MTH312 Project - 6
Group - 14

Analysis of Credit Card Risk Data (UDAAP Complaints Against Major US Banks)

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Abstract

This study examines the rise in **consumer complaints** about **unfair banking practice**s using data from the U.S. Consumer Financial Protection Bureau **(CFPB)**. Focusing on Unfair, Deceptive, or Abusive Acts/Practices **(UDAAP)** grievances, we analyze trends from 2012-2023 to identify key patterns and risks. Our findings reveal a significant surge in complaints since 2022, with certain banks like Goldman Sachs showing disproportionate growth relative to their financial performance. While macroeconomic factors like unemployment showed some correlation, inflation had minimal impact. The most frequent complaints involved **fraud, credit reporting errors, and unauthorized transactions**, varying by institution. We also found that **negatively worded complaints** faced slightly longer resolution times, suggesting emotional tone may influence processing. Regulatory actions targeting specific issues like debt collection proved effective, whereas broader policies showed limited results. These insights highlight opportunities for banks to improve transparency and for regulators to focus enforcement where most needed, ultimately fostering **fairer banking practices.**

1 Introduction

Trust and transparency are the cornerstones of the relationship between consumers and the financial sector. But that trust can be quickly eroded when customers feel they're being treated unfairly—whether it's through hidden fees, confusing terms, or poor responses to their concerns. **The U.S. Consumer Financial Protection Bureau (CFPB)** keeps a close eye on these issues through consumer complaints, especially those marked as **Unfair, Deceptive, or Abusive Acts or Practices (UDAAP).** These complaints often serve as red flags, signaling deeper, systemic problems.

In recent years, especially after the economic upheaval caused by the pandemic, complaints have drawn even more attention. **Rising inflation and shifting regulations** have prompted both regulators and the public to take a closer look at whether banks are genuinely addressing these issues—or just sweeping them under the rug.

This project dives into how UDAAP complaints have evolved, particularly after 2022. We're asking important questions: **Are complaints on the rise? Which banks are most often in the hot seat? How do broader economic trends impact complaint patterns?** We also take a closer look at the types of issues people are reporting—like fraud or mistakes on credit reports—and even consider whether the emotional tone of a complaint influences how quickly it gets resolved.

We also evaluate how past regulatory actions have fared. Have they made a difference in reducing unfair practices, or are there still major blind spots?

Our goal is to provide insights that help everyone involved. For regulators, it's about shaping smarter policies. For banks, it's an opportunity to be more responsive and rebuild consumer trust. And for everyday people, it's a way to better understand what to watch out for when dealing with financial services.

The sections ahead walk through our approach, what we uncovered, and our recommendations for creating a more transparent, consumer-friendly financial system.

2 Data Description

The Consumer Financial Protection Bureau (CFPB) maintains a comprehensive Consumer Complaint Database, which serves as a vital resource for understanding consumer experiences with financial products and services. This database is instrumental in identifying trends, informing regulatory actions, and enhancing transparency within the financial marketplace. The database includes various fields that provide insights into each complaint:

- **Date Received**: The date the CFPB received the complaint.
- **Product and Sub-product**: The type of financial product and its specific category involved in the complaint (e.g., "Checking or savings account" and "Checking account").
- **Issue and Sub-issue**: The specific problem reported by the consumer (e.g., "Managing an account" and "Deposits and withdrawals").
- **Consumer Complaint Narrative**: A description of the issue provided by the consumer, published only if the consumer consents.
- **Company Public Response**: The company's optional, public-facing response to the complaint.
- **Company**: The name of the company the complaint is about.
- **State and ZIP Code**: The consumer's mailing state and ZIP code, with certain privacy considerations applied.
- **Tags**: Indicators for specific consumer groups, such as "Older American" or "Servicemember."
- **Consumer Consent Provided?**: Indicates whether the consumer agreed to publish their narrative.
- **Submitted Via**: The method used to submit the complaint (e.g., "Web" or "Phone").

- **Date Sent to Company**: The date the CFPB forwarded the complaint to the company.
- **Company Response to Consumer**: How the company responded to the complaint (e.g., "Closed with explanation").
- **Timely Response?**: Indicates if the company responded within the required timeframe.
- **Consumer Disputed?**: Whether the consumer disputed the company's response.
- **Complaint ID**: A unique identification number for the complaint.

