI's differential impact on minority borrowers persists even after accounting for this key variable. Moreover, the granular fixed effects in columns (3) and (4) address concerns that our results might be driven by banks adopting AI precisely when they are shifting their portfolio

composition toward or away from particular loan segments that differ in minority representation. The stability of our core finding across these demanding specifications strengthens the interpretation that AI adoption itself contributes to widening racial disparities in mortgage lending.

7 Conclusion

This paper studies the distributional consequences of banks' adoption of artificial intelligence in mortgage lending. Using recent HMDA data and a novel measure of bank AI adoption based on AI-related hiring, we document that greater AI adoption is associated with worse approval and pricing outcomes for minority borrowers. These patterns are robust to rich controls and high-dimensional fixed effects, and are reinforced by instrumental variables estimates that exploit banks' historical exposure to local AI labor supply.

Our analysis sheds light on where these disparities arise. The effects are concentrated in underwriting decisions rather than at the application stage, and do not appear to operate through changes in applicant composition or minority loan-officer representation. Taken together, the evidence points to AI-assisted screening and underwriting as a central mechanism.

The findings contribute to the growing literature on algorithmic decision-making in finance by showing that technological adoption can alter the distribution of credit access and pricing across demographic groups. More broadly, the results highlight that efficiency-enhancing technologies may have unintended equity implications when embedded in core financial decision processes.

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Table 1: Summary Statistics

This table presents the summary statistics of variables. *Denial* is a dummy variable equal to one if a loan application is rejected, and zero otherwise. *Interest Rate* is the contractual interest rate of the loan. *Interest Spread* is the difference between a loan's Annual Percentage Rate (APR) and a comparable maturity Treasury security rate. *Minority* is a dummy variable equal to one if the borrower is African American or Hispanic, and zero otherwise. *Co-applicant* is a dummy variable equal to one if the loan application includes a co-applicant, and zero otherwise. *Loan-to-Income* is defined as the ratio of the loan amount to the applicant's income. *Log Income* is the natural logarithm of the applicant's reported income. *Loan Term* is the loan maturity in months. *CLTV* is the combined loan-to-value ratio. *Female* is a dummy variable equal to one if the applicant is female, and zero otherwise. *Applicant Age* categories are dummy variables for age groups. *Withdrawn or Incomplete* is a dummy variable for applications withdrawn or closed for incomplete information. *AI Job Number* is the number of AI skills-related job postings. *AI Job Share* is the proportion of AI skills-related job postings.

	(1) **N**	(2) **mean**	(3) **std**	(4) **p5**	(5) **p10**	(6) **p25**	(7) **p50**	(8) **p75**	(9) **p90**	(10) **p95**
Loan Characteristics										
Denial	13,915,800	0.201	0.400	0	0	0	0	0	1	1
Interest Rate	11,086,894	6.160	2.019	2.999	3.500	4.990	6.250	7.249	8.500	9.500
Interest Spread	10,463,635	0.465	1.374	-1.325	-0.710	-0.113	0.382	0.989	1.820	2.750
Minority	13,915,800	0.260	0.439	0	0	0	0	1	1	1
Co-applicant	13,915,800	0.413	0.492	0	0	0	0	1	1	1
Loan-to-Income	13,915,800	2.236	1.562	0.280	0.417	0.866	2.050	3.269	4.327	5
Log Income	13,915,800	4.627	0.680	3.584	3.807	4.174	4.595	5.030	5.489	5.820
Loan Term	13,915,800	356.5	106.2	180	240	300	360	360	360	420
CLTV	13,915,800	73.27	22.63	25.94	38.89	60.02	79.67	92.42	97	100
Female	13,915,800	0.370	0.483	0	0	0	0	1	1	1
Applicant Age ≤ 25	13,915,800	0.031	0.173	0	0	0	0	0	0	1
Applicant Age 26-35	13,915,800	0.219	0.414	0	0	0	0	0	1	1
Applicant Age 36-50	13,915,800	0.348	0.476	0	0	0	0	1	1	1
Applicant Age 51-65	13,915,800	0.279	0.448	0	0	0	0	1	1	1
Applicant Age > 65	13,915,800	0.123	0.328	0	0	0	0	0	1	1
Withdrawn or incomplete	18,975,690	0.191	0.393	0	0	0	0	0	1	1
Bank AI										
AI Job Number(scaled by 1000)	13,915,800	0.0399	0.172	0	0	0	0	0.0100	0.0410	0.190
AI job share	13,915,800	0.0114	0.0202	0	0	0	0	0.0153	0.0358	0.0603

