Econ 573: Project I

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1. Introduction

Visa Inc. is an American payment card services company based in San Francisco, California. It's one of the most well-known brands in the space, facilitating electronic transactions through credit, debit, and prepaid cards. Given the global shift toward digital payments, Visa fits firmly into the fintech category—an industry that continues to grow as cash use declines. From an investment standpoint, it's an attractive company, which is why I hold it in my own portfolio.

For this project, I'm modeling Visa's daily stock returns using different ARMA models to forecast future values. I'll be estimating the models using the BFGS algorithm in EViews. By applying these models to a stock I already own, my goal is to better understand the return dynamics and potential risks tied to the investment.

2. Methodology

I am using the MarketWatch site to download daily quotes for the stock. For this exercise, the in-sample period will cover January 3 through December 10, 2024. The out-of-sample period will run from December 11 through the end of the year.

While the dataset includes multiple metrics, I'll focus solely on the closing price to calculate return on investment. Daily returns (as percentages) are calculated using the following formula:

$$yt = 100 \cdot (\ln(P_t) - \ln(P_{t-1}))$$

Where:

- y_t represents the percentage return of the stock at time t,
- P_t is the stock's closing price at time t,
- P_{t-1} is the stock's closing price at the previous time period $(t-1)$,
- $\ln$ is the natural logarithm.

Using the in-sample data, I will model returns using ARIMA models with values of ***p*** = 0, 1, 2, 3 and ***q*** = 0, 1, 2, 3. The Schwarz Information Criterion (SIC) will be used as the benchmark for selecting the best-fitting model. The optimal orders will be denoted as ***p**** and ***q****, respectively.

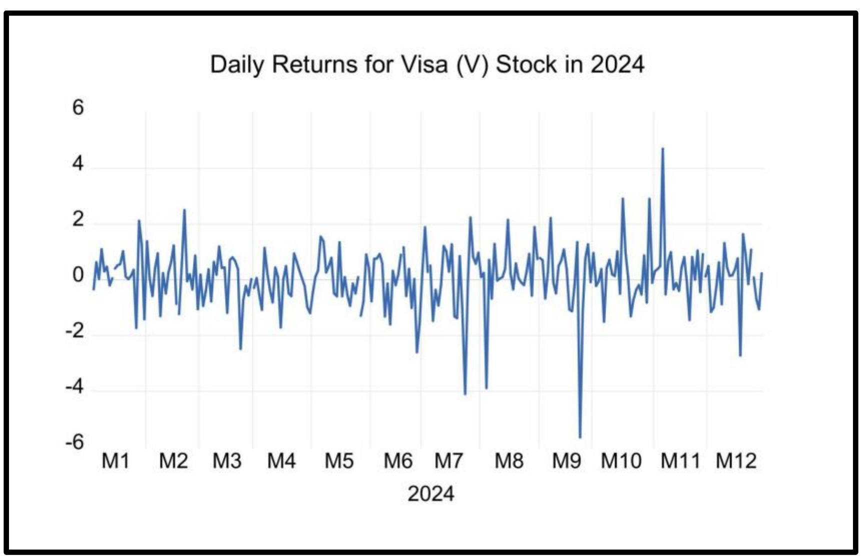
Out-of-sample forecasts will be performed using two approaches: a fixed scheme and a rolling sampling scheme. The objective is to capture the dynamics of daily returns under both setups and evaluate forecast accuracy by comparing their mean squared error (MSE).

3. Descriptive Statistics

Before diving into the estimation process, it's useful to take a quick look back at 2024 as a whole. Based on my prior research, Visa's stock closed the year at $311.01, marking a 20% increase from its 2023 year-end price.

When plotting daily returns as a time series, it's clear that most returns fall within a range of -2% to +2%. That said, there are a few notable outliers. The largest single-day gain is around 4%, while the steepest loss is closer to -6%.

