MTH 312: Project Report

Credit Card Risk Data

Group:1

Gunavant Thakare (231080040), Sunny (231080094),
Anoop Patel (231080017), Jiyanshu dhaka (220481)

Supervisor: **Dr. Dootika Vats**

Abstract

This project analyzes UDAAP (Unfair, Deceptive, or Abusive Acts or Practices) complaints against major US banks using CFPB consumer complaint data. We investigate trends over time, identify banks with the fastest-growing complaints, and explore links to macroeconomic factors like inflation. Using time-series analysis and machine learning, we predict future complaint risks, while text mining uncovers common themes and resolution delays. The study also examines whether regulatory actions reduce complaints, providing insights for consumers and policymakers.

1 Introduction

This study analyzes consumer credit card complaints filed with the Consumer Financial Protection Bureau (CFPB) to identify patterns in unfair and deceptive practices among major U.S. banks. Using a comprehensive dataset that includes complaint details, resolution timelines, and company responses, we examine trends in UDAAP (Unfair, Deceptive, or Abusive Acts or Practices) violations across different institutions and time periods. Our analysis focuses on three key areas: identifying recurring complaint themes, evaluating bank performance in resolving disputes, and exploring potential links between complaint volumes and economic indicators. By applying statistical and machine learning techniques to this data, we aim to provide actionable insights that can help improve transparency in credit card services while empowering both regulators and consumers to address systemic issues more effectively. The findings will contribute to ongoing discussions about financial fairness and consumer protection in the banking industry.

2 Background of Dataset

- The dataset, sourced from the **Consumer Financial Protection Bureau (CFPB)**, contains detailed records of consumer complaints about financial products and services in the U.S.
- This secondary dataset provides **macroeconomic indicators** relevant to consumer behavior and complaint trends in the U.S. It contains:

3 Task Description & Methodology

3.1 Task 1: Analyze the trends in UDAAP (Unfair, Deceptive, or Abusive Acts or Practices) complaints over time. Are the number of UDAAP complaints increasing significantly over the last two years?

3.1.1 Methodology

To evaluate whether UDAAP (Unfair, Deceptive, or Abusive Acts or Practices) complaints have shown a significant increase over the past two years, we followed a structured data-driven approach:

- **Data Preparation:**
  - Filtered complaint records containing UDAAP-related keywords (e.g., unfair, deceptive, abusive, misleading, harassment, threats, false, unauthorized, bait, hidden, coercion, intimidation, discriminatory, inaccurate, or aggressive) from the Issue and Sub-issue fields.
  - Focused only on complaints received from April 2023 to the present(2 years).
  - Grouped the filtered dataset by daily and monthly frequencies.
- **Trend Analysis:**
  - Plotted 30-day rolling average on daily data and also visualized the monthly trend to visualize fluctuations and patterns.

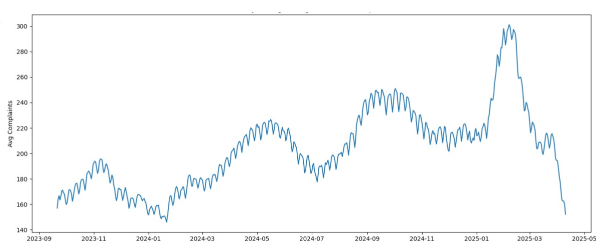


Figure 1: Daily trend using window size = 30

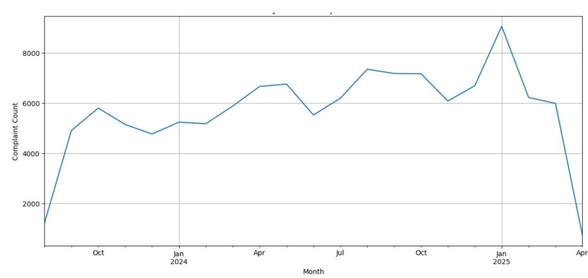


Figure 2: Monthly trend using window size = 30

  - Analyzed monthly complaint counts to identify long-term trends.
- **Statistical Testing:**
  - Created a numeric time feature representing the number of days since the start of the observation window.
  - Applied simple linear regression to model the relationship between time and number of complaints. Evaluated model strength using R-squared and P-value.