Table 2: Bank AI Adoption and Mortgage Underwriting

This table presents baseline results on the impact of bank AI adoption on mortgage underwriting. The dependent variable is *Denial*, equaling one if the loan is rejected and zero otherwise. The key independent variable is *Bank AI*×*Minority*, which is the interaction term between *Bank AI* and *Minority*. *Minority* equals one if the borrower is African American or Hispanic and zero otherwise. *Bank AI* is the share of the bank's AI skill-related job postings lagged by one year. The standard errors are clustered at the bank level, and t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
Bank AI × Minority	0.265***	0.375***	0.375***
	(2.67)	(3.20)	(3.24)
Minority	0.045***	0.045***	0.045***
	(12.89)	(12.52)	(12.55)
Bank AI	-0.352*		
	(-1.88)		
Co-applicant	-0.018***	-0.018***	-0.018***
	(-8.57)	(-8.48)	(-8.51)
Loan-to-Income	-0.007***	-0.007***	-0.007***
	(-2.90)	(-2.95)	(-2.94)
Log Income	-0.035***	-0.035***	-0.035***
	(-10.48)	(-10.53)	(-10.61)
Loan Term	0.000***	0.000***	0.000***
	(3.16)	(3.08)	(3.09)
CLTV	0.001***	0.001***	0.001***
	(7.76)	(7.88)	(7.94)
Female	0.001	0.001	0.001
	(1.48)	(1.46)	(1.51)
Bank FE	YES		
MSA FE	YES	YES	YES
Bank×Year FE		YES	YES
Census Tract×Year FE			YES
Census Tract FE	YES	YES	
Debt-to-Income FE	YES	YES	YES
Loan Type FE	YES	YES	YES
Loan Purpose FE	YES	YES	YES
Applicant Age Group FE	YES	YES	YES
Adjusted R-squared	0.365	0.369	0.370
Observations	13,918,119	13,918,066	13,916,130

Table 3: Bank AI Adoption and Mortgage Interest Rate

This table presents results on the impact of bank AI adoption on mortgage interest rates. The dependent variable is *Interest Rate*, the contractual interest rate of the loan. The key independent variable is *Bank AI*×*Minority*, which is the interaction term between *Bank AI* and *Minority*. *Minority* equals one if the borrower is African American or Hispanic and zero otherwise. *Bank AI* is the share of the bank's AI skill-related job postings lagged by one year. The standard errors are clustered at the bank level, and t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
Bank AI × Minority	2.069**	1.958**	2.019**
	(2.33)	(2.35)	(2.47)
Minority	-0.004	-0.001	0.000
	(-0.32)	(-0.11)	(0.04)
Bank AI	0.558		
	(0.24)		
Co-applicant	-0.073***	-0.067***	-0.066***
	(-9.18)	(-9.04)	(-9.05)
Loan-to-Income	-0.171***	-0.176***	-0.173***
	(-6.28)	(-6.44)	(-6.33)
Log Income	0.078**	0.067*	0.066*
	(2.17)	(1.87)	(1.84)
Loan Term	0.002***	0.002***	0.002***
	(6.53)	(6.35)	(6.35)
CLTV	0.002**	0.003***	0.003***
	(2.44)	(3.19)	(3.33)
Female	0.005	0.005	0.005
	(1.37)	(1.56)	(1.49)
Bank FE	YES		
MSA FE	YES	YES	YES
Bank×Year FE		YES	YES
Census Tract×Year FE			YES
Census Tract FE	YES	YES	
Debt-to-Income FE	YES	YES	YES
Loan Type FE	YES	YES	YES
Loan Purpose FE	YES	YES	YES
Applicant Age Group FE	YES	YES	YES
Adjusted R-squared	0.541	0.578	0.586
Observations	11,088,192	11,088,138	11,085,464

