Analyzing Bank of the West Lending Practices[1]

ELLIE DEGEORGES[2], VICTORIA GENCO[3], ISAAC GRODIN[4], ANNA HARVEY[5], JUAN MOZOS NIETO[6], MATTHEW ROMANO[7], SEBASTIAN STONEHAM[8], THOMAS SCARINGELLA[9], XIAOZHE ZHANG[10]

[1] Lehigh University, Bethlehem, PA 18015, USA. Course listing: "FinTech Capstone"; FIN 388. Advisors: Donald Bowen, Lehigh University; Matt Darragh, BMO Harris. Last revised: April 29, 2023

[2] Accounting, College of Business, Lehigh University. Email: esd223@lehigh.edu and edegeorges@hotmail.com
[3] Accounting, College of Business, Lehigh University. Email: vrg223@lehigh.edu and tori.genco@gmail.com
[4] Financial Engineering, College of Business and Engineering, Lehigh University. Email: irg223@lehigh.edu and isaacgrodin@gmail.com
[5] Financial Engineering, College of Business and Engineering, Lehigh University. Email: akh223@lehigh.edu and annaharv3@gmail.com
[6] Finance and Business Analytics, College of Business. Email: jum223@lehigh.edu and juanmozosn19@gmail.com
[7] Finance, College of Business, Lehigh University. Email: mcr323@lehigh.edu and romanomatt10@gmail.com
[8] Finance, College of Business, Lehigh University. Email: sds323@lehigh.edu and sebastian.stoneham@gmail.com
[9] Accounting, College of Business, Lehigh University. Email: tws223@lehigh.edu and thomasscaringella29@gmail.com
[10] Finance, College of Business, Lehigh University. Email: xiz423@lehigh.edu and zhangxiaozhegood@gmail.com

Table of Contents

1. Executive Summary

Historically, redlining prevented residents of specific areas from accessing credit due to race or ethnicity. Today, government regulations prevent financial institutions from making lending decisions based on an applicant's demographic attributes. As the Bank of Montreal (BMO), the sponsor financial institution of the Spring 2023 Lehigh Fintech Capstone class, completed its acquisition of Bank of the West in February 2023, this paper conducts a comprehensive examination of the lending behaviors of Bank of the West and reports our findings to personnel at the Bank of Montreal.

Specifically, this paper analyzes the lending behaviors of Bank of the West (BOW) in Arizona and California using the Home Mortgage Disclosure Act (HMDA) loan-level data and Census tract demographic information for 2021. The analysis aims to help BMO Harris (which recently acquired Bank of the West) understand if BOW's lending falls short of BMO Harris's goal to serve underserved communities and steps BMO Harris can take to address any shortcomings. The analysis uses maps, regression models, and an experiment with OpenAI's ChatGPT API to assess the impact of demographic information on loan decisions.

- In areas with high Black populations, BOW is **less likely** to receive any mortgage applications and **fewer applications** but has a **lower denial rate** than similar-sized banks.

- In areas with high Hispanic populations, BOW is **less likely** to receive any mortgage applications but receives **more applications** and has a **lower denial rate** than similar-sized banks.

- In areas with high Asian populations, BOW is **more likely** to receive mortgage applications and receives **more applications** but has a **higher denial rate** than similar-sized banks.

- ChatGPT makes lending decisions consistent with real loan outcomes, but adding demographic information changes the loan approval rates. Bias can be reduced by explicitly asking it to decide without prejudice.

- By segmenting the data by major minority groups, we can identify differences in loan practices towards different minority groups and understand the factors contributing to these differences. For example, the higher loan approval rates for Black and Hispanic/Latino groups at Bank of the West may be due to specific outreach programs or underwriting practices designed to support these groups.

- For San Francisco, BOW generally has a lower denial rate for majority-minority tracts than competitors. In Los Angeles, BOW does not receive loan applications in most majority-minority tracts.

2. Introduction

Fair lending is an essential practice providing equal access to credit while eliminating discrimination based on race, sex, age, or nationality. In this report, we offer a comprehensive analysis of the credit lending history of Bank of the West (BOW) in California and Arizona during the fiscal year 2021.

Our primary objective is to examine the impact of the acquisition of BOW by Bank of Montreal Harris (BMO Harris) in Q1 2023. Investigating BOW's lending practices is crucial, ensuring the bank's lending responsibly and avoiding unfair lending issues. By providing our insights, we aim to assist BMO Harris in avoiding potential penalties, fines, loss of reputation, or legal action. We aim to promote fair lending practices and emphasize the importance of giving all borrowers equal access to credit and financial services.

To conduct our analysis, we compiled loan data from Home Mortgage Disclosure Act (HMDA), which includes applications, approvals, and rejections. Our data allowed us to compare how BOW's lending practices differed from other financial institutions operating in the same tracts. We augment this data with demographic information from the Census to allow us to control for tract-specific traits.

In addition to analyzing the lending practices of BOW, our report discusses the regulatory background of fair lending practices and the introduction of machine learning and AI into the lending space. It will provide context for our analysis and demonstrate the importance of incorporating new technologies into the industry.

As part of our analysis, we conducted an experiment where we used ChatGPT as a mock loan officer to test its results against actual data. It allowed us to evaluate AI, as an unbiased loan officer, in the lending process and explore the potential benefits of incorporating this technology into financial institutions.

We utilized various techniques, such as exploratory data analysis, maps, and regressions, to analyze our findings, which we discuss in detail throughout our report. By examining the lending practices of BOW, we gained a deeper understanding of the intricacies of lending practices and the role of data analysis and machine learning in the financial sector.

Overall, our findings and insights can assist BMO Harris in evaluating its acquisition of BOW. As the financial industry continuously evolves and new technologies are introduced, staying current with the latest trends and best practices is necessary to succeed in this competitive field.

3. Discussion

Regulatory Background

The fair lending landscape is a multifaceted and constantly evolving area of law and regulation. It strives to ensure that potential borrowers have equal access to credit and other financial services. Banks must adhere to numerous federal and state laws and regulations when lending to underserved communities.

The Equal Credit Opportunity Act (ECOA) is the primary federal law that oversees fair lending practices. It mandates that lenders cannot discriminate against loan applicants based on race, color, religion, national origin, sex, marital status, or age. The ECOA requires that lenders consider all creditworthy applicants with complete impartiality (CFPB, 2013).

Compliance with the ECOA is crucial for lenders since the consequences of non-compliance can be severe, leading to enforcement actions and reputational harm. Banks may also face regulatory investigations for failing to adhere to the ECOA (U.S. Dep. of Justice, 2022). By complying with this law, lenders can establish a relationship of trust and confidence with their customers, enhancing their reputation and credibility. This statute promotes economic development, reduces poverty, and encourages financial stability by eradicating discriminatory lending practices (FDIC, 2018). Adherence to the ECOA is essential for lenders striving to achieve these goals.

Numerous other federal laws and regulations govern fair lending, including the Fair Housing Act, the Community Reinvestment Act, and the Home Mortgage Disclosure Act (U.S. Dep. of Justice, 2022). These impose requirements on lenders, including reporting and outreach requirements, and stipulations to provide certain types of loans to underserved communities. By adhering to these laws, lenders can ensure that they operate ethically and equitably, fostering a fair and inclusive lending environment for all borrowers (FDIC, 2018).