3 Background

This project investigates the evolution of UDAAP-related credit card complaints in the U.S. and aims to uncover trends, identify at-risk banks, and assess policy effectiveness. A combination of statistical modeling, time series forecasting, and text analysis techniques was employed. Below is a comprehensive overview of each method used.

3.1 Structural Break Analysis

Purpose: To evaluate whether there was a significant increase in complaints post-January 2022.

Structural break analysis identifies changes in the statistical properties of a time series. A dummy variable is introduced to model pre- and post-intervention effects. Regression is then used to test for significant changes in level and trend, with p-values indicating statistical significance.

3.2 Time Series Analysis using ARIMA

Purpose: To model complaint volume over time and forecast future trends.

An **ARIMA (AutoRegressive Integrated Moving Average)** model is used, which captures temporal dependencies in the data. It is denoted as ARIMA(p, d, q), where:

- p is the number of autoregressive terms,
- d is the degree of differencing,
- q is the number of lagged forecast errors.

This model helps detect patterns and forecast future complaints.

3.3 Compound Annual Growth Rate (CAGR)

Purpose: To quantify the annual growth in complaint volumes and compare it to stock performance.

CAGR is a measure of the mean annual growth rate of a value over time, assuming compounding:

$$\text{CAGR} = \left(\frac{\text{Final Value}}{\text{Initial Value}}\right)^{1/n} - 1$$

3.4 Complaint-to-Stock Growth Ratio

Purpose: To highlight banks with disproportionately high complaint growth relative to stock performance.

This custom metric is computed as:

$$\text{Metric} = \frac{\text{Complaint CAGR}}{\text{Stock CAGR}}$$

It highlights companies where consumer dissatisfaction outpaces financial growth.

3.5 Polynomial Regression (Order 3)

Purpose: To model non-linear trends in complaint volumes.

Polynomial regression of order 3 fits a cubic curve to the data:

$$y = ax^3 + bx^2 + cx + d$$

It provides a flexible model for capturing complex trends in complaints, especially when linear models fall short.

3.6 Correlation with Macroeconomic Factors

Purpose: To determine if external economic indicators affect complaints.

Pearson correlation coefficients were computed between complaint volumes and:

- Inflation: $r = 0.021$ (negligible correlation)
- Unemployment: $r = -0.534$ (moderate negative correlation)

3.7 Text Analysis and UDAAP Term Extraction

Purpose: To identify common themes and practices flagged by consumers.

Keyword matching was applied to narrative texts to flag terms like "fraud," "unfair," and "deceptive." Frequencies of these terms were aggregated to find top complaint types for each company.

3.8 Sentiment Analysis

Purpose: To analyze whether the emotional tone of a complaint affects resolution time.

Complaint narratives were scored using sentiment analysis. A Spearman correlation ($\rho = -0.0427$, $p < 0.0001$) indicated a weak but statistically significant relationship: more negative sentiment slightly increases resolution time.

3.9 Statistical Significance and p-values

Purpose: To determine whether the findings are likely due to chance.

- A p-value < 0.05 indicates statistical significance.
- Used in regression models and intervention impact tests.

3.10 Impact of Regulatory Enforcement

Purpose: To assess the effect of regulatory interventions on complaint volumes.

Regression analysis was used to compare complaint trends before and after key regulatory actions. Results:

- **Significant Impact:**
  - Regulation Rollbacks ($p = 0.0077$)
  - Debt Collection Scrutiny ($p = 0.0000$)
  - Enhanced Lending Oversight ($p = 0.0001$)
- **No Significant Impact:**
  - Payday Loan Enforcement ($p = 0.6301$)
  - Dodd-Frank Amendments ($p = 0.3675$)

This comprehensive approach allows for a predictive and diagnostic framework that supports better policy-making, risk analysis, and operational improvements in financial institutions.

4 Methodology and Results

This section outlines the methods applied and key findings for each of the research questions posed in the study of UDAAP-related credit card complaints against major U.S. banks. The data is sourced from the Consumer Financial Protection Bureau (CFPB), and spans from 2012 to 2023.

4.1 Trend Analysis of UDAAP Complaints Over Time

Methodology:

- Filtered the CFPB dataset to isolate complaints tagged under UDAAP (Unfair, Deceptive, or Abusive Acts or Practices).
- Aggregated complaints by month to form a time series.
- Applied structural break analysis using regression with a post-Jan 2022 intervention dummy variable.
- Used p-values to determine statistical significance of slope and level change.