Table 4: The Instrument and the Racial Gap in Mortgage Lending before 2008

This table presents the results of testing the instrument variable, *AI Strong*, on the racial gap in mortgage lending before 2008. The dependent variable is *Denial*, equaling one if the loan is rejected and zero otherwise. The key independent variable is *AI Strong*×*Minority*, which is the interaction term between the instrument *AI Strong* and *Minority*. *Minority* equal to one if the borrower is African American or Hispanic and zero otherwise. *AI Strong* equals one if at least one employee in 2008–2010 graduated from an AI strong university, and zero otherwise. The standard errors are clustered at the bank level, and t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1) 2005	(2) 2006	(3) 2007	(4) 2005-2007
AI Strong × Minority	0.002	0.000	0.012	0.005
	(0.31)	(0.05)	(1.60)	(0.77)
Minority	0.046***	0.052***	0.064***	0.054***
	(8.53)	(9.11)	(12.88)	(11.14)
Co-applicant	-0.035***	-0.036***	-0.042***	-0.038***
	(-12.16)	(-9.27)	(-8.98)	(-10.88)
Loan-to-Income	0.004***	0.004***	0.004***	0.004***
	(4.55)	(3.41)	(3.08)	(3.95)
Log Income	-0.045***	-0.047***	-0.044***	-0.045***
	(-9.33)	(-8.87)	(-6.99)	(-9.08)
Female	-0.007***	-0.005***	-0.008***	-0.007***
	(-4.55)	(-2.89)	(-3.96)	(-4.63)
Bank×Year FE	YES	YES	YES	YES
MSA FE	YES	YES	YES	YES
Census Tract×Year FE	YES	YES	YES	YES
Loan Type FE	YES	YES	YES	YES
Loan Purpose FE	YES	YES	YES	YES
R-squared	0.226	0.187	0.195	0.203
Observations	1,539,583	1,580,696	1,593,514	4,713,793

Table 5: IV 2SLS Results: Bank AI adoption and the Racial Gap in Mortgage Lending

This table presents IV 2SLS results instrumenting Bank AI adoption using banks' *ex ante* exposure to universities' supply of AI graduates following Babina et al. (2024). Column (1) reports the first-stage results. Columns (2) and (3) report the second-stage results for *Denial* and *Interest Rate*, respectively. The instrument variable, *Historical AI hiring*, measures banks' exposure to the geographic distribution of AI graduates from universities during the period 2008–2010. The standard errors are clustered at the bank level, and t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
	First stage	Second stage	
	Bank AI × Minority	Denial	Interest Rate
AI Strong × Minority	0.027**		
	(2.31)		
Bank AI × Minority		1.156**	3.552**
		(2.23)	(2.53)
Minority	0.010***	0.034***	-0.020
	(6.13)	(3.98)	(-1.06)
Co_applicant	-0.000	-0.018***	-0.065***
	(-1.33)	(-8.08)	(-8.63)
Loan-to-Income	0.000	-0.007***	-0.188***
	(0.76)	(-2.81)	(-6.69)
Log Income	0.000**	-0.035***	0.045
	(2.03)	(-9.58)	(1.22)
Loan Term	0.000*	0.000***	0.002***
	(1.82)	(2.93)	(6.00)
CLTV	-0.000**	0.001***	0.003***
	(-2.19)	(7.68)	(3.67)
Female	0.000	0.001	0.004
	(1.55)	(1.37)	(1.14)
MSA FE	YES	YES	YES
Bank×Year FE	YES	YES	YES
Census Tract×Year FE	YES	YES	YES
Debt-to-Income FE	YES	YES	YES
Loan Type FE	YES	YES	YES
Loan Purpose FE	YES	YES	YES
Applicant Age Group FE	YES	YES	YES
Adjusted R-squared	0.590		
Observations	12,423,664	12,423,664	9,903,992
F	10.26		

Table 6: Bank AI Adoption, the Composition of Loan Officers and Loan Applications

This table presents baseline results examining the impact of bank AI adoption on the composition of loan officers and loan applications. The sample is at the lender-year level. The dependent variables are *% Minority LO*, the percent of minority loan officers of the lender, in column (1), *#Application*, the total number of applications the lender receives, in column (2), and *% Minority Application*, the percent of minority loan applications in column (3). The key independent variable is *Bank AI*, the share of bank's AI skill-related job postings lagged by one year. The standard errors are clustered at the bank level, and t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1) %Minority LO	(2) #Application	(3) %Minority Application
Bank AI	0.025	1.853	-0.008
	(0.23)	(1.46)	(-0.07)
Bank FE	YES	YES	YES
Year FE	YES	YES	YES
Adjusted R-squared	0.742	0.987	0.93
Observations	7,900	0.987	7,900