When assessing a bank's compliance with fair lending laws and regulations concerning underserved communities, regulators consider various factors. Some factors include lending policies, such as underwriting criteria, loan pricing, and marketing strategies, compliance management that ensures compliance with fair lending regulations, or outreach initiatives directed towards underserved communities, including collaborations with community organizations. By evaluating these factors, regulators can determine whether a bank is fulfilling its fair lending obligations and fostering a level playing field for borrowers of all backgrounds.

For example, to identify infringements of the ECOA, regulators have two principal theories of liability: disparate treatment and disparate impact. Regulators often refer to the "three-part burden shifting test" as a framework originated by the U.S. Department of Housing and Urban Development to evaluate discrimination claims violating the ECOA and the FHA (FDIC, 2021). Regulators use "three-factor" tests, and in certain instances, "four-factor" tests, to identify whether a lender's policies result in higher denial rates or higher interest rates for minority borrowers (Federal Register, 2013). A three-factor test will look at differences in key redlining variables while analyzing the presence of disparity facing protected classes. A four-factor test incorporates the lender's business necessity for the policy. These tests often involve regression analysis or chi-square tests to identify a statistically significant impact on groups of underserved borrowers.

While no outline specifies how banks must lend to underserved communities, fair lending laws and regulations mandate that banks cannot discriminate against loan applicants based on their protected characteristics. Failure to comply with these laws and regulations may lead to enforcement actions by federal and state regulators and private lawsuits by individuals subjected to discriminatory lending practices.

Lenders also employ special purpose credit programs (SPCPs) to increase access to credit and financial services for underserved communities and populations. These programs typically involve partnerships between banks and community organizations, and may be supported by government funding or other incentives. A typical program may include targeted marketing and outreach efforts to underserved communities, as well as flexible underwriting criteria and loan terms to meet the specific needs of the target population. Many SPCP's provide financial education and other resources to help borrowers build credit and manage their finances more effectively. Examples of special-purpose credit programs include programs to support affordable housing, small business development, and community development projects. These programs can play an essential role in increasing access to credit and promoting economic development in underserved communities. Specific examples of SPCPs that banks employ to support underserved communities are available within the Appendix.

Impact of Machine Learning (ML) Models on Fair Lending

We did a literature review to explore the benefits and risks of implementing machine learning (ML) models in credit scoring, including addressing issues of credit invisibility among minority consumers, the potential for discrimination in ML algorithms, and the use of fairness processors to balance profit and fairness in credit scoring.

Courchane and Ross (2018) discuss the benefits and risks of implementing ML models to replace traditional credit scoring methods. Alternative models utilizing a more significant amount of data elements have the potential to broaden credit access to historically underserved populations.

Breevoort, Grimm, and Kambara (2015) combined CFPB Consumer Credit Panel data with Census and American Community Survey data for demographic information. It estimated that about 15% of blacks and Hispanics are “credit invisible” compared to 9% of Whites and Asians, signifying that they have no records at the national credit reporting bureaus. Because of this, alternative data sources and modeling approaches like ML are needed to broaden access to credit for minority consumers. However, this risk may not be eliminated if the data sources have inherent biases.

Fuster, Goldsmith-Pinkham, Ramadorai, and Walther (2021) examined the effects of machine learning algorithms in credit markets using HMDA and McDash data from 2009 to 2013. It found that while ML models had higher accuracy, they also resulted in less lending to minority borrowers, which may lead to discrimination. The study recommends that companies using or planning to use ML algorithms also develop internal monitoring mechanisms to ensure responsible and unbiased lending.

Kozodoi, Jacob, and Lessmann (2022) wrote the paper “Fairness in credit scoring: Assessment, implementation, and profit implications.” It contributed to developing statistical fairness criteria for credit scoring and explored algorithmic options for incorporating fairness goals in the ML model development pipeline. The study suggests that reducing discrimination while maintaining profit levels is possible and outlines techniques to help decision-makers analyze the profit-fairness trade-off specific to their context.

Context - The Merger of BMO and Bank of the West

In 2018, the National Community Reinvestment Coalition (NCRC) filed a complaint with the US Department of Housing and Urban Development (HUD), alleging that BMO Harris Bank, one of the largest banks in the midwest, engaged in illegal redlining practices. According to the NCRC's analysis, BMO's lending practices favored predominantly white neighborhoods over predominantly non-white communities, even when controlling for income and other factors. The complaint alleged that this resulted in a lack of access to credit and other financial services for residents of non-white neighborhoods.

Controversy over the merger between BMO Harris and Bank of the West (BOW) centers on concerns over both banks' lending practices to Black residents. The Fair Housing Center of Central Indiana has opposed the merger, arguing that BMO Harris has a poor track record of mortgage lending to Black residents, highlighting Marion County for evidence. Black homeowners account for nearly 30% of Marion County. Still, from 2018 to 2021, only 10% of applications for loans from BMO Harris were from black applicants, significantly lower than the 16% average from the county's top 50 lenders (Cheang, 2022). During the same timeframe, BMO Harris' denial rate for Black homeowners in Marion County was 56%, a vastly different number than white applicants' denial rate of 30%; additionally, the bank originated only 5% of its loans to Black applicants from 2018 to 2021, the fifth worst rate of mortgage origination to Black borrowers from all lenders in Marion County (Cheang, 2022).

The California Reinvestment Coalition (CRC) also raised concerns about the Bank of the West's activities. Bank of the West lent to Black borrowers at a rate of 1.2% of originations compared to the bank's peers, which lent to Black borrowers at 2.3% (CRC, 2022). The CRC highlighted BOW's poor lending track record to Black borrowers, as well as the hundreds of loans it made to predatory corporate landlords like Wedgewood Homes (a Los Angeles-based real estate investment company that was sued by the California Attorney General in 2021 after it was found to have unlawfully evicted tenants from properties purchased at foreclosure sales).

Similarly, BMO Harris was criticized for helping to secure a deal for Invitation Homes, one of the nation's most prominent corporate landlords, that has been investigated for negligence. The community groups requested that regulators require a strong Community Benefits Agreement (CBA) to be negotiated with community groups and enforced through Community Reinvestment Act evaluations.

BMO Harris denied the allegations, stating that it has a strong record of fair lending practices and is committed to serving all communities. However, the bank did agree to work with the NCRC and HUD to address the concerns raised in the complaint. BMO Harris has taken several steps to address the allegations of redlining that have been made against it. Some of these steps include: conducting an internal review of lending practices, increasing lending in underserved communities, investing in community development (affordable housing, small business development, and other programs), improving internal diversity and inclusion, and working with community organizations to better understand the needs of underserved communities and to develop strategies for addressing those needs.

BMO Harris has taken steps to address these allegations and improve its lending practices. However, the bank has a history of redlining that must be addressed. Financial institutions must ensure that their practices are fair and equitable for all communities and actively work to address any issues that may arise.

It is to be noted that Bank of the West does not have any officially documented history of confirmed redlining and that they have worked with community groups to develop a Special Purpose Credit Program mortgage product to target underserved BIPOC (Black, Indigenous, and People of Color) homebuyers in California and commit $100 million for such loans (OCC, 2023).

4. Data

Sample Construction

The analysis sample was a census-tract-by-bank level dataset containing information on census tracts in Arizona and California in 2021. We focus on these states because the Bank of the West has a significant presence. Demographic information about tracts comes from the United States Census Bureau.

