Forecasting US Revolving Consumer Loans

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Abstract

United States consumer credit card debt has reached all-time highs, surpassing $1 trillion in 2023. As credit card charge-off rates reach levels unseen since 2011, some fear these figures may indicate a struggling American consumer. Given the financial sensitivity of individuals holding credit-card debt, additional economic strain may trigger widespread delinquencies and the potential for falling consumer spending. In this report, we present a forecast of the next 52 releases of the series "Consumer Loans: Credit Cards and Other Revolving Plans, All Commercial Banks" as published by the Board of Governors of the Federal Reserve System [1]. We first provide a background regarding US consumer credit card debt and its relationship to other economic variables. We then provide a summary of the data and methods used to generate our forecasts. Finally, we address potential future areas of work. We will evaluate the result of our first forecast in a separate report following the next release of this series on April 26, 2024.

Background

Consumer Credit

As of Q4 2023, US households hold a record $17.5 trillion of debt [2]. Mortgages, totaling $12.3 trillion, comprise most of this debt, followed by auto loans and student loans each at $1.6 trillion. Below these categories lie two forms of revolving credit, credit card loans at $1.1 trillion and home equity accounts at $0.4 trillion [2].

As opposed to installment loans, revolving credit plans are those in which a lender, typically a bank, allots a customer a certain amount of credit at regular intervals. At the end of each interval, or cycle, the customer must pay off their balance in full. If the customer fails to do so within a limited grace period (often around three weeks), their account begins to accumulate interest at a fixed rate known as the annualized percent rate (APR). If a customer is unable to make the minimum payment on their outstanding balance (typically around 2% for credit card accounts), they are considered delinquent. If a bank deems a given account balance to be entirely uncollectable, the bank may choose to write off the account as a loss on their balance sheet and to potentially sell the account to a collection agency. The cumulative proportion of balances deemed uncollectable is known as a bank's charge-off rate on credit card accounts.

Despite forming a small proportion of the overall household debt composition, revolving accounts serve a vital role to US consumers as highly accessible, rapid lines of credit. Credit cards often provide consumers with vital liquidity at times when they would otherwise have no spending power. However, the convenience of such forms of revolving credit often comes at the price of comparably high interest rates. In fact, credit card APRs are commonly double or triple mortgage or auto loan rates. This combination of ease of acquisition, yet the high cost of missed payments, combine to form a potentially dangerous way to accumulate debt. Given this nature of credit card loans, many question whether the current record level of US consumer credit card debt is sustainable.

Recent Consumer Credit Trends

Despite the recent recession triggered by the COVID-19 pandemic, outstanding revolving loans fell from 2020 to 2021. This was an anomaly in the context of recent economic downturns, as consumers generally take on more debt when faced with immediate financial hardship. However, the pandemic marked a period of unprecedented savings as consumer spending dramatically decreased. American consumers leveraged much of this surplus to pay off outstanding debt, such as high-interest credit card loans. By Q3 2021, both consumer delinquency rates and charge-off rates had reached decade lows, while outstanding revolving loans were at their lowest point since 2017. As written in an FDIC Quarterly publication in early 2022, “The outlook for overall consumer loan performance is strong.” [3].

However, US consumers have since demonstrated signs of declining strength. Retail spending has largely flatlined in the last several years [4]. Outstanding revolving consumer loans have reached all-time highs. Both charge-off and delinquency rates have risen to levels unseen since 2012, and now reflect levels near those at the onset of the Great Financial Crisis [5, 6]. US consumers currently face several headwinds that may contribute to these trends. Despite stable employment rates, inflation has decreased the spending power of US households. Low-income individuals may be especially susceptible to high levels of inflation given their proportionally higher expenditure on necessary goods and services. High interest rates, along with the resumption of student loan payments, have placed additional pressure on consumers.

As more consumers approach their revolving credit utilization limits, consumers may be forced to reduce spending or face uncontrollable debt. The fate of US consumer revolving credit is thus closely linked to the health of the broader economy. If consumers face continued financial stress, this may push credit card loans to increasingly higher levels.

Data and Methods

Time Series Technical Details

The time series was obtained through the Federal Reserve Bank of St. Louis's Federal Reserve Economic Data (FRED) program and was originally sourced from the Board of Governors of the Federal Reserve System (FRB) [1]. Data for the Wednesday of the prior week is released weekly on Fridays (i.e., at a 9-day delay). The first report was on June 28, 2000, and the most recent as of this forecast was April 10, 2024.

Data comes from a sample of member and nonmember domestically chartered commercial banks and U.S. branches and agencies of foreign banks. They report selected balance sheet items in weekly form [7]. Voluntary weekly reporting banks consistently represent around 90 percent of commercial bank assets in the U.S., while non-weekly reporting banks are included through quarterly Consolidated Reports of Condition and Income [7]. The data only includes revolving consumer loans from commercial banks, not from thrift institutions such as state savings banks or consumer finance companies [7].