Table 7: Bank AI Adoption and Applicant Risk

This table examines whether bank AI adoption is associated with changes in applicant risk. The dependent variables are the combined loan-to-value ratio ($CLTV$) in Columns (1) and (3) and the loan-to-income ratio in Columns (2) and (4). *Bank AI* is the share of the bank's AI skill-related job postings lagged by one year. *Minority* equals one for African American or Hispanic applicants and zero otherwise. Columns (1) and (2) estimate specifications with *Bank AI* only, while Columns (3) and (4) additionally include the interaction term *Bank AI*×*Minority* to test whether AI adoption is associated with differential changes in applicant risk for minority applications. The standard errors are clustered at the bank level, and t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1) CLTV	(2) Loan-to-Income	(3) CLTV	(4) Loan-to-Income
Bank AI	-17.038	-0.517		
	(-1.19)	(-0.81)		
Bank AI × Minority			-38.880***	-0.902**
			(-5.57)	(-2.08)
Minority			5.149***	0.246***
			(30.36)	(17.78)
Bank FE	YES	YES		
Year FE	YES	YES		
MSA FE	YES	YES	YES	YES
Census Tract FE	YES	YES		
Bank×Year FE			YES	YES
Census Tract×Year FE			YES	YES
Adjusted R-squared	0.213	0.274	0.226	0.284
Observations	14,337,883	18,213,292	14,335,969	18,211,480

Table 8: Bank AI Adoption and Securitization

This table presents results on the impact of bank AI adoption on mortgage lending outcomes across different loan types. The dependent variable is *Interest Rate*, the mortgage contractual interest rate. The key independent variable is *Bank AI*×*Minority*, which is the interaction term between *Bank AI* and *Minority*. *Minority* equals one if the borrower is African American or Hispanic and zero otherwise. *Bank AI* is the share of the bank's AI skill-related job postings lagged by one year. The sample is split into three groups based on the loan's securitization status: loans that are not sold, loans sold to government-sponsored enterprises (GSEs), and loans sold to others. The standard errors are clustered at the bank level, and t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1) Not Sold	(2) GSE	(3) Other
Bank AI × Minority	2.446***	0.079	2.342*
	(2.83)	(0.36)	(1.76)
Minority	0.018	0.037***	-0.047***
	(1.10)	(7.97)	(-2.88)
Co-applicant	-0.079***	-0.023***	-0.020**
	(-8.03)	(-9.22)	(-2.10)
Loan-to-Income	-0.269***	-0.185***	0.259***
	(-7.29)	(-25.12)	(3.92)
Log Income	-0.125***	0.034***	0.721***
	(-3.22)	(3.24)	(6.81)
Loan Term	0.001**	0.005***	0.005***
	(2.57)	(49.38)	(8.05)
CLTV	0.005***	0.001***	-0.004**
	(5.87)	(2.70)	(-2.11)
Female	0.006	0.018***	0.021***
	(1.28)	(8.53)	(4.20)
Bank×Year FE	YES	YES	YES
MSA FE	YES	YES	YES
Census Tract×Year FE	YES	YES	YES
Debt-to-Income FE	YES	YES	YES
Loan Type FE	YES	YES	YES
Loan Purpose FE	YES	YES	YES
Applicant Age Group FE	YES	YES	YES
Adjusted R-squared	0.640	0.638	0.573
Observations	5,071,828	3,344,928	1,178,059