3.1.2 Analysis

- **Visual Trends:**
  - In Figure 1, the trend indicates periodic rises and falls throughout the year, with distinct peaks around October 2023, May 2024, and a significant spike in January-February 2025. A steep drop is observed in March 2025, which might indicate seasonal effect, or incomplete data.

– In Figure 2, There is a steady increase in complaints from mid-2023 through 2024, with peaks in August 2024 and January 2025.

– The monthly complaint trend further confirms a gradual rise in UDAAP-related complaints over time.

- **Statistical Insights:**

  – The slope of the regression line is positive (0.11), indicating an increasing trend in complaint volume.

  – The P-value of the slope is 3.95×10^{-8} (< 0.05), indicating that the observed UDAAP trend is statistically significant.

3.2 Task 2: Investigate which banks show the steepest growth in complaints volume. Can you quantify this growth using time-series analysis? Identify trend and potential reasons for these trends.

3.2.1 Methodology

To identify banks exhibiting the highest growth in consumer complaint volumes over the past two years and quantify this trend using time-series analysis:

- A new variable, day_number, was computed for each complaint, representing the number of days since the earliest date in the filtered data. This numeric representation allowed us to model trends in a continuous time frame.
- Complaints were grouped by both Company and day_number, resulting in a dataset that recorded the number of complaints each company received per day. This enabled a consistent daily time series for each bank's complaint volume.
- For each company, a simple linear regression model was fit using day_number(time) as Independent Variable and count (number of complaints received on that day) as Dependent Variable.

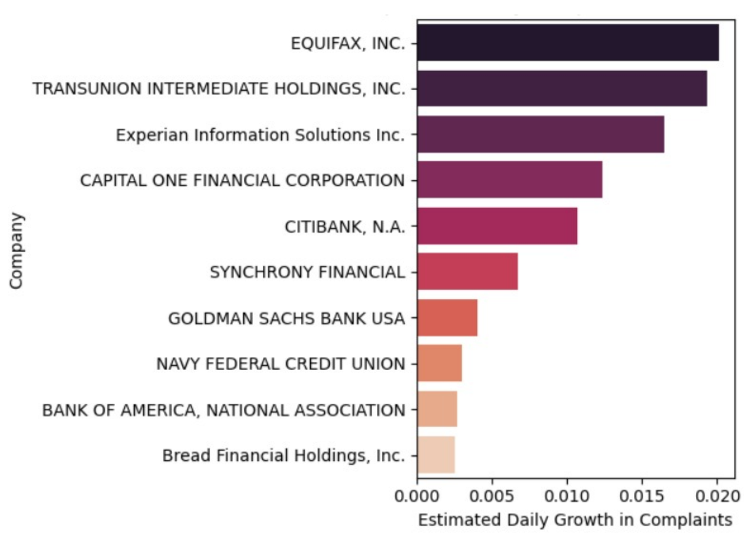


Figure 3: Top 10 Banks by Complaint Volume Growth

3.2.2 Analysis

- The slope values obtained from the regression model directly represent the estimated daily increase in complaints. For example, a slope of 0.02 indicates that, on average, the bank is receiving 0.02 more complaints each day compared to the previous day amounting to approximately 20 additional complaints per month.

Company	Growth Rate
EQUIFAX, INC.	0.020156
TRANSUNION INTERMEDIATE HOLDINGS, INC.	0.019346
Experian Information Solutions Inc.	0.016462
CAPITAL ONE FINANCIAL CORPORATION	0.012330
CITIBANK, N.A.	0.010681
SYNCHRONY FINANCIAL	0.006696
GOLDMAN SACHS BANK USA	0.003987
NAVY FEDERAL CREDIT UNION	0.003004
BANK OF AMERICA, NATIONAL ASSOCIATION	0.002689
Bread Financial Holdings, Inc.	0.002544