The time series units are billions of U.S. dollars, and the series is seasonally adjusted. The seasonal adjustment is a 2-step process [8]. First, data is monthly adjusted by the Census Bureau's X-13ARIMA-SEATS Seasonal Adjustment Program that automatically detects and adjusts for outliers, such as COVID-19 and the Global Financial Crisis. Second, a weekly seasonal estimation is applied, constrained by the results of the monthly estimation, which allocates seasonal factors across the weeks of a month. This should account for seasonal patterns such as consumers paying off debt at the end of each month.

The series has 19 jumps noted by the FRB which can be attributed to external factors [9]. The jumps and their corresponding dates are categorized by the following causes.

- Conversion of a thrift institution to a commercial bank: January 5, 2022 and April 21, 2004
- Acquisition of assets and liabilities of nonbank institutions: January 5, 2022; October 14, 2020; October 16, 2019; April 4, 2018; October 18, 2017; March 13, 2013; May 2, 2012; October 1, 2008; July 4, 2007; December 29, 2004; April 21, 2004; November 5, 2003 and July 2, 2003
- Adoption of FASB's Financial Accounting Statements No. 166 (FAS 166) and No. 167 (FAS 167): March 31, 2010
- Deconsolidation of some variable interest entities (VIEs): June 21, 2006
- Divesting assets and liabilities to nonbank institutions: November 20, 2013; October 5, 2005 and February 9, 2005
- Consolidation onto their balance sheets of variable interest entities (VIEs): December 17, 2003 and July 2, 2003.

The FRB reports the amount each change shifted the series. Later, we use these external shift amounts to regularize the data, effectively controlling for the external changes which were noted in the report.

Figure 1: Revolving Consumer Loans

The most notable of these jumps is on March 31, 2013, because of a change in regulation about how different accounts are to be recorded [9]. The following is the March 31, 2013, Notes on Data entry.

> "Because of the consolidation onto their balance sheets of off-balance-sheet vehicles, owing to the adoption of FASB's Financial Accounting Statements No. 166 (FAS 166), 'Accounting for Transfers of Financial Assets,' and No. 167 (FAS 167), 'Amendments to FASB Interpretation No. 46(R),' during the first quarter, the assets and liabilities of domestically chartered commercial banks increased $372.3 billion as of the week ending March 31, 2010. The major asset items affected were the following: ... **consumer loans, credit cards and other revolving plans, $334.9 billion**." [9]

The magnitude of the jump matches the amount stated in the March 13, 2013 release notes. Essentially, a regulatory change caused banks to bring a large amount of credit card and revolving loans onto their balance sheets which had previously been securitized off-balance sheet.

Data preparation

The jumps described previously are due to exogenous factors, not the underlying consumer loans. They skew the time series data in the sense that they are outliers. They have occurred 19 times over the past 24 years, so they are relatively uncommon. Additionally, no events which would cause another jump are known to have occurred since the last release on April 10, 2024. Thus, we are interested in the behavior of the series after adjusting for these jumps.

To adjust for the jumps, we incorporate the data from the FRB which describes the effect each jump has on the series in billions of U.S. dollars. Establishing notation, let $\{J_i\}_{i=1,\dots,T}$ denote the exogenous effect of a jump noted by the FRB at time index i. All entries of $\{J_i\}_{i=1,\dots,T}$ are zero, except the 19 entries corresponding to jump dates listed in the *Time Series Technical Details* section. Let $\{C_i\}_{i=1,\dots,T}$ denote the value of the time series, Consumer Loans: Credit Cards and Other Revolving Plans, All Commercial Banks, at time index i. We could construct the jump adjusted series $\{C_i{}'\}_{i=1,\dots,T}$ by subtracting jump effects from later elements of the series (form 1) or by adding jump effects to earlier elements of the series (form 2).

$$\text{(form 1)}\ C_i' = C_i - \sum_{k=1}^{i} J_k \ \text{ or (form 2) }\ C_i' = C_i + \sum_{k=i+1}^{T} J_k$$