Table 9: The Impact of AI on Purchase and Refinance Loans

This table presents results on the impact of bank AI adoption on mortgage lending for purchase and refinance loans separately. The dependent variables are *Denial* in columns (1) and (3) and *Interest Rate* in columns (2) and (4). The key independent variable is *Bank AI*×*Minority*, which is the interaction term between *Bank AI* and *Minority*. *Minority* equals one if the borrower is African American or Hispanic and zero otherwise. *Bank AI* is the share of the bank's AI skill-related job postings lagged by one year. The standard errors are clustered at the bank level, and t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Purchase Loans		Refinance	
	(1)	(2)	(3)	(4)
	Denial	Interest Rate	Denial	Interest Rate
Bank AI × Minority	0.413**	1.909***	0.209	0.018
	(2.51)	(3.75)	(1.45)	(0.04)
Minority	0.028***	-0.005	0.054***	0.044***
	(12.25)	(-0.54)	(18.78)	(5.91)
Co-applicant	-0.005***	-0.008**	-0.027***	-0.077***
	(-4.21)	(-2.31)	(-16.46)	(-12.12)
Loan-to-Income	-0.007***	0.064**	-0.006***	-0.436***
	(-3.29)	(2.30)	(-2.64)	(-15.31)
Log Income	-0.033***	0.389***	-0.043***	-0.311***
	(-11.29)	(8.85)	(-11.41)	(-10.99)
Loan Term	0.000	0.003***	0.000***	0.003***
	(1.03)	(6.07)	(5.23)	(7.58)
CLTV	0.001***	-0.004***	0.001***	0.010***
	(7.66)	(-4.74)	(9.89)	(12.14)
Female	-0.001	0.007***	-0.002*	0.008*
	(-1.19)	(3.37)	(-1.71)	(1.95)
MSA FE	YES	YES	YES	YES
Bank×Year FE	YES	YES	YES	YES
Census Tract×Year FE	YES	YES	YES	YES
Debt-to-Income FE	YES	YES	YES	YES
Loan Type FE	YES	YES	YES	YES
Applicant Age Group FE	YES	YES	YES	YES
Adjusted R-squared	0.293	0.432	0.346	0.662
Observations	6,873,021	6,172,708	3,191,518	2,410,863

Table 10: Bank AI Adoption and Mortgage Lending: FinTech Lenders

This table presents results on the impact of bank AI adoption on mortgage lending for FinTech lenders. The dependent variable is *Denial* in columns (1) through (3) and *Interest Rate* in columns (4) through (6). The key independent variable is *Bank AI*×*Minority*, which is the interaction term between *Bank AI* and *Minority*. *Minority* equals one if the borrower is African American or Hispanic and zero otherwise. *Bank AI* is the share of the bank's AI skill-related job postings lagged by one year. Columns (1) and (4) include bank and census tract fixed effects. Columns (2) and (5) replace bank fixed effects with bank×year fixed effects. Columns (3) and (6) further replace census tract fixed effects with census tract×year fixed effects. The standard errors are clustered at the bank level, and t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Denial			Interest Rate		
	(1)	(2)	(3)	(4)	(5)	(6)
Bank AI × Minority	-0.351	-0.293	-0.274	-2.806	0.252	0.293
	(-1.30)	(-1.00)	(-0.94)	(-1.53)	(0.21)	(0.33)
Minority	0.051***	0.050***	0.049***	0.002	-0.064**	-0.061**
	(4.77)	(4.30)	(4.33)	(0.05)	(-2.12)	(-2.36)
Co-applicant	-0.029***	-0.028***	-0.028***	-0.082***	-0.078***	-0.076***
	(-6.96)	(-6.92)	(-7.05)	(-4.95)	(-4.56)	(-4.46)
Loan-to-Income	-0.005*	-0.005*	-0.005*	-0.293*	-0.294*	-0.281*
	(-1.78)	(-1.75)	(-1.71)	(-1.79)	(-1.78)	(-1.71)
Log Income	-0.039***	-0.039***	-0.039***	-0.016	-0.019	-0.014
	(-7.15)	(-7.20)	(-7.85)	(-0.07)	(-0.09)	(-0.07)
Loan Term	0.000	0.000	0.000	0.003**	0.003**	0.003**
	(0.69)	(0.67)	(0.69)	(2.59)	(2.55)	(2.68)
CLTV	0.002***	0.002***	0.002***	0.006	0.006	0.006
	(5.61)	(5.68)	(5.94)	(0.92)	(0.99)	(1.03)
Female	-0.005*	-0.005*	-0.005*	-0.007	-0.007	-0.006
	(-1.83)	(-1.85)	(-1.93)	(-0.64)	(-0.62)	(-0.57)
Bank FE	YES			YES		
MSA FE	YES	YES	YES	YES	YES	YES
Bank×Year FE		YES	YES		YES	YES
Census Tract×Year FE			YES			YES
Census Tract FE	YES	YES		YES	YES	
Debt-to-Income FE	YES	YES	YES	YES	YES	YES
Loan Type FE	YES	YES	YES	YES	YES	YES
Loan Purpose FE	Yes	Yes	Yes	Yes	Yes	Yes
Applicant Age Group FE	YES	YES	YES	YES	YES	YES
Adjusted R-squared	0.307	0.309	0.312	0.494	0.517	0.519
Observations	3,053,454	3,053,454	3,043,112	2,401,901	2,401,901	2,386,945