We download loan-level data (the "HMDA" data) from the Modified Loan/Application Register (LAR)[11] from the CFPB website. We restrict the loans to applications in Arizona,

[11] The Modified Loan/Application Register (LAR) is loan-level data for an individual financial institution, as modified by the Bureau to protect applicant and borrower privacy. "A downloadable modified LAR file is available for every financial institution that has completed a HMDA data submission in the selected year. The modified LAR data represents the most current HMDA submission made by an institution." (see https://ffiec.cfpb.gov/data-publication/modified-lar/2022) or (see https://ffiec.cfpb.gov/data-browser/data/2021?category=states)

California, and to banks whose loan origination volume is within 50% and 200% of BOW's loan origination volume. This restriction ensures we are dealing with comparable banks. Next, we aggregate loan-level HMDA data to bank-tract level. In doing this, we combine all other banks as "competitors" of Bank of the West.

The final sample includes data on loan volumes, types, characteristics, and outcomes, along with borrower demographics and local demographics. Therefore, it allows us to examine their fair lending performance and identify potential areas for improvement.

Descriptive Statistics

The final dataset contains 13837 observations for 7511 unique census tracts in Arizona and California. Of these observations, 4500 are associated with Bank of the West loans, while the remaining 9337 are from all other banks in the dataset.[12]

- **Loan Numbers (approved and accepted)**: The maximum number of approved loans in a single census tract is 836, while the minimum is 1. It indicates significant variation in loan volume across different census tracts. The average number of applications per tract is 44.74, with a min of 1 and a max of 954, showing a considerable variation again.
- **Denial Rate**: Among all banks, the mean denial rate (denial_rate) is about 18%, which indicates that, on average, 18% of loan applications in the dataset/tracts were denied. The lowest denial rate in the sample is 0, meaning there were some instances where all loan applications were approved, while the largest denial rate is 0.857, indicating that a large proportion of loan applications were denied in some cases. Overall, the summary statistics suggest that a significant proportion of loan applications are denied, and the sample has a high degree of variability in denial rates. It is an important factor to consider when evaluating fair lending practices across different census tracts.
- **Average Approved Loan Amount**: This variable describes the mean (average) approved loan size as $482,531.43, and the standard deviation of approved loan sizes is $998,587.47, indicating a considerable variation in the loan sizes. Overall, the summary statistics suggest a wide range of approved loan sizes, with a large amount of variation in the loan amounts. The median (50th percentile) loan size is smaller than the mean, indicating that the distribution of loan sizes may be skewed to the right, with some enormous loan amounts pulling up the average.
- **Total Request Loan Amount**: The mean of the sum of all requested loans in a tract is $20,570,612. It can be used to compare loan amounts to other census tracts. Some census tracts have higher loan amounts than others. We can combine this with median income, minority percentage, or other relevant variables to see where questions arise.

[12] In our regression analysis, we will use two derived datasets. When the outcome requires us to know lending outcomes, we only use tracts where BOW and competitors are active. When we are examining lending volumes, we augment the dataset to include tracts where BOW is not active and set the number of loan applications to zero.

- **Approved Loan Interest Rate**: The mean interest rate for approved loans is 3.14%, with a minimum of 1.58% and a maximum of 7.68%. It suggests that there is variation in interest rates across different census tracts, which signals a correlation to specific areas.
- **Loan-to-Value (LTV) Ratio**: LTV ratio expresses the ratio of a loan to the appraised value or market value of an asset. In our analysis, the mean LTV ratio (mean_LTV) is 63.66%, with a minimum of 2.88% and a maximum of 1,815.71%. A 63.66% loan-to-value (LTV) ratio means that a borrower has taken out a loan that is equal to 63.66% of the appraised value or purchase price of the asset that is being used as collateral for the loan. This mean ratio is generally considered to be a fair and reasonable LTV ratio in most cases. However, the max LTV ratios might be a recording error from the raw dataset because it is unrealistic to have such a ratio.

Table 1 compares lending practices between Bank of the West and its competitors, highlighting significant variations in the number, value, and interest rates of loans across different bank tracts. Additionally, descriptive statistics for the entire dataset are provided. Notably, the mean denial rate across all banks is approximately 18%, and Bank of the West has a slightly higher denial rate than its competitors. Taking a closer look at the mean values for Bank of the West (BOW) and its competitors, BOW shows a higher mean denial rate for loan applications and a higher mean interest rate for approved loans.

Denial rate refers to the percentage of loan applications the bank denied, which varies based on the loan product and purpose. **Table 2** shows the denial rates for different loan products and loan purposes offered by all other banks and Bank of the West. Something worth noting is that Bank of the West has higher denial rates than all other banks in every loan type and purpose. Therefore, stakeholders need to consider what caused such high denial rates from this table and provide reasoning to back up the high rate or develop new strategies to mitigate the possible fair lending issue.

Table 3 shows the median income of loan applicants for different loan products and purposes offered by all other banks and Bank of the West. Bank of the West's applicants has a higher median income for most loan products and purposes. Besides, the median income of FHA loan applicants is generally lower than conventional loans. FHA loans are a type of mortgage loan that the Federal Housing Administration backs. These loans are designed to make homeownership more affordable and accessible, especially for people with lower incomes or credit scores. As a result, FHA loans may be more accessible to people with lower median incomes than conventional loans.

Table 1: Descriptive Variables of Whole Dataset

					Means		
	Count	Std	Min	Max	All Obs	Bank of the West	All Other Banks
Loan Applications	13,837	54.44	1.00	964.00	44.74	3.38	64.67
Number of Approved Loans	13,837	46.54	1.00	836.00	37.49	2.39	54.40
Denial Rate	13,837	0.16	0.00	0.86	0.18	0.21	0.17
Average Approved Loan Amount ($ Million)	13,837	1.00	0.02	55.25	0.48	0.48	0.48
Total Requested Loan Amount ($ Million)	13,837	31.99	0.02	827.75	20.57	1.77	29.63
Total Approved Loans Amount ($ Million)	13,837	28.30	0.02	638.74	17.81	1.31	25.76
Avg Approved Loan Interest Rate	13,837	0.45	1.58	7.68	3.14	3.41	3.02
Avg Approved Rate Spread	13,249	0.38	-1.21	4.01	0.36	0.47	0.31
LTV (%)	13,833	19.76	2.88	1815.71	63.66	61.05	64.91

Table 2 Denial Rates by Product and Purpose

		All Other Banks	Bank of the West
Loan Type	**Loan Purpose**		
	Cash-out refinancing	0.13	0.26
	Home improvement	0.37	0.38
Conventional	**Home purchase**	0.09	0.13
	Other purpose	0.36	0.45
	Refinancing	0.12	0.34
	Cash-out refinancing	0.29	0.76
	Home improvement	0.18	1
Federal Housing Administration FHA	**Home purchase**	0.11	0.38
	Other purpose	0.23	1
	Refinancing	0.18	0.67

Table 3 Median Income of Applicants by Product and Purpose

Loan Type	Loan Purpose	All Other Banks	Bank of the West
Conventional	Cash-out refinancing	105	135
	Home improvement	128	146
	Home purchase	131	225
	Other purpose	134	151
	Refinancing	123	183
Federal Housing Administration FHA	Cash-out refinancing	75	69
	Home improvement	51	79
	Home purchase	80	91
	Other purpose	29	36
	Refinancing	28	83

Table 4 splits the data into 5 different quintiles based on the percentage of the population that is not white (minority groups) for a given tract. The patterns for BOW and other banks are quite similar: The fraction of loans (in units and dollars) declines dramatically across the quintiles; approval rates for loans are generally high and have minor deviations across both banks and for all minority rate quantiles.