The following regression model was used to detect structural change:

$$\mathbf{Complaints}_t = \beta_0 + \beta_1 \cdot \mathbf{Time}_t + \beta_2 \cdot \mathbf{Intervention}_t + \beta_3 \cdot (\mathbf{Time}_t \times \mathbf{Intervention}_t) + \varepsilon_t$$

Where:

- Complaints_t = Number of consumer complaints at time t
- Time_t = Time trend variable

- $\text{Intervention}_t = 1$ if $t \geq$ Jan 2022, else 0
- $\text{Time}_t \times \text{Intervention}_t$ = Interaction term to capture change in slope post-intervention
- β_0 = Intercept
- β_1 = Coefficient for time trend
- β_2 = Coefficient for level shift (intervention effect)
- β_3 = Coefficient for slope change post-intervention
- ε_t = Error term

Results:

- Found a statistically significant increase in both the level and slope of complaints after January 2022.
- Indicates a structural shift possibly due to economic recovery, changing consumer expectations, or weakening regulatory constraints.

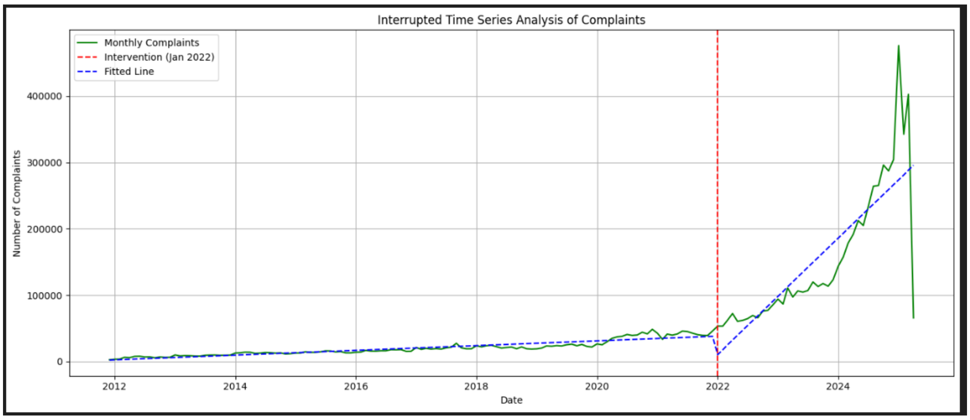


Figure 1: Trend of UDAAP Complaints Over Time

4.2 Identifying Banks with Steepest Complaint Growth

Methodology:

- Calculated the Compound Annual Growth Rate (CAGR) for each bank's complaint volume from 2012 to 2023.
- Retrieved stock price growth data from 2011 to 2025 for major banks.
- Developed a custom metric:

$$\text{New Metric} = \frac{\text{Complaint CAGR}}{\text{Stock CAGR}}$$

- Ranked banks based on both raw complaint growth and the new metric to highlight disproportionate risk.

Results:

- Banks like *Goldman Sachs Bank USA*, *Alliance Asset Management*, and *Hunt Leibert Jacobson* showed high complaint growth.
- These banks demonstrated a disconnect between consumer satisfaction and financial growth, raising red flags.

4.3 Forecasting UDAAP Risks and Macroeconomic Correlation

Methodology:

- Fitted a third-order Polynomial Regression and ARIMA model on monthly complaint data.
- Trained models on data up to 2022 and tested forecasts on 2023 data.
- Computed Pearson correlation coefficients with inflation and unemployment rates sourced from the Bureau of Labor Statistics.

  The following Ploynomial Regression model is used :

$$\log(\mathbf{Complaints}_t) = \beta_0 + \beta_1 \cdot \mathbf{Time}_t + \beta_2 \cdot \mathbf{Time}_t^2 + \beta_3 \cdot \mathbf{Time}_t^3 + \varepsilon_t$$

Results:

- Polynomial regression fitted training data well but overestimated test values.
- ARIMA provided better generalization for forecasting.
- Correlation findings:
  - Complaints vs Inflation: $r = 0.021$ (negligible correlation)
  - Complaints vs Unemployment: $r = -0.534$ (moderate negative correlation)