Table 11: Bank AI adoption, Minority Lending, and the Stages of Mortgage Lending

This table examines the impact of bank AI adoption on mortgage lending at different stages, i.e. applicant withdrawal or incompleteness and denial by underwriting. Column (1) reports results where the dependent variable is *Withdrawn or Incomplete*, an indicator equal to one if a loan application is withdrawn by the applicant or remains incomplete, and zero otherwise. Column (2) reports results where the dependent variable is *Denial Conditional on Underwriting*, defined as an indicator equal to one if a loan application is denied after entering the underwriting process. The key independent variable is *Bank AI* × *Minority*, which captures whether bank AI adoption differentially affects minority applicants across decision stages. The standard errors are clustered at the bank level, and t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)
Dependent variable	withdrawn or incomplete	Denial conditional on underwriting
Bank AI×minority	0.100	0.417***
	(1.38)	(3.49)
Minority	-0.001	0.044***
	(-0.93)	(12.31)
Co-applicant	-0.001*	-0.022***
	(-1.85)	(-10.04)
Loan-to-Income	-0.002	-0.019***
	(-1.52)	(-5.74)
Log Income	0.002	-0.049***
	(0.74)	(-13.03)
Loan term	0.000***	0.000
	(3.06)	(0.99)
CLTV		0.000***
		(3.13)
Female	0.001	-0.002***
	(1.50)	(-2.73)
Bank×Year FE	YES	YES
MSA FE	YES	YES
Census Tract×Year FE	YES	YES
Debt to income FE	YES	YES
Loan Type FE	YES	YES
Applicant Age Group FE	YES	YES
Adj.R^2	0.912	0.369
Observations	18,211,027	13,418,494

Table 12: Bank AI Adoption and Mortgage Origination Fees

This table presents results on the impact of bank AI adoption on mortgage origination fees. The dependent variables are *Total Loan Cost*, the sum of borrower paid origination charges and borrower paid third party charges, such as appraisal fees and title insurance fees scaled by loan amount in percentage points, in column (1), *Origination Charges*, the total fees charged by the lender for originating the loan, including discount points designated as borrower paid scaled by loan amount in percentage points, in column (2), *Discount Points*, the total amount spent on discount points scaled by loan amount in percentage points, in column (3), and *Rate Spread*, the difference between the loan's annual percentage rate (APR) and the average prime offering rate (APOR) on comparable loans, in column (4). The key independent variable is *Bank AI*×*Minority*, which is the interaction term between *Bank AI* and *Minority*. *Minority* equals one if the borrower is African American or Hispanic and zero otherwise. *Bank AI* is the share of the bank's AI skill-related job postings lagged by one year. The standard errors are clustered at the bank level, and t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1) Total Loan Cost	(2) Origination Charges	(3) Discount Points	(4) Rate Spread
Bank AI×Minority	0.312	0.202	-0.033	1.782**
	(0.65)	(0.86)	(-0.10)	(2.25)
Minority	0.008	0.039***	0.039***	0.006
	(0.85)	(5.23)	(5.58)	(0.51)
Co-applicant	0.025***	0.011***	0.011***	-0.036***
	(4.04)	(3.35)	(5.25)	(-5.11)
Loan-to-Income	0.007	0.037***	0.055***	-0.091***
	(0.54)	(4.58)	(13.16)	(-3.35)
Log Income	-0.395***	-0.128***	0.018**	-0.041
	(-16.48)	(-11.37)	(2.44)	(-1.11)
Loan Term	0.001***	0.001***	0.000***	-0.001***
	(2.80)	(3.66)	(2.74)	(-2.86)
CLTV	-0.005***	-0.003***	-0.001***	0.006***
	(-9.21)	(-8.59)	(-5.66)	(7.64)
Female	0.029***	0.020***	0.014***	0.003
	(8.36)	(8.82)	(12.37)	(0.87)
Bank×Year FE	YES	YES	YES	YES
MSA FE	YES	YES	YES	YES
Census Tract*Year FE	YES	YES	YES	YES
Debt-to-Income FE	YES	YES	YES	YES
Loan Type FE	YES	YES	YES	YES
Loan Purpose FE	YES	YES	YES	YES
Applicant Age Group FE	YES	YES	YES	YES
Adjusted R-squared	0.571	0.431	0.365	0.416
Observations	11,123,364	11,123,364	11,123,364	10,461,449