In this paper, we use form 2. However, this approach has an issue. The value of a dollar at time index i is different from the value of a dollar at time index k. For example, the $14.1 billion jump on April 4, 2018, shouldn't lead to a $14.1 billion increase in the June 28, 2000, element of the jump adjusted series. Inflation occurs, and jump effects should be inflation adjusted so that more recent jumps don't have inflated importance on early dates in the series. To measure inflation, we use the series, Gross domestic purchases (chain-type price index), which measures changes in prices paid for goods and services produced in the United States, including those exported to other countries [10]. This inflation metric was selected due to its use as the BEA's featured measure of inflation for the U.S. economy overall [10]. Letting G_i denote the value of the Gross domestic purchases (chain-type price index) series at time index i, we can obtain the inflation adjustment factor from time k to time i by $I_{ik} = G_i/G_k$. Multiplying by I_{ik} inflation adjusts money from time index k to equivalently valued money at time index i. Thus, we obtain our final jump adjusting formula

$$C_i' = C_i + \sum_{k=i+1}^{T} J_k * I_{ik}.$$

Applying this adjustment to the original series, we see the transformation adjusts for all major jumps seen in *Figure 1*, leaving the consumer loan values independent from exogenous factors such as banking acquisitions and reporting regulatory changes.

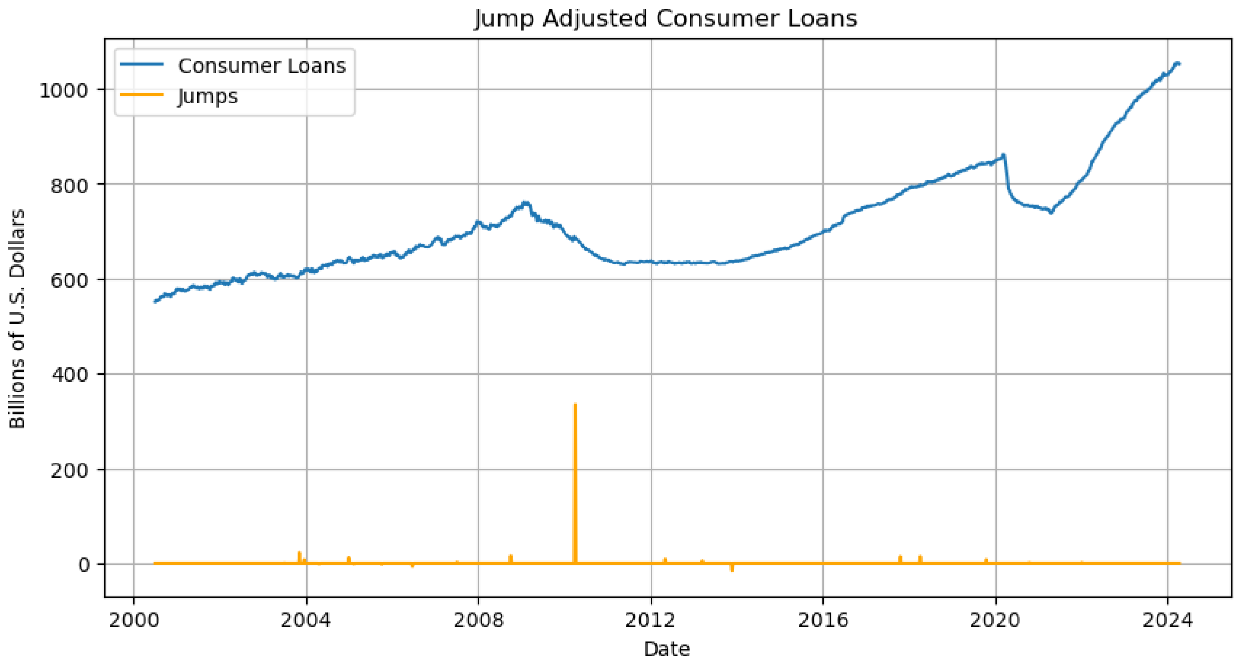

Figure 2: Revolving Consumer Loans (Adjusted)

This adjusted series is more appropriate for analysis given no notable jumps have occurred between the time of writing and April 10, 2024. Thus, the rest of the analysis will center around this series.

Exogenous Variables

We considered several additional variables to use as exogenous regressors. We began the selection process by hypothesizing possible quantities that may be leading indicators of revolving consumer debt. We outline the considered variables and respective justifications below.

Variable	**Possible Correlation**	**Justification**
Retail Sales	+/-	Retail sales may be a positive predictor of consumer revolving debt if individuals may take on additional debt to fund excess retail spending. Retail sales may, however, also be a negative predictor of credit card debt reduced spending implies increased frugality and a greater tendency to pay off outstanding debt.

Inflation	+	May be a positively correlated leading indicator if consumers taken on additional credit card debt to pay for higher costs of goods and services.
Unemployment Rate	+	May be a positively correlated leading indicator of revolving consumer debt. Unemployed individuals may take on credit card debt to make up for lost salary.
Federal Funds Rate	+	The federal funds rate is positively associated with lending rates across the US economy. If consumers face higher interest rates on other loans, they may take on additional credit card debt.
Average Credit Card APR	+	A higher average APR may cause credit card debt to accumulate more quickly.
Commercial Bank Deposits	-	If consumers have additional savings, they may be more likely to pay down existing credit card debt.