Table 4 Minority Quintiles Loan Analysis

	% of Loans Made		% of Dollars Loaned		Approval Rate (%)	
	All Other Banks	Bank of the West	All Other Banks	Bank of the West	All Other Banks	Bank of the West
Minority Rate Quantile						
1 (Lowest)	32	29	32	33	85	71
2	37	35	36	35	84	72
3	19	18	19	16	84	71
4	10	14	10	12	84	69
5 (Highest)	3	4	3	4	86	70

Table 5 examines how lending behavior in a census tract relates to residents' income in the census tract. The results demonstrate that higher median income is associated with higher loan approval rates. It might be because tracts of higher-income residents have more financial resources and may be more likely to qualify for larger loans. In contrast, tracts where residents have lower income may have more financial constraints, including lower credit scores, more debt, and less stable employment. It may result in lower loan approval rates and smaller loan amounts for tracts of lower median income quintiles. Overall, the relationship between median income quintiles and approved loan amounts reflects loan applicants' financial resources and creditworthiness in different income groups and the lending practices of banks and financial institutions.

Table 5: Median Income Quintiles Loan Approval Analysis

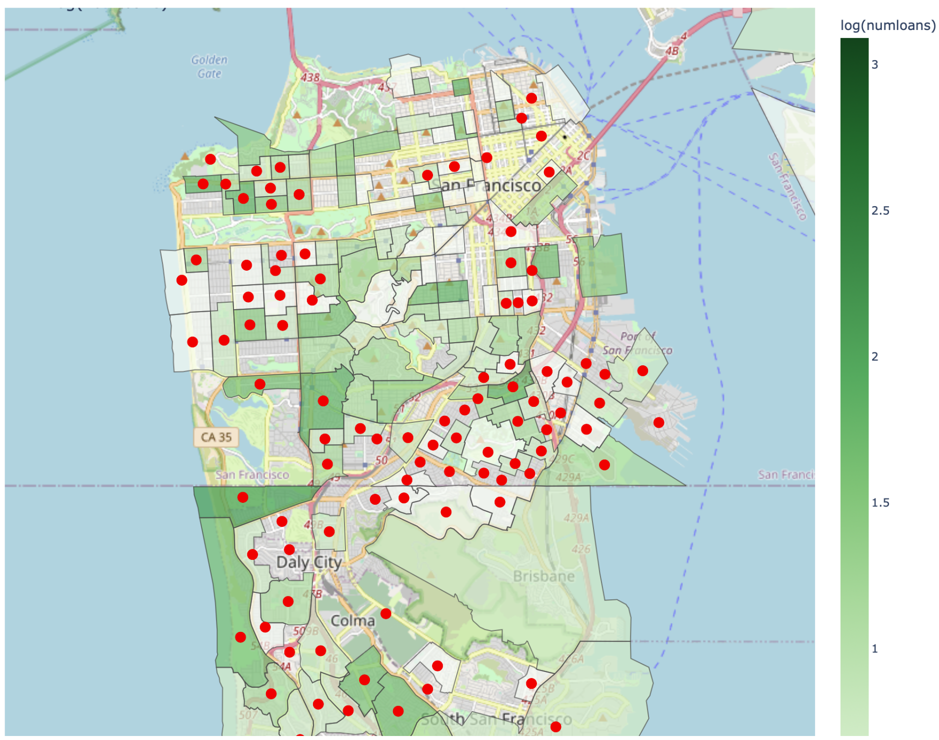
	Average Loan Portfolio ($ Millions)		**Approval Rate (%)**	
	All Other Banks	Bank of the West	All Other Banks	Bank of the West
Median Income Quintiles				
1 (Lowest)	10.13	0.39	80	65
2	16.31	0.64	82	67
3	23.99	0.65	84	68
4	33.02	1.07	87	71
5 (Highest)	65.56	2.43	89	72

Maps

Before turning to our regression analysis, we consider visual evidence.

Figure 1 displays the logarithmic number of loans BOW made in San Francisco, CA. The red dots signify tracts with a majority-minority population. This means that the percentage of white people is less than 50% of the population in that tract. The darker the green shading, the more loans the Bank of the West has in that tract. The shaded white tracts with red dots indicate tracts where BMO Harris might want to increase lending activity.

Figure 1: BOW Loan Volume in San Francisco



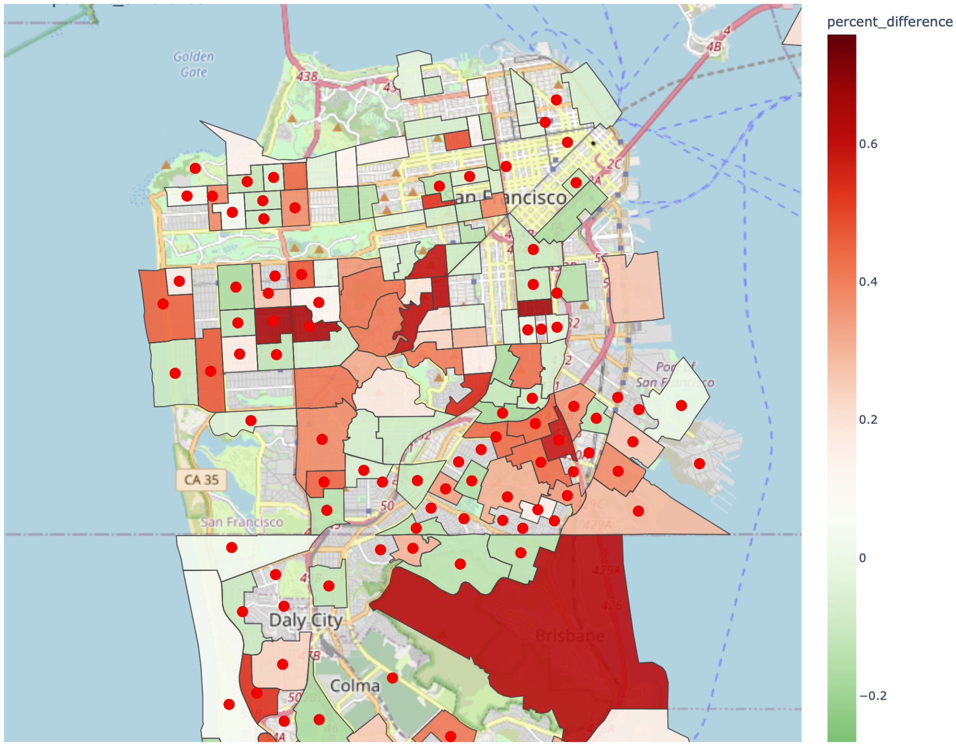
(An interactive version of this graph can be found here)

Figure 2 displays the difference between the denial rate of the Bank of the West and all other competitor banks. Dark red means the denial rate of Bank of the West is higher than all other competitor banks, while green means lower. For San Francisco, there are generally more green shades, meaning BOW has a lower denial rate for majority-minority tracts than competitors for this city. The shaded red tracts with red dots indicate tracts where BMO Harris might want to examine lending decisions.

Figure 3 repeats the same information for Los Angeles. The biggest issue to be noted from LA's maps is BOW's lack of loans in the bulk of LA's majority-minority tracts.

Interactive plots for other variables of interest can be found at https://github.com/LeDataSciFi/FinTech-Capstone-2023/tree/main/images.