Table 13: Bank AI Adoption and Mortgage Lending: McDash Data

This table presents results on the impact of bank AI adoption on mortgage lending using data from McDash Analytics. The dependent variable is *Interest Rate* in all columns. The key independent variable is *Bank AI*×*Minority*, which is the interaction term between *Bank AI* and *Minority*. *Minority* equals one if the borrower is African American or Hispanic and zero otherwise. *Bank AI* is the share of the bank's AI skill-related job postings lagged by one year. Column (1) presents the baseline specification. Column (2) additionally controls for loan-to-value ratio (LTV) and borrower credit score. Column (3) includes the loan-to-value ratio (LTV) and borrower credit score bucket×year fixed effects to control for time-varying differences across loan segments. Column (4) includes bucket×year-month fixed effects to control for more granular time-varying differences across loan segments. The standard errors are clustered at the bank level, and t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Bank AI × Minority	0.845***	0.885***	0.848***	0.632**
	(3.01)	(2.99)	(2.89)	(2.27)
Minority	0.041***	0.029***	0.033***	0.005
	(5.37)	(3.23)	(4.12)	(0.72)
Co_applicant	-0.022***	-0.022***	-0.025***	-0.007**
	(-6.00)	(-5.46)	(-6.47)	(-2.19)
Loan_to_Income	-0.187***	-0.182***	-0.182***	-0.130***
	(-21.32)	(-22.57)	(-21.09)	(-15.73)
Log_Income	0.011	0.003	0.021	-0.034*
	(0.60)	(0.16)	(1.14)	(-1.80)
Loan Term	0.005***	0.005***	0.005***	0.004***
	(23.95)	(23.47)	(23.68)	(18.34)
CLTV	0.001***	-0.002***	0.001**	0.004***
	(2.96)	(-2.81)	(2.52)	(11.12)
Female	0.018***	0.018***	0.016***	-0.006***
	(9.80)	(9.01)	(8.73)	(-4.77)
LTV		0.328***		
		(4.30)		
Credit Score		-0.001***		
		(-7.14)		
Bank×Year FE	YES	YES	YES	YES
MSA FE	YES	YES	YES	YES
Census Tract×Year FE	YES	YES	YES	YES
Debt-to-Income FE	YES	YES	YES	YES
Loan Type FE	YES	YES	YES	YES
Loan Purpose FE	YES	YES	YES	YES
Applicant Age Group FE	YES	YES	YES	YES
Bucket×Year FE			YES	
Bucket×Year-Month FE				YES
Observations	2,026,830	1,695,175	2,025,115	2,025,104
Adj R-squared	0.641	0.652	0.643	0.849

Table A1: Definitions of Variables

Variable	**Definition**
Bank AI	The level of bank investment in AI, measured by the share of the bank's AI skills-related job postings in a year.
Denial	An indicator equaling one if the loan is rejected and zero otherwise.
Interest Rate	The contractual interest rates of the loan.
Interest Spread	The difference between a loan's Annual Percentage Rate (APR) and a comparable maturity Treasury security rate, used to identify higher-priced mortgage loans.
Minority	An indicator equaling one if the borrower is African American or Hispanic and zero otherwise.
Co-applicant	An indicator equaling one if the loan has a co-applicant and zero otherwise.
Loan-to-Income	The loan amount to income ratio.
Log Income	The natural logarithm of applicant's income
Loan Term	Loan maturity in months.
Loan Purpose	An indicator equaling one if the loan purpose is a home purchase and zero if it is a refinance.
Debt-to-Income	The ratio of the applicant's monthly debt obligations to monthly income.
Applicant Age	Categorical variables representing the applicant's age group: Age $\leq$ 25, Age 26-35, Age 36-50, Age 51-65, and Age $>$ 65.
CLTV	Combined loan-to-value ratio.
Female	An indicator equaling one if the borrower is female and zero otherwise.
Withdrawn or Incomplete	An indicator equaling one if the application was withdrawn or closed for incomplete information and zero otherwise.
AI Job Number	The number of AI skills-related job postings at the bank in a given year.
AI Job Share	The proportion of the bank's job postings that require AI-related skills, calculated as AI job postings divided by total job postings in a year.