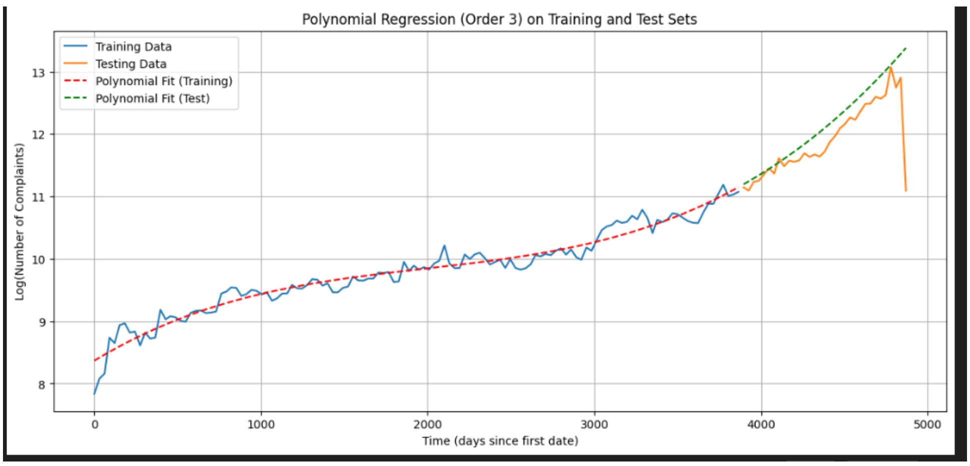


Figure 2: Polynomial Regression (Order 3) on Training and Test Sets

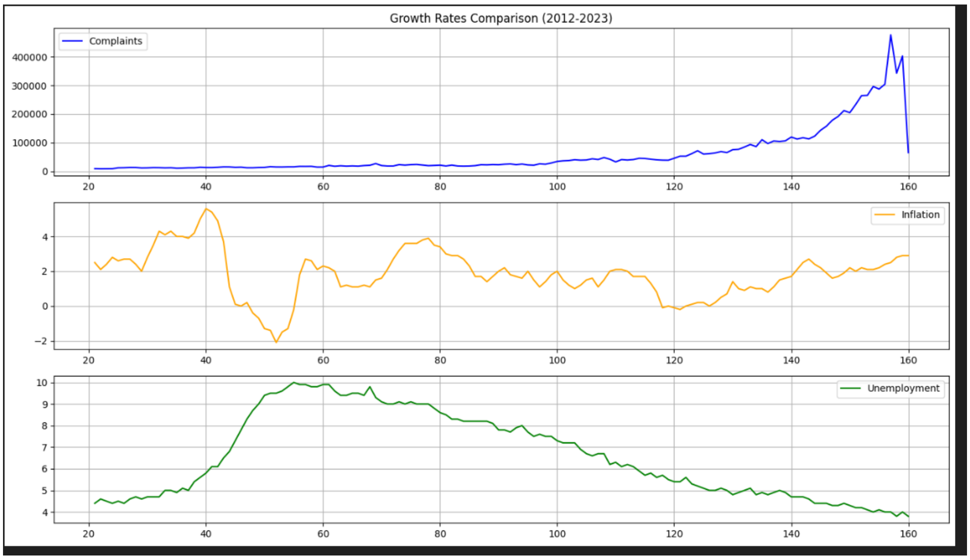


Figure 3: Growth Rates Comparison

4.4 Text Analysis of UDAAP Complaint Themes

Methodology:

- Applied keyword-based text mining to narrative complaints.
- Extracted and counted UDAAP-related terms like “fraud,” “unauthorized,” “credit score,” “unfair,” and “deceptive”.
- Grouped results by company to identify most frequent themes.

Results:

- Fraud emerged as the most common theme across top banks.
- Notable mentions:
  - Capital One: 10,099 fraud mentions
  - JPMorgan Chase: 13,229 fraud mentions
  - Wells Fargo: 10,949 fraud mentions
  - Bank of America: 13,378 fraud mentions

4.5 Analysis of Delayed Complaints and Theme of the Complaints in Leading Banks

Methodology:

- Calculated resolution time as the difference between complaint received and company response dates, focusing on major U.S. banks and complaints with valid narratives.
- Identified top complaint themes associated with long resolution durations, including mishandled credit reports, fraud disputes, and poor communication.

- Applied VADER sentiment analysis to complaint narratives, scoring sentiments from -1 (very negative) to 1 (very positive).
- Computed Spearman correlation between sentiment scores and resolution time, visualizing patterns by grouping complaints into sentiment buckets.