Exogenous Variable Data Analysis

We obtained data for each of the above variables from the sources indicated below.

Variable	**Series Title**	**Frequency**
Retail Sales [4]	Advance Retail Sales: Retail Trade	Monthly
Inflation [11]	Gross domestic purchases (chain-type price index)	Monthly
Unemployment [12]	Initial Claims	Weekly
Federal Funds Rate [13]	Federal Funds Effective Rate	Weekly
Average Credit Card APR [14]	Commercial Bank Interest Rate on Credit Card Plans, All Accounts	Monthly
Commercial Bank Deposits [15]	Deposits, All Commercial Banks	Weekly

We were unable to source data at weekly frequency for all variables; some are only released monthly or quarterly. We chose to drop variables without a weekly frequency as they would be unlikely to substantially improve the strength of a weekly multi-step forecast. This holds especially true given the difference between the date of a given release and the date of the value reported on that release. For example, the Census Bureau reports retail sales figures for the prior month on the 15^{th} of the current month. Choosing to use this series in a forecast would imply using values over a month old. Even if retail sales is truly a leading indicator of credit card debt, it is likely that older values would have already been factored-in to available credit-card debt figures. As such, our use of an ARIMA model would likely be sufficient to account for any substantial potential influence.

We then restricted our analysis to unemployment claims, the federal funds rate, and commercial bank deposits.