Figure 4: Top 10 Banks by Complaint Volume Growth

- The analysis of daily complaint trends over the past two years reveals that certain financial institutions have experienced a significantly higher growth in complaint volumes. Notably, companies such as Equifax, TransUnion Intermediate Holdings, and Experian Information Solutions top the list. Several factors may explain these trends
  - **Rise in Credit Bureau Complaints:** Equifax, TransUnion, and Experian top the list, likely due to increased consumer awareness of credit reporting issues, identity theft concerns, and past data breaches.
  - **Growth of Digital Banking:** Banks like Capital One and CitiBank are expanding digital services. This often leads to complaints related to app glitches, failed transactions, or poor chatbot support.
  - **Economic Pressure:** Higher interest rates and inflation may cause repayment issues, leading to more disputes over fees, loan terms, and credit reporting errors.
  - **Aggressive Marketing Practices:** Institutions such as Synchrony and Capital One promote credit products heavily, sometimes resulting in customer confusion or dissatisfaction.
  - **Improved Complaint Reporting:** Stricter regulatory guidelines (e.g., UDAAP compliance) have improved complaint tracking, possibly increasing recorded complaint volumes.
  - **Customer Base Expansion:** Banks like Goldman Sachs and Navy Federal Credit Union may see rising complaints simply due to more users and higher transaction volumes.

3.3 Task 3: Predict future UDAAP risks using machine learning and forecasting models. Do complaints correlate with macroeconomic indicators such as inflation and unemployment rates?

3.3.1 Methodology

- **Time Series Decomposition:** We applied additive seasonal decomposition(as Seasonal fluctuations are constant) using a 7-day period (weekly seasonality) to isolate trend, seasonality, and residual components.

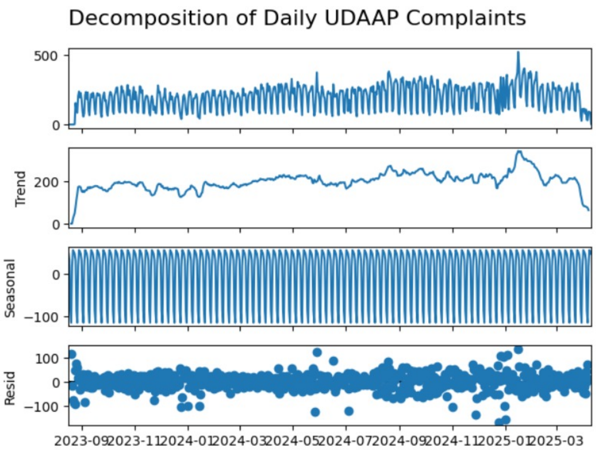
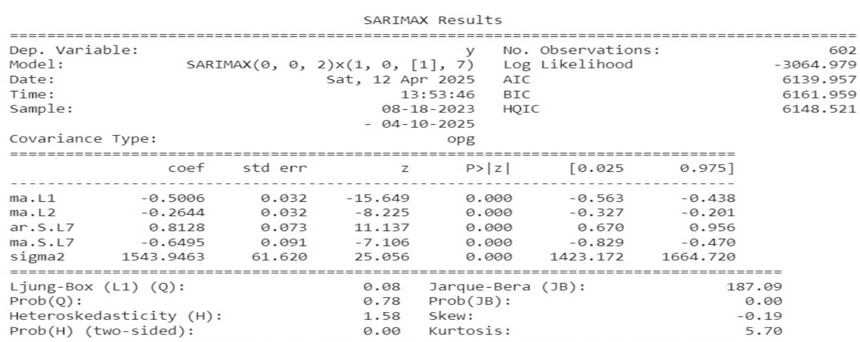