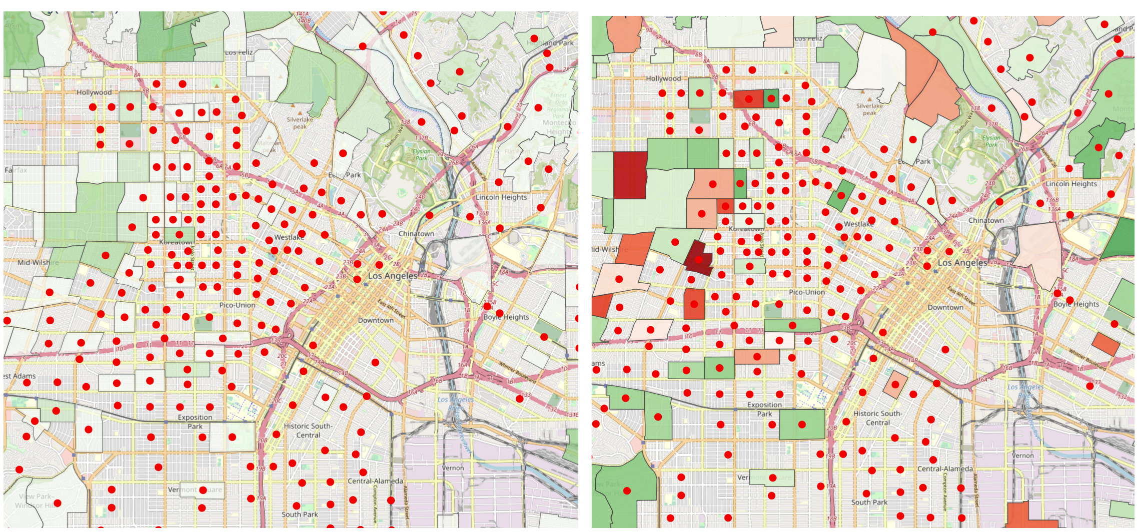
Figure 2: BOW Denial Rates in San Francisco



(An interactive version of this graph can be found here)

Figure 3: BOW Lending in Los Angeles

Panel A: Loan Amounts **Panel B: Denial Rates**



5. Analysis

Regression Analysis

As regulators often focus first on access issues (National Credit Union Administration, 2009), we first discuss pipeline issues. Building on the map-based discussion in the prior section of how loan volume in a tract is related to the demographics of the tract, we now formalize that analysis with regressions. Specifically, we estimate regressions of the form:

$$y = a + b*BOW + c*HighMinority + d*BOW*HighMinority$$
$$+ e*TractDemoVars + f*BankApplicantVars + u$$

where BOW is an indicator equal to one for BOW's observations. HighMinority is an indicator equal to one if the tract is a "high minority" tract (precise definition depends on the model and we elaborate later). TractDemoVars is a vector of tract-level controls, specifically *log(1+Median Household Income)* and *Poverty Ratio*. BankApplicantVars is a vector of controls describing the applicant pool BOW or its competitors have in a given tract, specifically *Mean Loan to Value*. Depending on the table, y is an indicator for receiving any loans in a given tract, (logged) loan volume, denial rate, or average interest rate spread.

The coefficient of interest in all regressions is d. This coefficient tells us how BOW's lending changes in high minority tracts relative to low minority tracts, and compares this difference to the corresponding change at competitor banks.

Table 6[13] focuses on BOW's probability of receiving loan applications in minority census tracts. First, the model for census tracts with a high Hispanic population shows how the likelihood of receiving any applications is lower if BOW were present in that census tract and higher probability if the census tract just has a Hispanic population over the median. The negative coefficient of interest in this model (interaction term) suggests that census tracts served by Bank of the West with a Hispanic population above the median Hispanic rate are even less likely to receive loan applications. The model developed for black minorities follows the same pattern, census tracts in areas served by Bank of the West are less likely to receive loan applications, and census tracts with a black population above the median black rate across all regions are more likely to receive applications (all other variables held constant). The interaction term is also interpreted in the same manner. Census tracts served by the Bank of the West with a black population above the median are even less likely to receive loan applications. The model developed for Asian minorities follows a different pattern, census tracts served by the Bank of the West are less likely to receive loan applications, and census tracts with an Asian population above the median are also less likely to receive applications. In this case, the

[13] Table 6 and Table 7 omit the inclusion of BankApplicantVars as control variables given that there are tracts where BOW receives no applications, hence the bank related variables for these observations are null.

positive coefficient for the interaction term suggests that census tracts served by BOW with an Asian population above the median are more likely to receive loan applications.

Table 6: Does the bank receive any applications?

Minority Group for Column:	Hispanic (1)	Black (2)	Asian (3)	All (4)
Intercept	-1.426***	-1.437***	-1.185***	-1.427***
	(0.109)	(0.105)	(0.108)	(0.105)
BOW	-0.415***	-0.475***	-0.610***	-0.517***
	(0.007)	(0.007)	(0.007)	(0.005)
High Minority	0.087***	0.035***	-0.064***	0.000***
	(0.007)	(0.007)	(0.007)	(0.000)
High Minority:BOW	-0.192***	-0.083***	0.197***	0.000
	(0.010)	(0.010)	(0.010)	(0.000)
log(1+Median Household Income)	0.212***	0.215***	0.198***	0.216***
	(0.009)	(0.009)	(0.009)	(0.009)
Poverty Ratio	0.092**	0.093**	0.060	0.090**
	(0.041)	(0.042)	(0.041)	(0.042)
R-squared	0.407	0.397	0.409	0.395
R-squared Adj.	0.407	0.397	0.409	0.395
No. observations	18658	18658	18658	18658

Sample: All tract-bank pairs. We augment the dataset to include tracts where BOW is not active and set the number of loan applications to zero. The independent variable is a binary variable indicating whether BOW received a loan in a tract. High minority equals one in tracts where the minority in that column has an above median population share. In column (4), Minority group over median equals one in tracts where less than 50% of the population is white. Standard errors are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 7 instead looks at the intensive margin; how many loan applications does a bank receive in a tract? Judging by the coefficients of the model developed for Hispanic minorities, it is apparent that the number of applications is expected to decrease in tracts where the Bank of the West is active and when the tract has a Hispanic population above the median. The number of applications is also expected to decrease when Bank of the West is present in the tract and when the tract has a Hispanic population above the median. Nevertheless, it is also true that, on average, the logarithm of the number of applications is 0.085 higher in areas where the Hispanic rate is above the median. The loan application is for Bank of the West, compared to areas where the Hispanic rate is below the median, and the loan application is not for Bank of the West. Regarding the model developed for the black minority group, the number of applications is expected to decrease when BOW is present in the tract, and they will increase in tracts where the black population is above the median. Judging by the interaction term coefficient in this model, the number of applications is expected to decrease if a given tract has a black rate above the median and is serviced by the Bank of the West compared to a tract with a black rate above the median and serviced by competitor banks. For the Asian minority group, the number of applications is expected to decrease in tracts where BOW has a presence and in tracts with an Asian population above the median. Regarding the interaction term for this model, the number of applications is expected to increase in tracts where the Asian rate is above the median Asian rates and the bank is BOW, compared to areas where the Asian rate is below or equal to the median Asian rates and the bank is BOW.