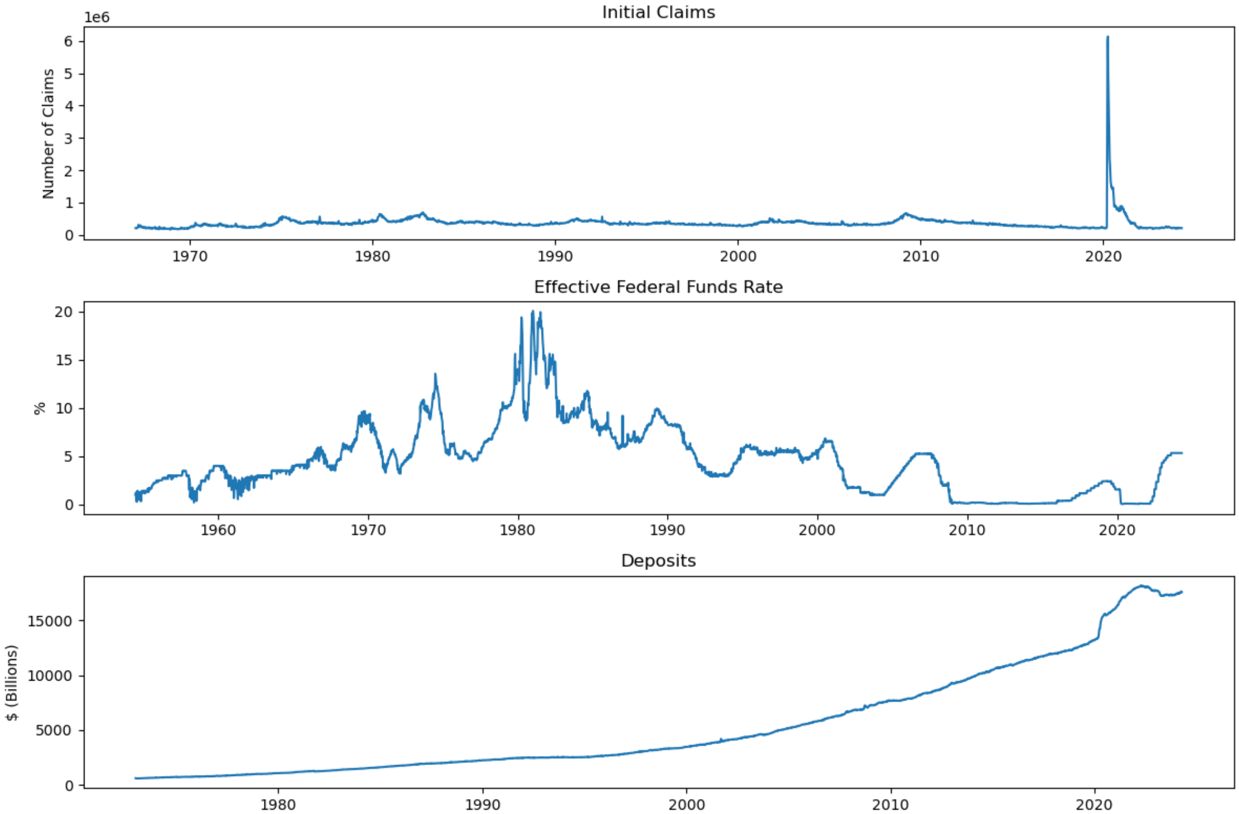

Figure 3: Exogenous Variables

We note several observations in the above graphs. The commercial bank deposits series appears to grow exponentially with time. To ensure stationarity, we chose to use the differenced logarithm of this series rather than the level as a regressor in our model. As shown in the below graph, the resulting series is approximately stationary. Further, the initial claims series has a spike during the COVID-19 pandemic. Rather than take steps to minimize the effects of these values on the model, we chose not to use the initial claims series entirely. This decision was also supported by a low p-value on the regression coefficient when we fit an ARIMA model including all three variables.

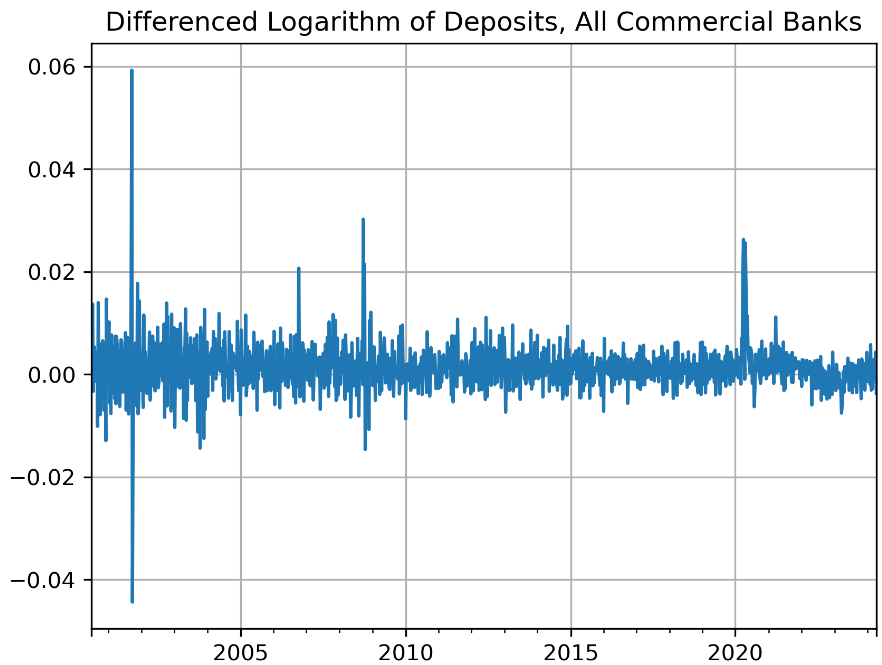

Figure 4: Differenced Log Deposits

That leaves two exogenous variables, differenced log commercial bank deposits and the federal funds rate. The commercial bank deposits data is released weekly along with the revolving consumer loans data. Incorporating it as an exogenous variable into a one-week-ahead forecast is statistically significant with a z-score of -7.1. However, for future values, we don't have strong estimates for what differenced log commercial bank deposits will be, so it is not included in forecasts beyond the first week. On the other hand, we do have good estimates for future values of the federal funds rate, since options based on the secured overnight financing rate (SOFR) are traded on the Chicago Mercantile Exchange [16]. These options define an implied probability distribution for what the Federal Open Market Committee will set as the federal funds target rate. This implied probability distribution is assumed to be reasonably efficient, since it is the consensus of a market consisting largely of sophisticated investors. Thus, we use the implied federal funds rate in our forecasts for the next 52 weeks.

Model Selection

We chose to use an ARIMAX(p, d, q) (Autoregressive Integrated Moving Average with Explanatory Variable) model to forecast revolving consumer loans. The exogenous variables are included according to the following model specification:

$$y_t = \beta_t x_t + u_t,\ \phi_p(L)\Delta^d u_t = c + \theta_q(L)\epsilon_t.$$

We did not include a seasonal component in our model as our data was already seasonally adjusted. We set the differencing parameter, d, to 1 for all models considered as the differenced consumer loans series appear to be stationary. We were not aware of a clear causal mechanism that would suggest a particular choice of p and q parameters. As such, we applied grid search over the AR (p) and MA (q) parameters for all combinations in the range $0 \leq p \leq 6$ and $0 \leq q \leq 6$. We limited the number of available observations to each model according to the maximum of their p and q parameters to allow for the direct comparison of AIC values. We fit models both with and without exogenous variables.

We conducted initial model selection using the Akaike information criterion (AIC). See **table 1** and **table 2** in the appendix for complete tables of AIC values. We then selected the model with the lowest AIC, ARIMAX(3,1,6), for further evaluation. We predicted one week ahead forecasts for the dates within our time series data and checked the autocorrelation function of the residuals.