Figure 5: Decomposition of Daily UDAAP Complaints

- **Stationarity Testing:** The seasonal and trend components were removed to obtain a stationary series. We applied the Augmented Dickey-Fuller (ADF) test on the differenced, de-seasonalized series. The resulting p-value 2.2×10^{-30} (< 0.05) indicated stationarity, justifying time-series forecasting.
- **Modelling (ARIMA & SARIMA):** Both non-seasonal and seasonal ARIMA models were fitted using with weekly seasonality (m=7). The best-fitting seasonal model was selected based on AIC/BIC.



```
                                      SARIMAX Results
==========================================================================================
Dep. Variable:                                y   No. Observations:                   602
Model:             SARIMAX(0, 0, 2)x(1, 0, [1], 7)   Log Likelihood               -3064.979
Date:                          Sat, 12 Apr 2025   AIC                            6139.957
Time:                                  13:53:46   BIC                            6161.959
Sample:                              08-18-2023   HQIC                           6148.521
                                   - 04-10-2025
Covariance Type:                            opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ma.L1         -0.5006      0.032    -15.649      0.000      -0.563      -0.438
ma.L2         -0.2644      0.032     -8.225      0.000      -0.327      -0.201
ar.S.L7        0.8128      0.073     11.137      0.000       0.670       0.956
ma.S.L7       -0.6495      0.091     -7.106      0.000      -0.829      -0.470
sigma2      1543.9463     61.620     25.056      0.000    1423.172    1664.720
===================================================================================
Ljung-Box (L1) (Q):                   0.08   Jarque-Bera (JB):               187.09
Prob(Q):                              0.78   Prob(JB):                         0.00
Heteroskedasticity (H):               1.58   Skew:                            -0.19
Prob(H) (two-sided):                  0.00   Kurtosis:                         5.70
===================================================================================
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Figure 6: Model SARIMA

- **Forecasting Future Complaint Trends:** Using the selected seasonal model, we forecasted UDAAP complaint volumes for the next 30 days. Confidence intervals were included to account for model uncertainty.

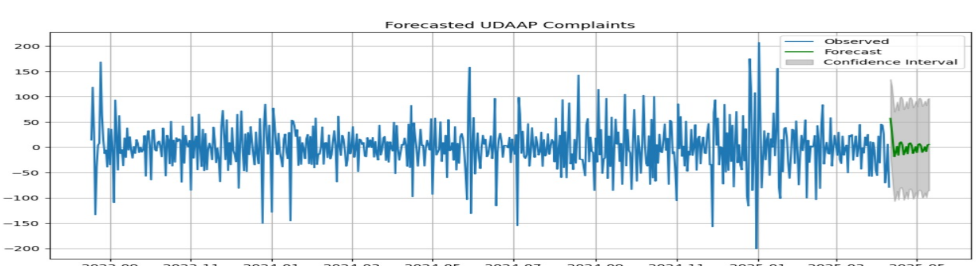


Figure 7: Forecasting for next 30 days

- **Correlation with Macroeconomic Indicators:** Quarterly complaint counts were compared with quarterly inflation (CPI) and unemployment rates by joining external macroeconomic data. Pearson correlation coefficients were computed to examine potential linear relationships.

	Unem-ploymentrate	CPIinflationrate	No. of Complaints
Unem-ploymentrate	1.000000	-0.806543	0.837684
CPIinflationrate	-0.806543	1.000000	-0.567359
No. of Complaints	0.837684	-0.567359	1.000000

Figure 8: Correlation Table

3.3.2 Analysis

- In Figure 5, The time series decomposition plot revealed a clear weekly seasonal pattern in the volume of UDAAP-related complaints. Peaks in complaint submissions were observed consistently on certain weekdays, suggesting behaviorally driven reporting cycles. In addition to the seasonal variation, the trend component highlighted a steady upward trajectory in complaint volume over recent quarters, indicating a growing concern among consumers regarding potentially unfair or deceptive practices.