Table 7: Logged Application Volume

Minority Group for Column:	Hispanic (1)	Black (2)	Asian (3)	All (4)
Intercept	-3.555***	-3.993***	-4.204***	-3.921***
	(0.221)	(0.213)	(0.220)	(0.212)
BOW	-3.304***	-3.201***	-3.355***	-3.259***
	(0.015)	(0.014)	(0.014)	(0.010)
High Minority	-0.102***	0.079***	-0.162***	0.000***
	(0.015)	(0.014)	(0.015)	(0.000)
High Minority:BOW	0.085***	-0.114***	0.207***	0.000
	(0.020)	(0.020)	(0.020)	(0.000)
log(1+Median Household Income)	0.680***	0.711***	0.740***	0.708***
	(0.019)	(0.018)	(0.019)	(0.018)
Poverty Ratio	-0.741***	-0.764***	-0.703***	-0.755***
	(0.084)	(0.084)	(0.084)	(0.084)
R-squared	0.857	0.857	0.857	0.856
R-squared Adj.	0.857	0.857	0.857	0.856
No. observations	18658	18658	18658	18658

Sample: All tract-bank pairs. We augment the dataset to include tracts where BOW is not active and set the number of loan applications to zero. The independent variable is the logarithm of the number of applications plus one. High minority equals one in tracts where the minority in that column has an above median population share. In column (4), Minority group over median equals one in tracts where less than 50% of the population is white. Standard errors are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Now we turn to understanding the loan process. **Table 8** explores how denial rates are related to tract demographics. Column 1 represents the model developed for the Hispanic minority group, and the denial rate will tend to increase in census tracts with a greater Hispanic population than the median if Bank of the West is reviewing the given application. Nevertheless, it is also suggested by the coefficient on the interaction term that in areas where Bank of the West has a presence, the effect of being in a census tract with a Hispanic rate above the median on the denial rate may be less robust than in areas where other banks are present. Regarding the black minority models, the denial rate will also increase if the black population exceeds the median. If the Bank of the West receives the loan application, and just like for the Hispanic models, the effect of being in a census tract with a high black population on the denial rate is less when the Bank of the West reviews the applications. Regarding the Asian minority models, the denial rate will increase if BOW reviews the applications and decrease census tracts where the Asian population is above the median. Judging by the interaction term coefficient in this model, the effect of being in a census tract with an Asian rate above the median on the denial rate may be stronger in tracts where BOW is present than in tracts where other banks are present.

Finally, we examine loan pricing. **Table 9** uses the average interest rate spread on loans the banks approve in a tract as the dependent variable. The first model developed looks at how interest rate spread is affected in tracts with a high Hispanic population. The average interest rate spread is 2.66%, which will tend to increase if BOW is pricing the loans and if a tract has a Hispanic population above the median. Judging by the interaction term of this model, it is also apparent that the effect of being in a census tract with a Hispanic rate above the median on the interest rate spread may be stronger in tracts where BOW has a presence than in tracts where other banks are present. The average interest rate spread for Black communities is 3.067%, which is higher than in Hispanic communities. This rate will increase if BOW is pricing the loans and if a tract has a black population above the median. In the same manner, as the Hispanic minority model, the effect of being in a census tract with a black population rate above the median on the interest rate spread may be stronger in tracts where BOW has a presence than in tracts where other banks are present. Regarding the model developed for the Asian minority group, the average spread is 3.077%, which again will increase if BOW is pricing the loans and if a tract has an Asian population above the median. In this case, the interaction term suggests that the effect of being in a census tract with an Asian population rate above the median on the interest rate spread may be less strong in tracts where BOW has a presence than in tracts where other banks are present.

Table 8: Denial Rates

Minority Group for Column:	Hispanic (1)	Black (2)	Asian (3)	All (4)
Intercept	0.085	0.128	0.189**	0.134
	(0.087)	(0.083)	(0.085)	(0.083)
BOW	0.088***	0.070***	0.002	0.050***
	(0.005)	(0.005)	(0.006)	(0.004)
High Minority	0.054***	0.022***	−0.040***	−0.000*
	(0.006)	(0.005)	(0.006)	(0.000)
High Minority:BOW	−0.088***	−0.044***	0.084***	0.000
	(0.008)	(0.007)	(0.008)	(0.000)
log(1+Median Household Income)	0.006	0.002	0.001	0.003
	(0.007)	(0.007)	(0.007)	(0.007)
Poverty Ratio	0.025	0.031	0.028	0.031
	(0.036)	(0.036)	(0.036)	(0.036)
Mean Loan−To−Value	−0.000***	−0.000*	−0.000**	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)
R−squared	0.035	0.024	0.033	0.020
R−squared Adj.	0.034	0.023	0.033	0.019
No. observations	8990	8990	8990	8990

Sample: Tracts where BOW approves at least one loan. The independent variable is denial rate. High minority equals one in tracts where the minority in that column has an above median population share. In column (4), Minority group over median equals one in tracts where less than 50% of the population is white. Standard errors are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Interpreting regression models is crucial to understanding relationships between variables and making informed decisions. Our analysis of multiple regression models shows several key takeaways and areas of concern. Regarding the models that focus on the probability of receiving applications, the negative takeaway is that census tract served by BOW with a Hispanic or Black population above the respective median are less likely to receive loan applications. The opposite can be observed for census tracts served by BOW with an Asian population above the median. A positive take away from the models using the logarithm for the number of loan applications is that census tracts served by the Bank of the West with a Hispanic or Asian population above the median are associated with a higher number of loan applications. This is not the case for census tracts with a black population above the median, which is associated with lower numbers of loan applications. The positive takeaway from the denial rate models is that for census tracts with black and Hispanic populations above their respective medians, and where BOW has a presence, the effect on the denial rate may be less strong than in areas where other banks are present. Nevertheless, an area of concern could be that for census tracts with an Asian population above the median where BOW has a presence, the effect on the denial rate is stronger than in tracts where other banks are present. The positive take away from the interest rate spread regression models is that for the Asian minority group, the effect of being in a census tract with an Asian population rate above the median on the interest rate spread may be less strong in tracts where BOW has a presence than in tracts where other banks are present. This is not the case for the Hispanic and Black minority groups, where the effect of being in a census tract with a black or Hispanic population rate above the median on the interest rate spread may be stronger in tracts where BOW has a presence than in tracts where other banks are present.

Table 9: Interest Rate Spread

Minority Group for Column:	Hispanic (1)	Black (2)	Asian (3)	All (4)
Intercept	2.666***	3.067***	3.077***	3.115***
	(0.198)	(0.190)	(0.194)	(0.189)
BOW	0.205***	0.234***	0.263***	0.241***
	(0.011)	(0.012)	(0.013)	(0.009)
High Minority	0.028**	0.015	0.014	-0.000***
	(0.013)	(0.012)	(0.012)	(0.000)
High Minority:BOW	0.088***	0.016	-0.037**	0.000
	(0.018)	(0.017)	(0.018)	(0.0000)
log(1+Median Household Income)	-0.243***	-0.278***	-0.279***	-0.2814***
	(0.016)	(0.016)	(0.016)	(0.016)
Poverty Ratio	-0.392***	-0.388***	-0.376***	-0.3825***
	(0.085)	(0.085)	(0.085)	(0.085)
Mean Loan-To-Value	0.006***	0.006***	0.006***	0.006***
	(0.000)	(0.000)	(0.000)	(0.000)
R-squared	0.181	0.175	0.174	0.174
R-squared Adj.	0.180	0.174	0.174	0.174
No. observations	8433	8433	8433	8433

Sample: Tracts where BOW approves at least one loan. The independent variable is approved interest rate spread. High minority equals one in tracts where the minority in that column has an above median population share. In column (4), Minority group over median equals one in tracts where less than 50% of the population is white. Standard errors are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

6. ChatGPT Loan Officer

The mortgage lending industry is undergoing a technological revolution, with new developments in artificial intelligence technology (AI) and other technologies poised to reshape how loans originated and were underwritten. AI, in particular, has the potential to transform the lending process by improving accuracy, streamlining workflows, and enhancing the customer experience. However, as with any new technology, there are opportunities and shortcomings to consider. This section of the report will explore the role of developing technologies, including our experiment using OpenAI's ChatGPT and API.