Figure 1. 2024 Daily Returns Plotted

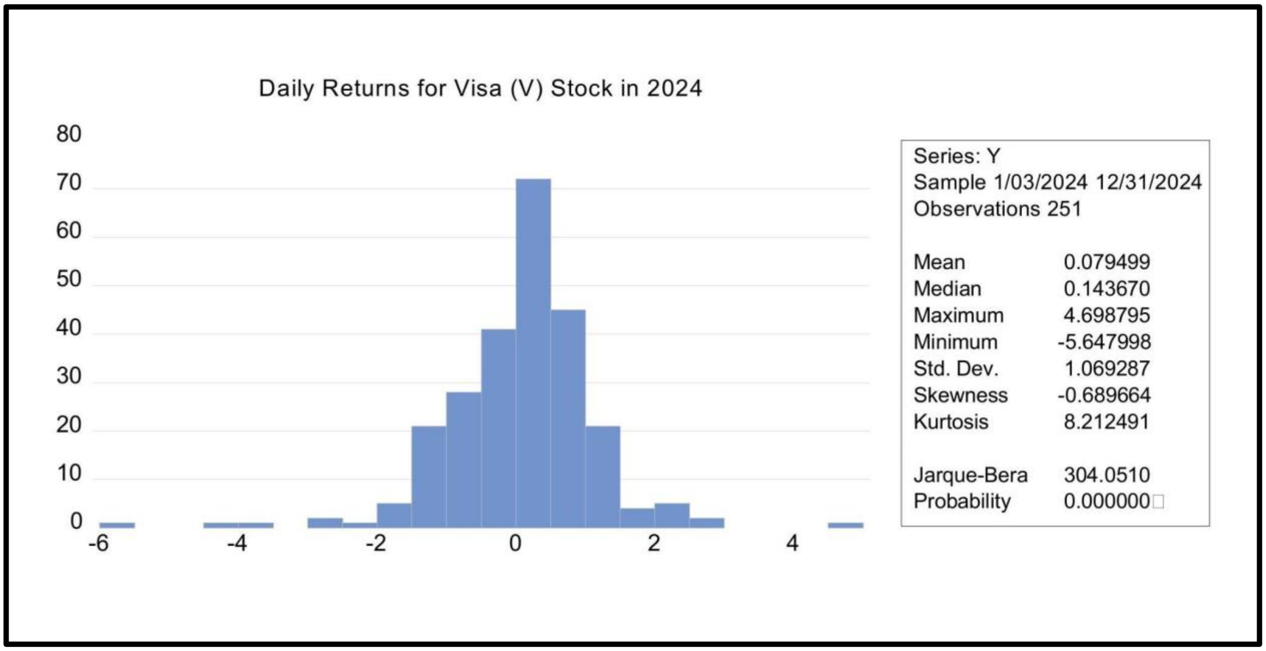


When looking at the histogram, we can see that about 110 instances of daily returns fall between 0% and +1%. The mean daily return for Visa (V) is 0.08%, which suggests the stock tends to grow exponentially rather than in large waves. These are characteristics of growth stocks and many consider Visa to be in this category as its revenue and earnings are expected to grow steadily.

Skewness is measured at approximately -0.69, indicating a slight lean toward more extreme negative returns compared to positive ones.

Some of the more meaningful descriptive statistics include kurtosis, which is greater than 3. This suggests that the distribution of daily returns is not normal. This is further supported by the Jarque-Bera test, which rejects the null hypothesis of normality.

Figure 2. Visualizing Daily Returns Spread through Histogram



4. Estimating an Optimal Model

Using the sample data from January 3rd to December 10th, 2024, I estimated ARMA models in EViews, with the values for both ***p*** and ***q*** set at 0, 1, 2, and 3. The optimal model orders are indicated with an asterisk (*). Below are the results:

	AR(0) *	AR(1)	AR(2)	AR(3)
MA(0) *	3.00	3.04	3.06	3.08
MA(1)	3.04	3.06	3.08	3.10
MA(2)	3.06	3.08	3.09	3.12
MA(3)	3.08	3.10	3.11	3.13

Based on the SIC criteria, the optimal model is an ARMA(0,0). This suggests that the variable we're trying to forecast—one step forward—does not depend on past values or error terms. Essentially, this means that daily stock returns are behaving like white noise: a sequence of uncorrelated values with a constant mean and variance. Very simply, each value is a random shock, with no correlation over time.

5. Diagnostic Tests

After selecting the optimal model, I performed diagnostic tests to evaluate the model and its assumptions. Using the ACF/PACF, I confirmed that the residuals of the ARMA(0,0) model are not autocorrelated at any lag. Additionally, when the residuals are squared and plotted against time, they show no apparent memory, although there are significant spikes from July through November.

However, the residuals do not follow a normal distribution, as indicated by the Jarque-Bera test. This is concerning, as it suggests that the model may be overlooking important information or dynamics in the data, potentially leading to model misspecification.

Figure 3. ACF & PACF Correlogram

Date: 04/08/25 Time: 18:20
Sample: 1/03/2024 12/10/2024
Included observations: 237