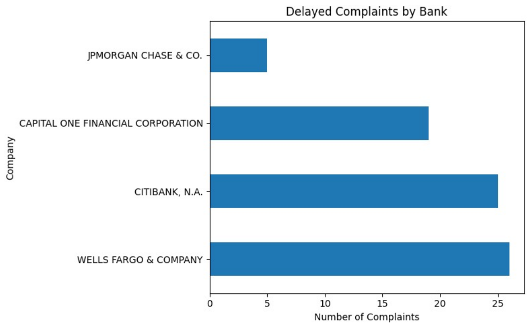


Figure 4: Comparing Delayed Complaints between Leading Banks

Figure 5: Theme in Delayed Complaints in the Leading Banks

Results:

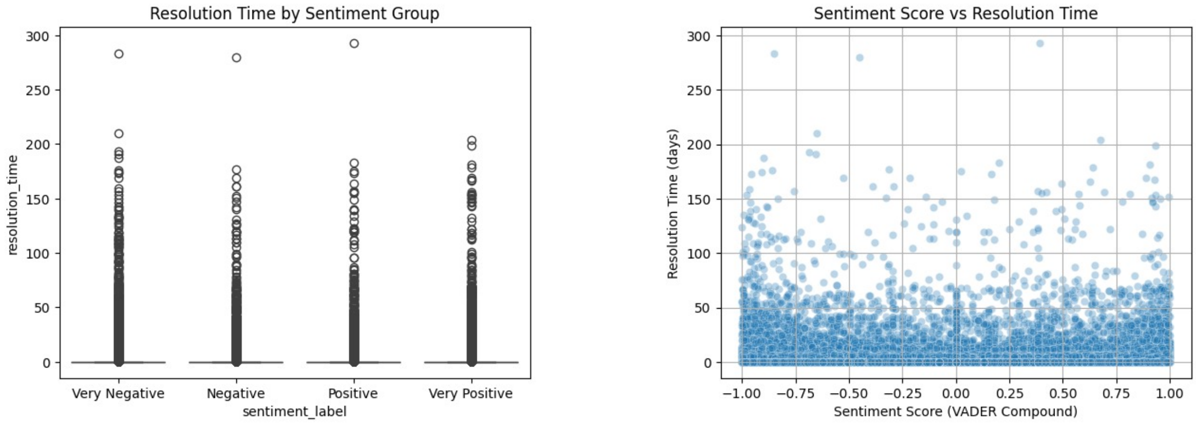
- Delays in resolution were largely tied to systemic inefficiencies in consumer grievance redressal, particularly related to mishandled credit reports and fraud disputes.
- Wells Fargo and Citibank have the highest number of delayed complaints among the leading U.S. banks, while JPMorgan Chase has the fewest.
- The Spearman correlation was found to be $\rho = -0.0427$, with $p < 0.0001$, indicating a weak but statistically significant relationship between sentiment and resolution time.
- More negative complaints tended to take slightly longer to resolve, suggesting that emotionally charged complaints may reflect deeper or more complex issues.
- Common themes in complaints highlighted the need for improved communication and follow-up processes to enhance resolution efficiency.
- The repetition of xxxx or xxxxx reflects redacted or anonymized information in the complaint text, often replacing sensitive info like: Account numbers, Personal details, Dates or amounts, This shows consumers often reference personal details that get auto-masked by the complaint system.

4.6 Analysis of Resolution Delays and Sentiment in Leading Banks

Methodology

- Each complaint's narrative was analyzed using VADER sentiment analysis to obtain a compound sentiment score (ranging from -1 [very negative] to +1 [very positive]).
- The resolution time for each complaint (in days) was calculated.
- A scatter plot was drawn with sentiment scores on the x-axis and resolution time on the y-axis to visually explore any correlation.

- Sentiment scores were grouped into four categories: Very Negative, Negative, Positive, Very Positive.
- For each group, the distribution of resolution time was visualized using a box plot, showing medians, IQRs, and outliers.