To explore the potential of AI, we experimented using OpenAI's ChatGPT and API to determine whether the system could accurately assess and approve or deny loans based on specific variables. We began by selecting 100 random loans from our census tract-bank dataset with specific variables such as ‘loan_amount’, 'loan_purpose', 'property_value', 'income', 'total_units', and more. We then tasked ChatGPT with writing code that would accept or deny these loans based on the selected variables, excluding any demographic information. If ChatGPT accepted a loan, it had to provide an interest rate it would charge.[14]

The results are in **Table 10 Panel A**. The "Approval Rate" column shows the percentage of loans that ChatGPT approved. The "Interest Rate" column shows the average interest rate ChatGPT charges for loans approved in each demographic group. The t-stat column shows the results from an Unequal Variance t-test comparing "No Race" to each of the other inputs.

Our first trial, "No Race," fed the raw application data to ChatGPT without information regarding the loan applicant's race. Relative to the real outcomes ("Original Data"), ChatGPT rejects more applications and suggests a higher interest rate. We viewed this test as a "calibration" test. Differences between "No Race" and "Original Data" are likely due to ChatGPT's more accurate pulse on the economy and lending conditions than loan decisions made in 2021.

We repeated this exercise two more times to test for consistency and randomness with ChatGPT's outputs. We recognized that the results were all statistically similar and had very similar average interest rates. This instills confidence that the decisions made by ChatGPT were not made in complete randomness but instead were determined based on the inputs provided.

Then we resubmitted the loans to ChatGPT but added demographic information. We did this for "White," "Black," "Hispanic," and "Asian," where a new column was added to the dataset that said every applicant was of that race. Looking at the results for the "White" and "Asian," the resulting t-stats are -0.69 and -1.47, implying that the mean interest rate for these demographics is not statistically distinct from the rates in the "No Race" experiment. Looking at the results for "Black" and "Hispanic" applicants, the t-stats are -6.94 and -5.25, respectively, implying that the mean interest rates for these pseudo-applicants are not statistically similar to the rates charged for "No Race" applicants.

Based on our results, we attempted to reduce the bias ingrained in our original prompt results. In Panel B Table 10, we used the same prompt but added the caveat that the AI should use no bias in making its decision, changing the prompt question to "You should use no bias in making this decision. Should this loan be granted? If so, at what interest rate?" These results differed significantly from the results seen in Panel A. Comparing the new results to the "No Race" results. Each test resulted in t-stats below the typical thresholds.

[14] 2.6% of the approved loans across our experiments had no listed interest rate.

Table 10: ChatGPT Loan Officer

Panel A: "Given the following loan data:... Should this loan be granted? If so, at what interest rate?"

Test	Evaluator	Approval Rate (%)	t-stat	Interest Rate (%)	t-stat
Original Data	Real Data	95		3.40	
No Race	ChatGPT	88		4.75	
No Race 2	ChatGPT	87	0.21	4.77	-0.21
No Race 3	ChatGPT	89	-0.22	4.78	-0.30
White	ChatGPT	90	-0.45	4.82	-0.69
Black	ChatGPT	89	-0.22	5.42	-6.94
Asian	ChatGPT	86	0.42	4.90	-1.47
Hispanic	ChatGPT	88	0.00	5.27	-5.25

Panel B: "Given the following loan data:... You should use no bias in making this decision. Should this loan be granted? If so, at what interest rate?"

Test	Evaluator	Approval Rate (%)	t-stat	Interest Rate (%)	t-stat
Original Data	Real Data	95		3.40	
No Race	ChatGPT	83		4.84	
White	ChatGPT	88	-1.00	4.71	1.05
Black	ChatGPT	83	0.00	5.06	-1.53
Asian	ChatGPT	92	-1.93	4.81	0.21
Hispanic	ChatGPT	87	-0.79	4.83	0.06

Looking forward to the possibility of AI technology being used in practice for loan decision-making, our results raise some red flags. Using the same loan information yet changing the race assigned to the "applicant" yielded very different results in how many loans were accepted and the interest rates charged, indicating that the AI had an inherent bias. Additionally, the drastic change in the results by adding a simple change in the prompt of "You should use no bias in making this decision" sheds concern on how AI platforms analyze data, and there is significant importance to training the data properly and creating a prompt that shies away from adding any bias into the results.

7. Conclusion

In conclusion, this report comprehensively analyzes Bank of the West's (BOW) lending practices and its acquisition by Bank of Montreal Harris (BMO Harris) in California and Arizona during the fiscal year 2021. The report aims to promote fair lending practices and eliminate discrimination in credit lending. Through our analysis of loan data from HMDA, census tract data, maps, and regression models, we found that BOW's lending practices vary depending on the demographic makeup of the census tracts it serves. Specifically, we found that BOW's presence in census tracts with many Hispanic or Black people is less likely to receive loan applications. In contrast, the opposite is true for the Asian population. Additionally, the experiment with OpenAI's ChatGPT and API highlighted the importance of avoiding biases in loan decisions, particularly when using AI and machine learning technologies, to promote fair and unbiased lending practices for equitable access to credit.

Overall, this report provides valuable insights into BOW's lending practices and emphasizes the importance of promoting fair and unbiased lending practices to ensure equitable access to credit for all borrowers. Our analysis underscores the need for proper data training, compliance with regulations, regular audits, and ongoing monitoring to avoid biases in lending decisions. As the financial industry continuously evolves and new technologies are introduced, staying current with the latest trends and best practices is crucial to ensuring fair and unbiased lending practices.

Appendix

The Impact of ChatGPT

ChatGPT has played a significant role in the Lehigh University Spring 2023 FinTech Capstone project. ChatGPT is a large language model trained by OpenAI that uses deep learning algorithms to generate natural language responses to text input.

While the team members have the required coding expertise, the team found that ChatGPT acts as a supportive tool to debug the code and generate some code for specific requests. The support provided by ChatGPT has undoubtedly increased the team's overall capability in the project, allowing them to delve deeper into the project's technical aspects without being limited by their knowledge or experience. Overall, ChatGPT has made the workflow of the FinTech Capstone project team smooth and quick, enabling them to complete their project effectively and efficiently.

In conclusion, the team's ability to leverage the power of ChatGPT has helped them gain insights into their project that they may only have discovered with the input of an intensive amount of time. Therefore, ChatGPT has been a crucial support tool for the FinTech Capstone project team.

Replication - Github

The repository at https://github.com/LeDataSciFi/FinTech-Capstone-2023/ contains the code to reproduce the datasets and analysis in this report.