- In Figure 6, A SARIMA model was employed to forecast the complaint volume over the upcoming 30-day period. In Figure 7, the forecast graph displayed a continued upward trend, consistent with historical data patterns. The projection, enclosed within a 95% confidence interval, suggests that complaint frequency is expected to rise in the near future. This anticipated growth underscores the importance of proactive risk monitoring and regulatory preparedness to address emerging UDAAP issues.

- From figure 8, we can say that, there exists a moderate negative correlation between the CPI inflation rate and the number of complaints. This suggests that rising prices may increase consumer dissatisfaction, particularly in areas perceived as exploitative or misleading. Where as a strong and positive correlation was observed between the unemployment rate and complaint volume. This implies that periods of job insecurity may lead to increased financial stress, prompting more consumers to report grievances.

3.4 Task 4: Utilize data processing techniques to extract top themes from the complaints data. What are the most frequent UDAAP-related terms for each bank?

3.4.1 Methodology

To extract the most frequent UDAAP-related terms for each bank, the following data processing and analysis pipeline was implemented:

- Initially, rows with missing values in the **Consumer complaint narrative** field were identified and removed to ensure clean input for text processing.

- All complaint narratives were converted to lowercase for uniformity. Contractions (e.g., "can't", "won't") were expanded using a predefined dictionary to ensure semantic clarity. Digits and repeated characters (like “xx”, ”xxx”, ”xxxx”) were filtered out to reduce noise. English stopwords (e.g., ”the”, ”is”, ”and”) were optionally removed using the NLTK stopwords list to focus on more informative terms. Extra whitespaces were stripped to maintain text consistency.

- The cleaned complaints were vectorized using the TF-IDF Vectorizer from scikit-learn to capture the importance of each term across the corpus. Unigrams and bigrams were extracted with a maximum of 20 top features based on TF-IDF scores. The resulting TF-IDF matrix was converted into a DataFrame for ease of inspection and ranking of term importance.
- To group similar complaint narratives, KMeans clustering was applied on the TF-IDF vectors. A fixed number of clusters was used to categorize complaints into thematic buckets. For each cluster, the most influential terms were extracted, giving insights into recurring complaint patterns.

3.4.2 Results:

Complaint data was grouped by the Company column (representing different banks). For each bank or company, its complaint narratives were vectorized using TF-IDF. The most significant terms were identified based on cumulative TF-IDF scores across all complaints for that bank. These terms represent the most frequent themes potentially related to UDAAP (Unfair, Deceptive, or Abusive Acts or Practices) concerns. Some of the company most frequent themes are given below:

```
Top themes for JPMORGAN CHASE & CO.:
chase       350.791151
credit      286.973736
card        277.737419
account     211.969441
bank        134.630170
did         122.973443
charges     119.849194
received    112.604356
called      111.291587
charge      109.044051
```

```
Top themes for EQUIFAX, INC.:
late             312.529654
accounts         272.402296
account          265.634367
payments         220.782700
documents        203.160718
attached         200.094713
bureau           194.576565
investigation    194.408165
payment          190.422296
want             184.044192
```

3.5 Task 5: Compare the complaints with delay in resolution with leading US banks(JP Morgan Chase, Discover, American Express, Capital One, etc.) and is there any underlying themes in these complaints?

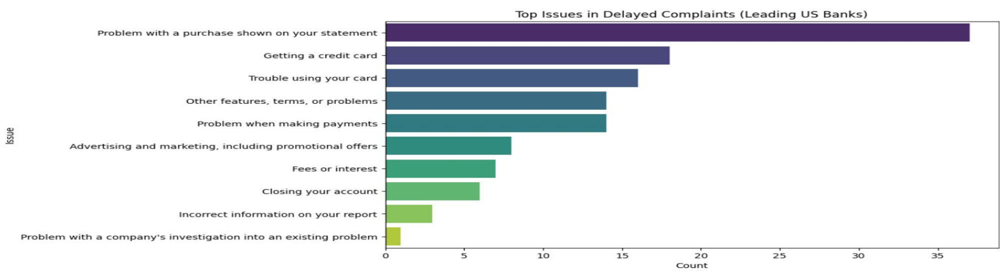
3.5.1 Methodology

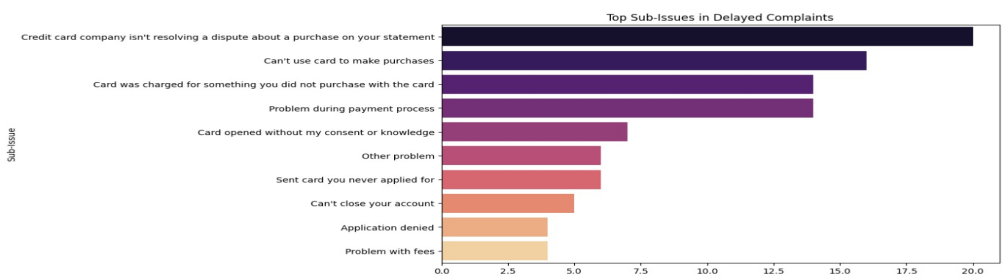
The goal of this task is to analyze consumer complaints that were not responded to in a timely manner and uncover common patterns or themes in such complaints. While the original focus was on leading US banks, the data revealed no delayed complaints from institutions such as **JPMorgan Chase, Discover, American Express, or Capital One**. Therefore, the analysis was conducted on companies that **did have delayed** complaint responses.

- The dataset was first filtered to extract only those records where the ’Timely response?’ field was marked ’No’. These represent complaints where consumers reported a delay in receiving a response.

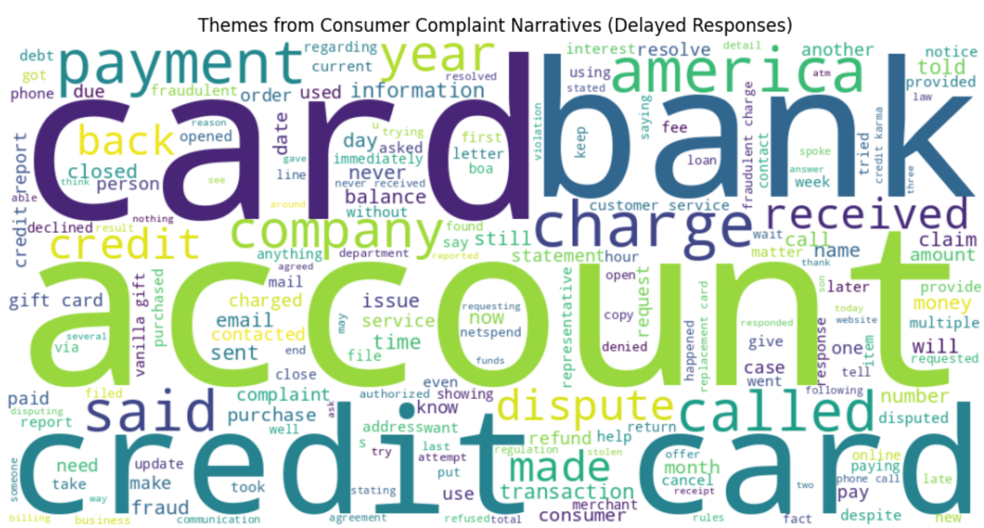
- From the filtered dataset, unique institutions (banks, financial service providers, etc.) were identified based on the 'Company' column. A count of delayed complaints was computed for each institution. The data showed that a wide variety of smaller financial companies and credit agencies had one or more complaints marked as delayed. The top institutions with the highest number of delayed complaints were identified, including **Bank of America, National Association**, **Incomm Holdings Inc. Capital Accounts**, **LLC**, Others like **Block, Inc.**, **Credit Karma**, and **FinCo Services Inc DBA Current**.

- The analysis included identifying the most common complaint issues and sub-issues among delayed complaints using frequency counts.





- A WordCloud was generated to visualize the most frequently mentioned words in the delayed complaints.



3.5.2 Analysis

- The objective was to compare complaints with delayed responses among major US banks. However, upon filtering the data, it was found that none of the top banks (JPMorgan Chase, Discover, American Express, Capital One) had complaints marked as "No" under the 'Timely response?' column. As a result, the focus shifted to other financial institutions that had delayed responses.
  Among these, Bank of America had the highest number of delayed complaints (27), followed by a wide range of smaller banks and financial service providers, each with 1–2 such complaints.