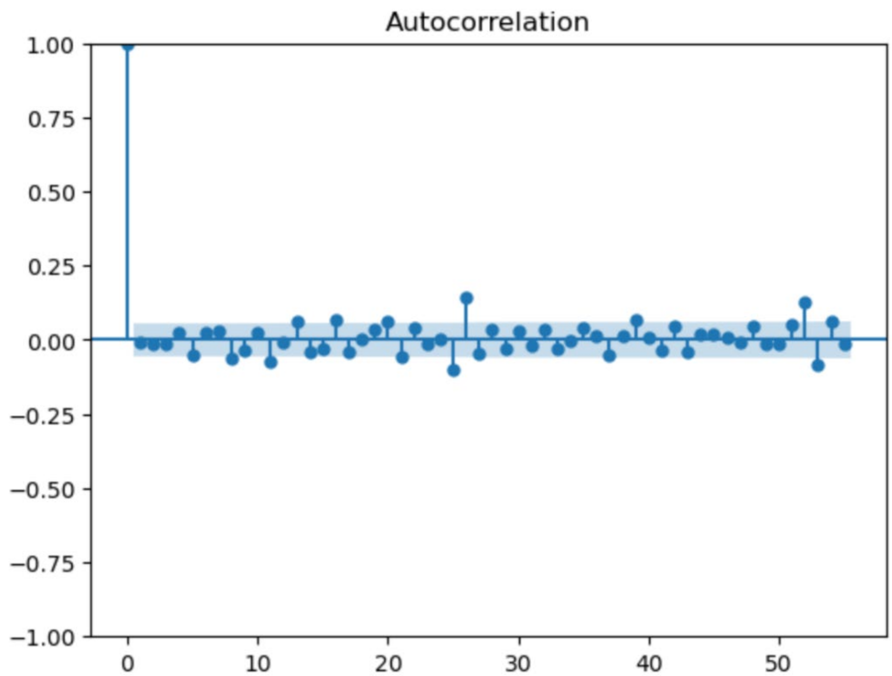

Figure 5: ACF of our Model's Residuals

The autocorrelation for the lags was small and nearly resembles what we might expect from white noise. Lags 25, 26, 52 and 53 fall outside of the confidence band which suggests there is some underlying seasonality within our data that hasn't been forecasted. However, the original series is already seasonally adjusted by the Census Bureau through the process described in the *Technical Details* section, so we did not seasonally adjust again [8]. We also checked to ensure that the variable coefficients were generally significant as determined via their p-values. See **table 3** in the appendix for the regression results of our selected model.