Special Purpose Credit Programs

Bank Name	Details	Attestation
First Republic Bank	Eagle Community Home Loan Program - made more than 10,400 Eagle Community Home Loans totaling $4.6 billion, and 55% of these loans were made to minority individuals.	Minority Race Attestation
MUFG Union Bank, National Association	(125 grant recipients, $2 mill in grants) MUFG Union Bank Community Recovery Program (CRP), a $10 million initiative to support nonprofit organizations that are dedicated to social and economic justice within communities of color.	Any race
PNC Bank, National Association	Community Benefits Plan to provide $88 billion in loans, investments, and other financial support to bolster economic opportunity for underserved individuals.	Low income or community of color. Any race technically.
Citibank, National Association	Citi is allocating $50 million to its own impact investment fund that supports exclusively Black business owners. Citi is also putting down some $550 million toward affordable housing.	Of color
Homebridge Financial Services, Inc.	No specific program. Diversity and equity program for internal corporate structure and employees.	N/A
Bank of the West	Work with community groups to develop a Special Purpose Credit Program (SPCP) mortgage product to target underserved BIPOC homebuyers in California and commit $100 million for such loans.	BIPOC (Black indigenous and people of color)
Charles Schwab Bank, SSB	Community Reinvestment Act program, the company serves the credit needs of communities in which it operates by offering loans, investments, grants and services to support affordable housing, small business and sustainable job creation, and financial education. Since its inception in 2004, Charles Schwab Bank, SSB has invested, lent, and granted over $2 billion to underserved communities.	Of Color
Movement Mortgage, LLC	Black American Homeownership initiative landing page (campaign launched in 2019 to raise awareness of the gap in homeownership)	Of color (Black Americans primarily)

Navy Federal Credit Union	Provide credit lending assistance for black homeowners who are current or former military service members.	Black households
Guaranteed Rate Affinity, LLC	This new initiative aims to make homeownership more accessible by providing up to $8,000 in assistance to underserved potential homebuyers. The program expands home purchase opportunities by helping more people overcome accessibility challenges such as deposit minimums and move-in repair and maintenance costs.	Of color

References

Brevoort, K. P., Grimm, P., & Kambara, M. (2016). Credit Invisibles and the Unscored. *Cityscape*, *18*(2), 9–34. http://www.jstor.org/stable/26328254

CFPB Consumer Laws and Regulations ECOA. (2013). Retrieved from https://files.consumerfinance.gov/f/201306_cfpb_laws-and-regulations_ecoa-combined-june-2013.pdf

Cheang, K. L. (2022, July 14). Fair housing center opposes BMO Harris merger, citing poor record of lending to Black Hoosiers. The Indianapolis Star. https://www.indystar.com/story/news/2022/07/14/bmo-harris-merger-opposed-by-fair-housing-center-indiana-low-minority-lending/65373593007/

Consumer Compliance Examination Manual. (n.d.). FDIC. Retrieved from https://www.fdic.gov/resources/supervision-and-examinations/consumer-compliance-examination-manual/index.html

Courchane, M. J., & Ross, S. L. (2018). Evidence and actions on mortgage market disparities: Research, fair lending enforcement, and consumer protection. Housing Policy Debate, 29(5), 769–794. https://doi.org/10.1080/10511482.2018.1524446

CRC, Community Groups Voice Opposition to the Proposed BMO Harris-Bank of the West Merger at Public Hearing: CRC. (2022, July 16). California Reinvestment Coalition. https://calreinvest.org/crc-community-groups-voice-opposition-to-the-proposed-bmo-harris-bank-of-the-west-merger-at-public-hearing/

FDIC, "Fair Lending —Fair Lending Laws and Regulations.", 4 Mar. 2021, https://www.fdic.gov/resources/supervision-and-examinations/consumer-compliance-examination-manual/documents/4/iv-1-1.pdf.

Federal Register, "Implementation of the Fair Housing Act's Discriminatory Effects Standard.", 15 Feb. 2013, https://www.federalregister.gov/documents/2013/02/15/2013-03375/implementation-of-the-fair-housing-acts-discriminatory-effects-standard.

Fuster, A., Plosser, M., Sabarwal, T., & Schmidt, L. D. W. (2021). Predictably unequal? The effects of machine learning on credit markets. The Journal of Finance, 77(1), 5–47. https://doi.org/10.1111/jofi.13090

Kozodoi, N., Schlosser, A., Stelzer, R., & Wagner, M. (2022). Fairness in credit scoring: Assessment, implementation and profit implications. European Journal of Operational Research, 297(3), 1083–1094. https://doi.org/10.1016/j.ejor.2021.06.023

National Credit Union Administration. Interagency Fair Lending Examination Procedures. https://www.ffiec.gov/PDF/fairlend.pdf.

OCC announces approval of Bank of the West – BMO Harris Bank, National Association merger. (2023, January 17). OCC. Retrieved from https://www.occ.treas.gov/news-issuances/news-releases/2023/nr-occ-2023-8.html

The Equal Credit Opportunity Act. (n.d.). The United States Department of Justice. Retrieved from https://www.justice.gov/crt/equal-credit-opportunity-act-3

Biographies

Student Biographies

Ellie DeGeorges is a Senior at Lehigh University who is majoring in Accounting with a minor in FinTech and Religion. Upon graduating this Spring of 2023, she will be working at PwC in their New York City Office. Outside of the classroom, Ellie is the former Women in Business President and the former Vice President of TAMID.

Victoria Genco is a Senior at Lehigh University who will be obtain a Bachelor of Science in Accounting and minors in Business Information Systems and Financial Technology. After graduating in May 2023 she will be working as a Financial Services Technology Risk Consultant at Ernst & Young in New York City.

Isaac Grodin is an IBE Honors student majoring in Financial Engineering, with a minor in Financial Technology. After he graduates this Spring, he will be joining BNY Mellon’s Technology Services Group. Isaac is the president of the Lehigh Men’s Club Basketball team, and has deep interest in the financial markets.

Anna Harvey is an IBE Honors student who is graduating this Spring of 2023 with a degree in Financial Engineering and a minor in FinTech. She played four years of D1 basketball and one year of D1 Tennis. She is excited to be joining EY in NYC on the FSO-Tech Consulting-Technology Solution Delivery Team.

Juan Mozos Nieto is a senior at Lehigh University who will be graduating in the Fall of 2023. He is majoring in Finance and Business Analytics and minoring in Financial Technology.

Matthew Romano is a Senior at Lehigh University who is graduating with a Finance Degree and Minors in Financial Technology and Religious Studies.

Thomas Scaringella is a senior at Lehigh University who is majoring in Accounting and minoring in Financial Technologies. He has excelled in both finance and accounting courses, helping him create success during his internships. Upon graduation he will be working full time at PwC in their New York City office. Outside of the classroom he is on the board of Beta Alpha Psi, and formerly was the Vice President of the Accounting Club. He has a strong interest in capital markets and accounting practices.

Sebastian Stoneham is a senior at Lehigh University who is graduating with a Finance Degree and a minor in Financial Technology. After graduating, he is relocating from Houston to New York to pursue a career in banking. He is continuing his job from last summer as an analyst at CitiBank. Sebastian has a deep interest in finance and is fascinated by the technological advancements the finance industry is adopting. Throughout his time at Lehigh he has excelled in his finance courses and is excited to enter the workforce in the industry. Additionally, Sebastian has a passion for music and attending concerts in his free time and hopes to incorporate that into his career in the future.

Xiaozhe Zhang is an international student from China. He is a driven and accomplished graduating senior at Lehigh University. Throughout his academic career, Xiaozhe has pursued a rigorous course in Finance and Business Information Systems, building a solid foundation of knowledge in both fields. Xiaozhe has always been fascinated by the intersection of technology and finance, and his academic interests reflect this passion. He has demonstrated a strong aptitude for programming, statistics, and data analysis and has explored various applications of these skills in finance. In particular, Xiaozhe is deeply interested in AI, Machine learning, algorithmic trading, and quantitative finance.

Faculty Biographies

Donald Bowen is a highly respected scholar in the field of corporate finance and a valuable member of the faculty at Lehigh University's Perella Department of Finance. Throughout his career, Professor Bowen has made significant contributions to the field, with his research published in leading academic journals and presented his work at several prestigious academic conferences.