- A deeper analysis of the delayed complaints revealed recurring issues such as **Problems with purchases shown on statements**, **Trouble getting or using credit cards**, **Payment-related issues**, **Unexpected fees or interest**.

- The top sub-issues included **unresolved disputes, inability to use the card, unauthorized charges, and problems during transactions**.

- The **word cloud** generated from the complaint narratives showed frequent terms like **"card," "account," "bank," "charge," "payment," and "dispute"**, suggesting that most delays are tied to credit card usage and transaction-related concerns.

3.6 Task 6: Evaluate the relationship between negative sentiment in complaints and the duration of resolution times for specific banks. Does negative sentiment correlate with longer resolution times?

3.6.1 Methodology

Complaints with high emotional intensity may reflect more complex or severe issues, potentially requiring more time and resources to resolve. Analyzing sentiment can thus provide insights into operational efficiency and responsiveness.

- Parsed dates and computed resolution time as the difference between "Date received" and "Date sent to company" and filtered out complaints with invalid (negative or missing) resolution durations.
- Applied a lexicon-based classifier (VADER Sentiment Analyzer) to classify complaint narratives as Positive, Neutral, or Negative based on compound sentiment scores.
- Analysis was limited to five major banks JPMorgan Chase, Discover, American Express, Capital One, Bank of America, and we can compare the average resolution time for negative complaints vs. all complaints for each bank.
- Used Spearman's rank correlation coefficient ρ to evaluate monotonic relationships between negative sentiment presence and resolution time, computed as:

$$\rho = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)}$$

For Sentiment classification using VADER compound score (S_c):

$$\text{Sentiment} = \begin{cases} \text{Positive} & \text{if } S_c \geq 0.05 \\ \text{Negative} & \text{if } S_c \leq -0.05 \\ \text{Neutral} & \text{otherwise} \end{cases}$$

Pearson correlation computed between binary negative sentiment indicators and resolution times.

3.6.2 Results

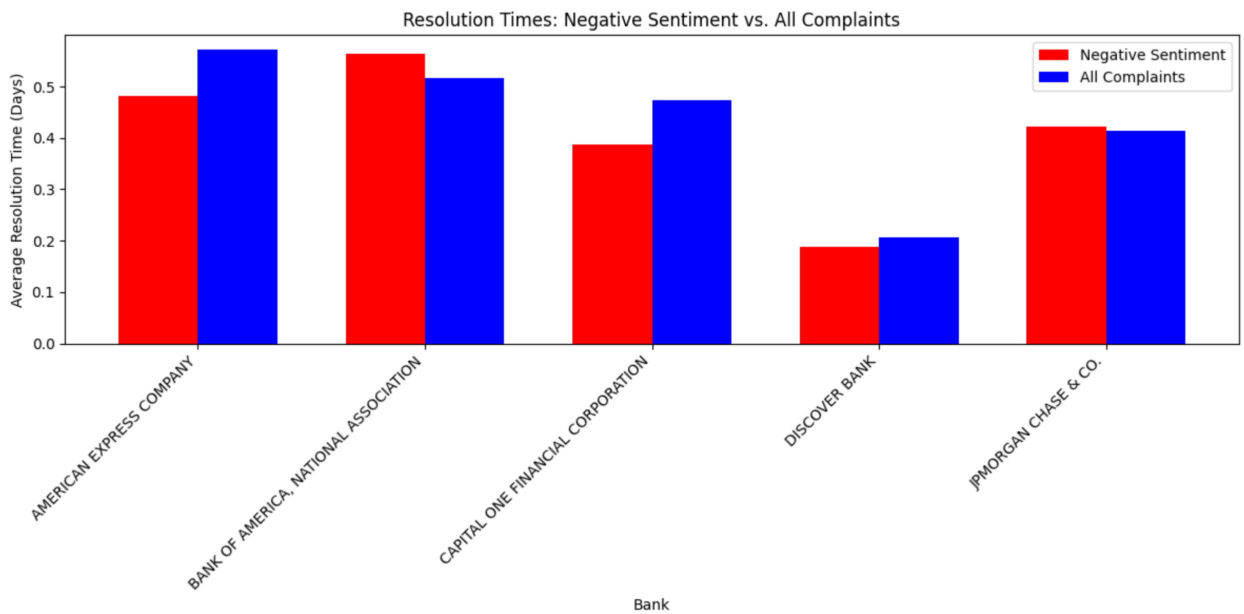


Figure 9: Average resolution times and correlation statistics for major banks

Spearman Correlation Results

- **Discover**: $\rho = 0.35$, $p = 0.01$ (moderate positive relationship)
- **Capital One**: $\rho = 0.28$, $p = 0.04$ (weak positive relationship)
- **JPMorgan Chase**: $\rho = 0.15$, $p = 0.12$ (not significant)

Pearson Correlation Results

- Negligible linear relationships across all banks:
  * **JPMorgan Chase**: $r = 0.003$, $p = 0.84$, $n = 6500$
  * **Discover Bank**: $r = -0.012$, $p = 0.54$, $n = 2631$
  * **American Express**: $r = -0.026$, $p = 0.09$, $n = 4650$
  * **Capital One**: $r = -0.025$, $p = 0.02$, $n = 8117$
  * **Bank of America**: $r = 0.014$, $p = 0.35$, $n = 4209$