Results

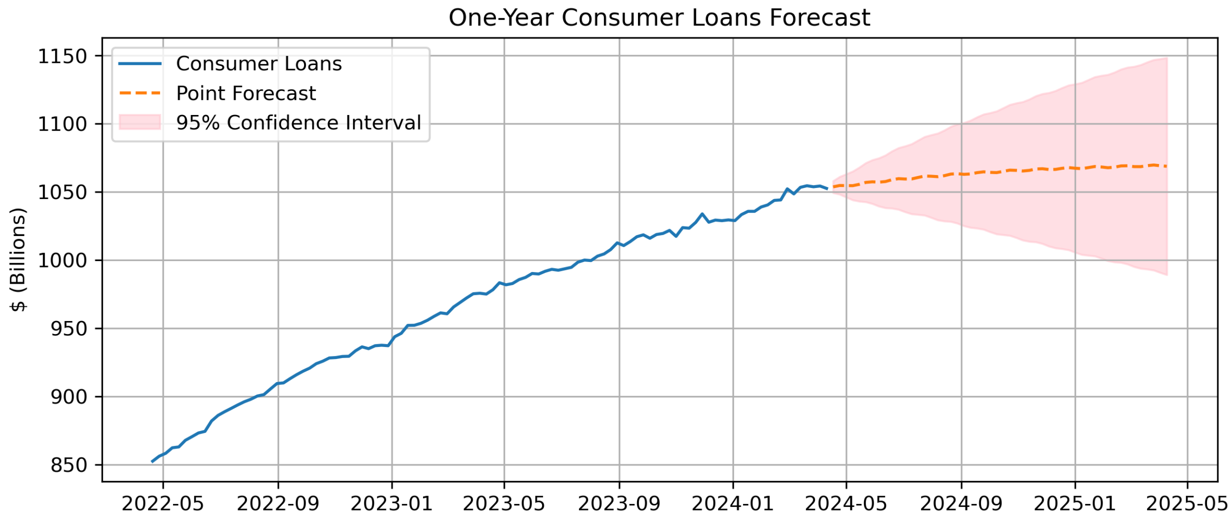

Figure 6: One Year Forecast

The forecast presented in **Figure 6** is the combination of the one week forecast using both exogenous variables and the weeks 2-52 forecasts which only use the implied federal funds rate as an exogenous variable. The results show a point forecast that slowly increases from the current value $1052 billion to around $1069 billion by April 9, 2025. This is a continuation of the current upward trend, although it is a slower increase than what we have seen over the past three years. It is important to note that the 95% confidence interval, shaded in pink, reflects a considerable range of uncertainty in the projections. This uncertainty grows as the forecast extends further into the future, implying that while the expected trend is an increase in consumer loans, actual values could vary significantly. For precise values of the point forecast and 95% confidence interval, see **Table 4** in the appendix section. The forecast for the next release to take place on April 26, 2024 is given below.

Date	**Point Forecast**	**5th Percentile Forecast**	**95th Percentile Forecast**
2024-04-17	1053.88	1049.51	1058.25

Figure 7: One-Step Forecast

Discussion

There exist several potential directions of future work to improve the accuracy of our forecasts. Foremost, it is likely that abnormal data around the COVID-19 pandemic significantly influenced our model. Each of the variables used by our forecast demonstrated jumps/historically strange behavior during this period, and it is likely that this data would no longer be directly applicable to the current economic environment. As such, it may make sense to explore ways to reduce the influence of pandemic-era data, or to ensure the model is robust to the outlying training data. Another avenue of future work could be the addition of a seasonal component to the model. Although we used seasonally adjusted variables to train our model, **Figure 5** demonstrates the potential for lingering seasonality our model failed to address. Finally, our forecasts beyond one step ahead may fail to consider the uncertainty in the exogenous regressors. The ARIMAX model needs values of the exogenous variables at each timestep to make a prediction. We trained our model using the exogenous variables at a one-step lag, meaning values were available for the one-step-ahead forecast. However, we used estimated values (the implied federal funds rate and 0 for the difference of log deposits) for the remaining forecasts. One potential way to address this discrepancy would be to generate multiple forecasts using simulated values for the exogenous variables and to use the simulations to construct point and interval forecasts.

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Appendix

Table 1: ARIMA AIC Values

MA Lags (q)

AR Lags (p)		0	1	2	3	4	5	6
	0	5893	5858	5854	5854	5772	5760	5762
	1	5852	5769	5768	5768	5762	5730	5728
	2	5848	5769	5770	5770	5764	5730	5597
	3	5832	5767	5766	5579	5582	5770	5694
	4	5744	5739	5605	5571	5581	5570	5562
	5	5735	5736	5577	5562	5563	5585	5593
	6	5734	5735	5580	5579	5556	5591	5590

Table 2: ARIMAX AIC Values

MA Lags (q)

AR Lags (p)		0	1	2	3	4	5	6
	0	5881	5844	5841	5841	5762	5746	5748
	1	5838	5758	5757	5756	5749	5719	5715
	2	5835	5757	5758	5758	5751	5719	5593
	3	5821	5754	5753	5561	5562	5553	5535
	4	5732	5725	5585	5555	5564	5552	5544
	5	5720	5719	5561	5551	5545	5568	5570
	6	5717	5718	5559	5559	5536	5574	5568

Table 3: Regression Results

Dep. Variable:	loans	**No. Observations:**	1242
Model:	ARIMA(3, 1, 6)	**Log Likelihood**	-2755.68
Date:	Thu, 25 Apr 2024	**AIC**	5535.361
Time:	17:21:21	**BIC**	5596.845
Sample:	6/28/2000 - 4/10/2024	**HQIC**	5558.483
Covariance Type:	opg		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
eff_funds_l1	1.4951	0.464	3.224	0.001	0.586	2.404
deposits_l1_log_ret	-37.0718	5.197	-7.134	0	-47.257	-26.887
ar.L1	1.2138	0.015	79.085	0	1.184	1.244
ar.L2	-1.2371	0.005	-247.044	0	-1.247	-1.227
ar.L3	0.9636	0.015	63.42	0	0.934	0.993
ma.L1	-1.1312	0.023	-49.845	0	-1.176	-1.087
ma.L2	1.3249	0.034	39.125	0	1.259	1.391
ma.L3	-0.9401	0.045	-21.106	0	-1.027	-0.853
ma.L4	0.0752	0.046	1.646	0.1	-0.014	0.165
ma.L5	-0.0271	0.033	-0.829	0.407	-0.091	0.037
ma.L6	-0.0875	0.024	-3.695	0	-0.134	-0.041
sigma2	4.9601	0.129	38.402	0	4.707	5.213