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.017	0.017	0.0681	0.794
		2	-0.048	-0.049	0.6328	0.729
		3	-0.036	-0.034	0.9468	0.814
		4	0.001	-0.000	0.9471	0.918
		5	-0.089	-0.092	2.8647	0.721
		6	-0.087	-0.086	4.7064	0.582
		7	-0.070	-0.079	5.9214	0.549
		8	0.051	0.037	6.5672	0.584
		9	0.072	0.058	7.8573	0.549
		10	0.092	0.084	9.9607	0.444
		11	-0.047	-0.055	10.523	0.484
		12	0.001	-0.006	10.523	0.570
		13	0.075	0.074	11.934	0.533
		14	-0.018	-0.008	12.013	0.605
		15	-0.070	-0.031	13.270	0.581
		16	-0.093	-0.080	15.475	0.490
		17	0.050	0.045	16.124	0.515
		18	0.106	0.094	19.017	0.391
		19	-0.010	-0.009	19.044	0.454
		20	-0.029	-0.023	19.260	0.505
		21	0.027	0.009	19.457	0.556
		22	-0.009	-0.033	19.480	0.616
		23	0.002	0.011	19.481	0.673
		24	-0.072	-0.034	20.873	0.646
		25	0.031	0.051	21.122	0.686
		26	0.019	0.004	21.216	0.731
		27	-0.043	-0.076	21.723	0.751
		28	0.058	0.064	22.631	0.751
		29	-0.057	-0.053	23.527	0.752
		30	0.055	0.054	24.350	0.756
		31	-0.034	-0.065	24.663	0.783
		32	-0.036	-0.031	25.024	0.805
		33	-0.096	-0.078	27.587	0.733
		34	-0.060	-0.063	28.587	0.730
		35	0.057	0.047	29.503	0.730
		36	-0.055	-0.093	30.357	0.734

Figure 4. Error Term Squared Graphed

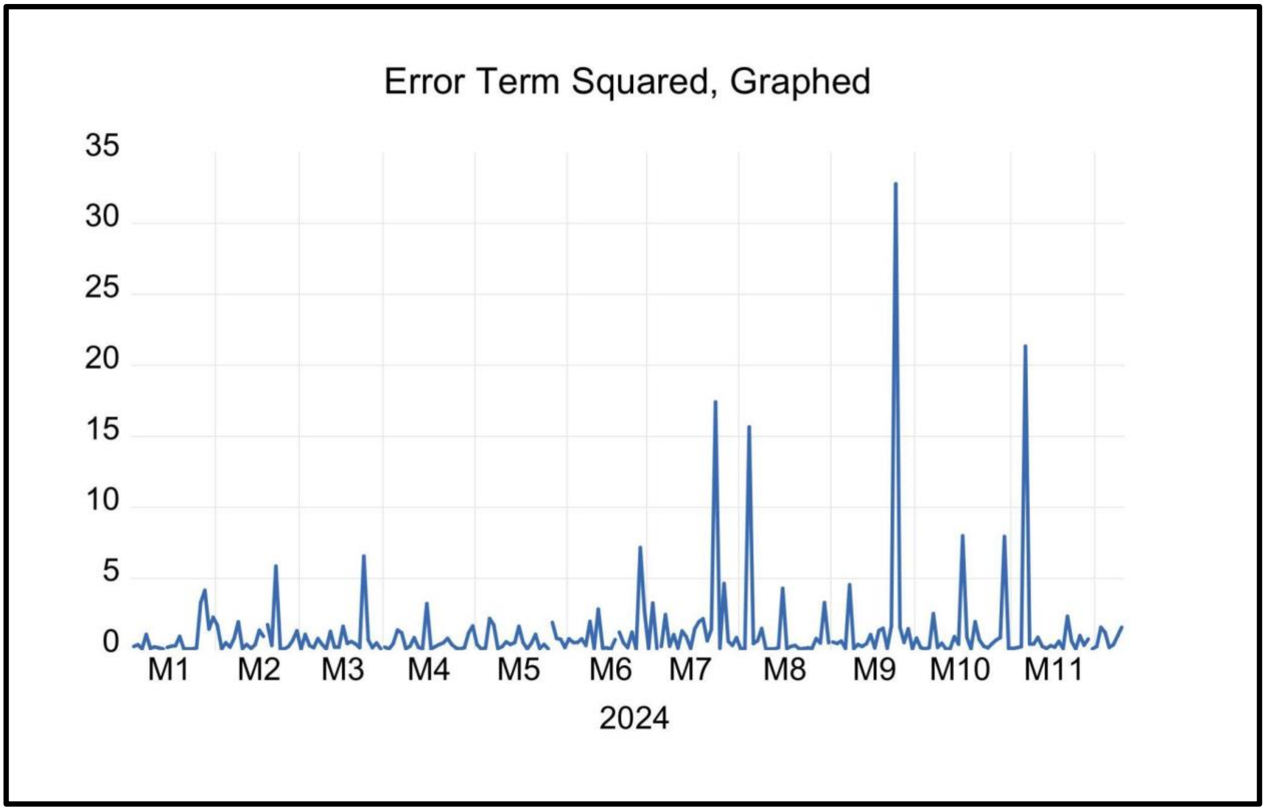
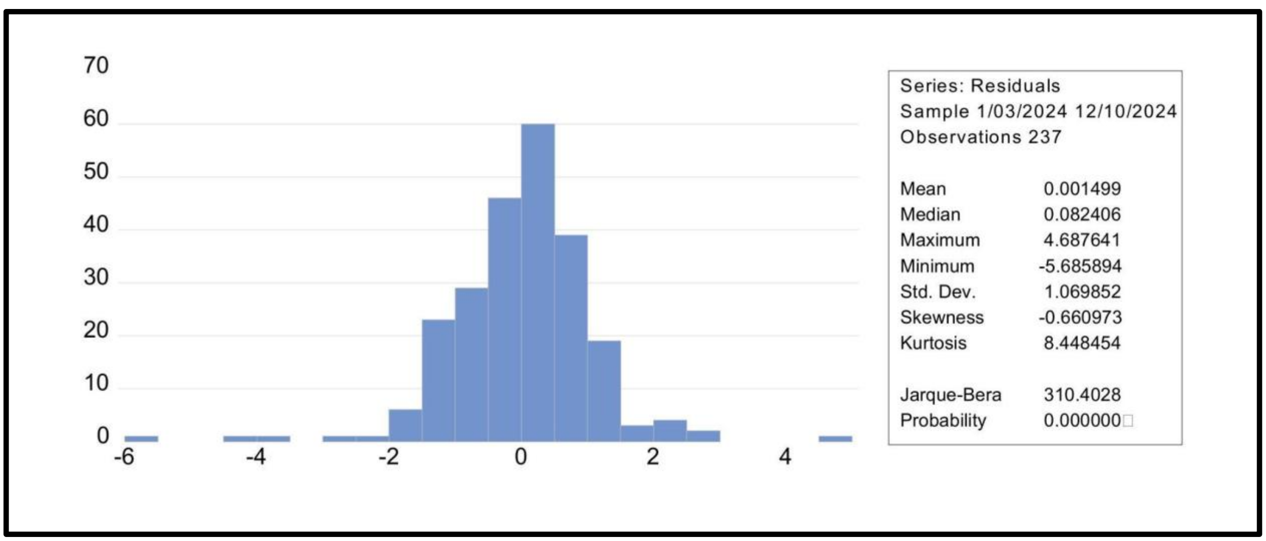