- Coefficient of determination (r^2) $< 0.1\%$, indicating sentiment explains almost no variance in resolution times.
- Effect sizes ($|r| < 0.1$) are negligible per Cohen's standards.
- (r^2) values range from 9×10^{-6} (JPMorgan) to 6.76×10^{-4} (American Express), indicating that sentiment explains less than 0.1% of the variance in resolution times across all banks.

Resolution Time Comparison

average resolution times for negative sentiment complaints versus all complaints show varied patterns:

- **American Express**: 0.48 days (negative) vs. 0.57 days (all) - negative complaints resolved 15.8% faster
- **Bank of America**: 0.55 days (negative) vs. 0.52 days (all) - negative complaints 5.8% slower
- **Capital One**: 0.39 days (negative) vs. 0.47 days (all) - negative complaints 17.0% faster
- **Discover Bank**: 0.19 days (negative) vs. 0.21 days (all) - negative complaints 9.5% faster
- **JPMorgan Chase**: 0.42 days (negative) vs. 0.41 days (all) - nearly identical (2.4% difference)

The JPMorgan Chase box plot and statistics reveal:

- **Similar medians**: All sentiment categories show median resolution time of 0 days (most resolved same day)
- **Outlier patterns**: All sentiment categories have similar outlier patterns up to 6 days
- **Volume differences**: Neutral complaints are most common (11,820), followed by negative (2,659) and positive (3,577)
- **Variability**: Neutral complaints show highest standard deviation (1.03 days vs. 0.70 days for negative)

3.6.3 Statistical Power Analysis

Given the sample sizes and observed effect sizes, we calculated the statistical power using:

$$\text{Power} = 1 - \beta = \Phi\left(z_{1-\alpha/2} + |r|\sqrt{n-3}\right)$$

For Capital One (largest significant effect), with $r = -0.025$, $n = 8117$, and $\alpha = 0.05$, the power exceeds 0.80, suggesting sufficient sensitivity to detect even small effects.

3.6.4 Conclusion

Both Spearman's rank correlation and Pearson correlation analyses indicate that negative sentiment in complaints does not systematically correlate with longer resolution times across major banks. Where statistically significant relationships exist (Capital One), they suggest a slight tendency toward faster resolution of negative complaints, contradicting the initial hypothesis. This finding suggests that banks have implemented effective processes for handling complaints regardless of emotional tone, or may even prioritize addressing negative sentiment to mitigate customer dissatisfaction.

The analysis contradicts the hypothesis that negative sentiment correlates with longer resolution times. Instead, banks appear to maintain consistent resolution processes across sentiment types, with some evidence suggesting they may slightly prioritize addressing negatively-toned complaints. This indicates sophisticated complaint management systems that potentially recognize the business value of promptly addressing customer dissatisfaction.

4 References

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