Ljung-Box (L1) (Q):	0.1	**Jarque-Bera (JB):**	1307.46
Prob(Q):	0.75	**Prob(JB):**	0
Heteroskedasticity (H):	0.96	**Skew:**	-0.56
Prob(H) (two-sided):	0.65	**Kurtosis:**	7.9

Table 4: 52 Week Forecast Results

Date	**Point Forecast**	**5th Percentile Forecast**	**95th Percentile Forecast**
2024-04-17	1053.88	1049.51	1058.25
2024-04-24	1054.75	1048.31	1061.18
2024-05-01	1054.7	1046.2	1063.2
2024-05-08	1054.65	1044.15	1065.15
2024-05-15	1055.63	1043.21	1068.05
2024-05-22	1057.04	1042.77	1071.32
2024-05-29	1057.49	1041.49	1073.49
2024-06-05	1057.24	1039.62	1074.86
2024-06-12	1057.68	1038.44	1076.92
2024-06-19	1059.03	1038.14	1079.93

2024-06-26	1059.81	1037.3	1082.32
2024-07-03	1059.57	1035.52	1083.62
2024-07-10	1059.6	1034.03	1085.18
2024-07-17	1060.7	1033.56	1087.85
2024-07-24	1061.76	1033.05	1090.47
2024-07-31	1061.59	1031.37	1091.81
2024-08-07	1061.29	1029.59	1092.98
2024-08-14	1062.0	1028.79	1095.2
2024-08-21	1063.18	1028.45	1097.91
2024-08-28	1063.46	1027.23	1099.68
2024-09-04	1063.01	1025.34	1100.67
2024-09-11	1063.26	1024.14	1102.39
2024-09-18	1064.22	1023.61	1104.83
2024-09-25	1064.84	1022.76	1106.93
2024-10-02	1064.45	1020.94	1107.95
2024-10-09	1064.28	1019.36	1109.2
2024-10-16	1065.18	1018.81	1111.54
2024-10-23	1066.08	1018.27	1113.9
2024-10-30	1065.92	1016.71	1115.13
2024-11-06	1065.46	1014.87	1116.05
2024-11-13	1065.91	1013.92	1117.9
2024-11-20	1066.95	1013.55	1120.35
2024-11-27	1067.13	1012.35	1121.91
2024-12-04	1066.56	1010.43	1122.69
2024-12-11	1066.65	1009.17	1124.13
2024-12-18	1067.44	1008.59	1126.29
2024-12-25	1067.98	1007.76	1128.19
2025-01-01	1067.5	1005.96	1129.03
2025-01-08	1067.2	1004.35	1130.04
2025-01-15	1067.95	1003.77	1132.12
2025-01-22	1068.76	1003.26	1134.27
2025-01-29	1068.44	1001.63	1135.24
2025-02-05	1067.87	999.8	1135.95
2025-02-12	1068.26	998.9	1137.62
2025-02-19	1069.2	998.55	1139.86
2025-02-26	1069.33	997.4	1141.27
2025-03-05	1068.69	995.52	1141.87
2025-03-12	1068.66	994.25	1143.08
2025-03-19	1069.39	993.71	1145.06
2025-03-26	1069.88	992.96	1146.8
2025-04-02	1069.35	991.22	1147.49
2025-04-09	1068.96	989.62	1148.3

Table 5: Implied Federal Funds Rates [17]

Date	Implied FFER (%)

2024-04-17	5.33
2024-04-24	5.33
2024-05-01	5.32
2024-05-08	5.32
2024-05-15	5.32
2024-05-22	5.32
2024-05-29	5.32
2024-06-05	5.32
2024-06-12	5.286
2024-06-19	5.286
2024-06-26	5.286
2024-07-03	5.286
2024-07-10	5.286
2024-07-17	5.286
2024-07-24	5.286
2024-07-31	5.204
2024-08-07	5.204
2024-08-14	5.204
2024-08-21	5.204
2024-08-28	5.204
2024-09-04	5.204
2024-09-11	5.204
2024-09-18	5.086
2024-09-25	5.086
2024-10-02	5.086
2024-10-09	5.086
2024-10-16	5.086
2024-10-23	5.086
2024-10-30	5.086
2024-11-06	5.086
2024-11-13	5.039
2024-11-20	5.039
2024-11-27	5.039
2024-12-04	5.039
2024-12-11	5.039
2024-12-18	4.91
2024-12-25	4.91
2025-01-01	4.91
2025-01-08	4.91
2025-01-15	4.91
2025-01-22	4.91
2025-01-29	4.842
2025-02-05	4.842
2025-02-12	4.842
2025-02-19	4.842
2025-02-26	4.842

2025-03-05	4.842
2025-03-12	4.842
2025-03-19	4.735
2025-03-26	4.735
2025-04-02	4.735
2025-04-09	4.735