(a) Resolution Time by Sentiment Group

(b) Sentiment Score Vs Resolution Time

Figure 6: Comparison of Resolution Time and Growth Rates

Table 1: Comparison of Sentiment Label and Resolution Time

Sentiment label	Very Negative	Negative	Positive	Very Positive
Resolution time	0.279915	0.234692	0.204973	0.235003

Results

- The plot reveals a very weak negative trend — complaints with more negative sentiment may take slightly longer to resolve.
- However, resolution times are quite scattered across all sentiment levels, with a large concentration below 50 days.
- No clear linear relationship is observed by eye, aligning with the small negative correlation coefficient ($\rho \approx -0.043$).
- Median resolution time is slightly higher for "Very Negative" and "Negative" complaints than for "Positive" or "Very Positive".
- Still, all groups show similar distribution shapes, with many outliers extending beyond 150 days.
- This supports the earlier finding: while negative sentiment may be linked to longer resolution times, the effect is small and not practically impactful.
- From the table we can see complaints labeled as Very Negative have the highest average resolution time (≈ 0.280), indicating they take longer to resolve. Positive complaints are resolved the fastest ($\approx 0.205 on average$). Interestingly, Negative and Very Positive complaints have similar resolution times (≈ 0.235), suggesting that extreme positive sentiment does not necessarily lead to faster resolutions.

4.7 Impact of Regulatory Enforcement Actions on UDAAP Complaint Volumes

Results:

- **Regulation Rollbacks** (p-value = 0.0077): Statistically significant. Likely led to changes in complaint volumes.
- **Debt Collection Scrutiny** (p-value = 0.0000): Highly significant, showing a clear impact on complaints.
- **Enhanced Lending Oversight** (p-value = 0.0001): Statistically significant intervention, indicating that complaints may have reduced post-action.
- **Payday Loan Enforcement** (p-value = 0.6301): Not significant, showing no clear effect on complaints.
- **Dodd-Frank Act Amendments** (p-value = 0.3675): Not significant, suggesting little to no impact on complaint volumes.

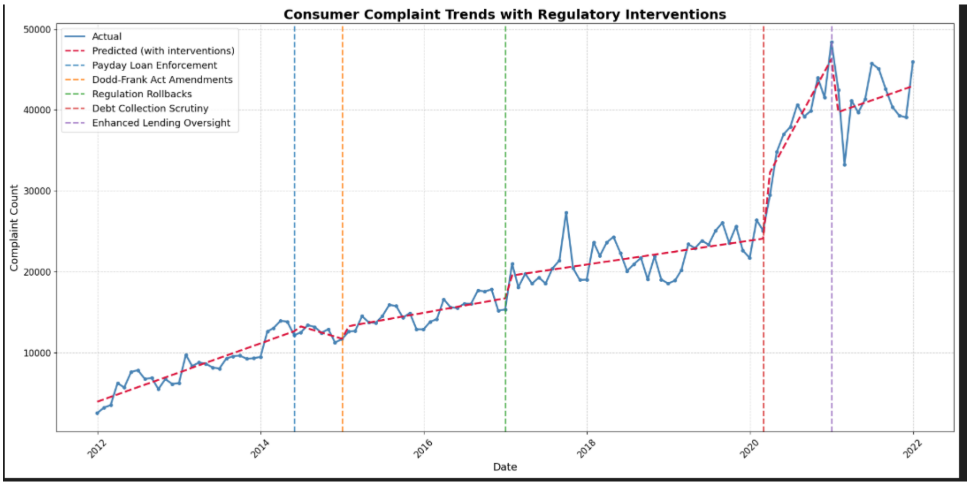


Figure 7: Consumer Complaints Trends with Regulatory Interventions

5 Conclusion

This project investigated **UDAAP complaints** against major U.S. credit card banks using consumer-reported data from the **CFPB**. The analysis revealed a **significant rise in complaints post-January 2022**, confirmed through a regression model capturing structural changes in trend and level.

Banks were evaluated using **Compound Annual Growth Rate (CAGR)** for complaints and stock prices. A new metric—**Complaint Growth / Stock Growth**—identified institutions like *Goldman Sachs Bank USA* with disproportionately high complaint volumes.

Time series forecasting using **ARIMA** and **polynomial regression** showed ARIMA to be more stable for predicting future trends. Correlation analysis revealed a **moderate negative correlation** between complaints and unemployment, and **negligible correlation** with inflation.

Text analysis uncovered frequent themes such as **fraud**, **unauthorized access**, and **credit score issues**, especially among top banks. **Resolution delays** were commonly linked to dispute complexity and poor communication.

Finally, **sentiment analysis** showed that **more negative complaints tend to have longer resolution times**, with a weak but statistically significant correlation.

Overall, the project offers a data-driven approach to identify **consumer risk**, evaluate **institutional performance**, and support **policy recommendations** for fairer financial practices.