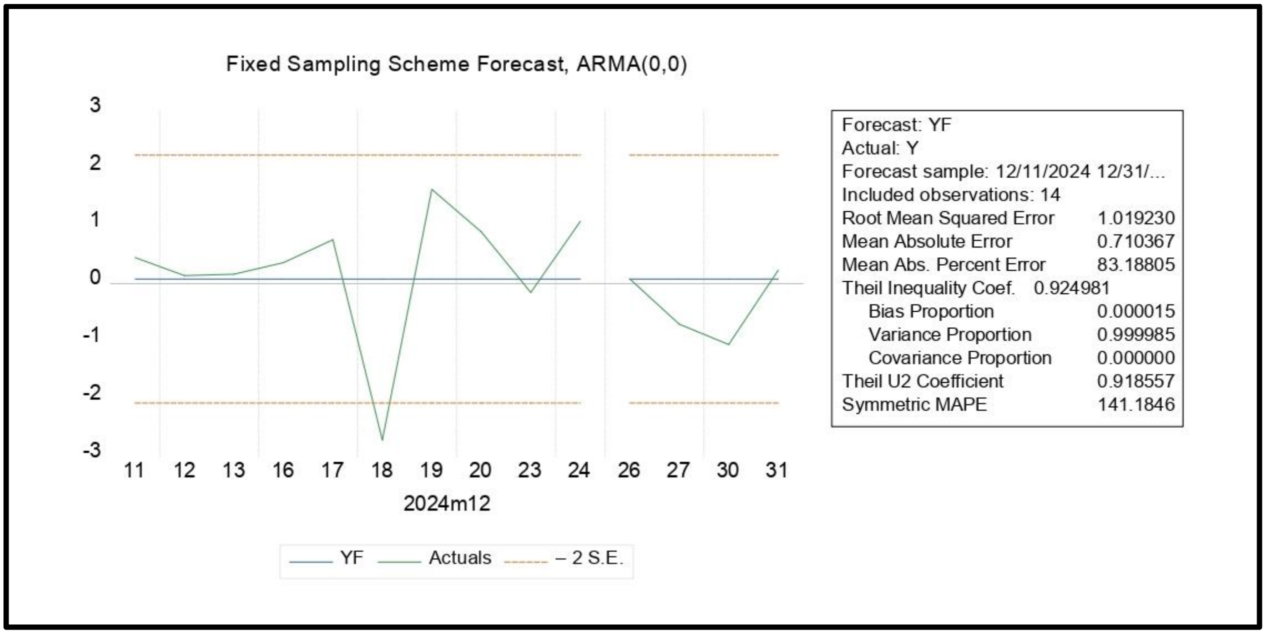
Figure 5. Residual Histogram



6. Out of Sample Forecasting Results

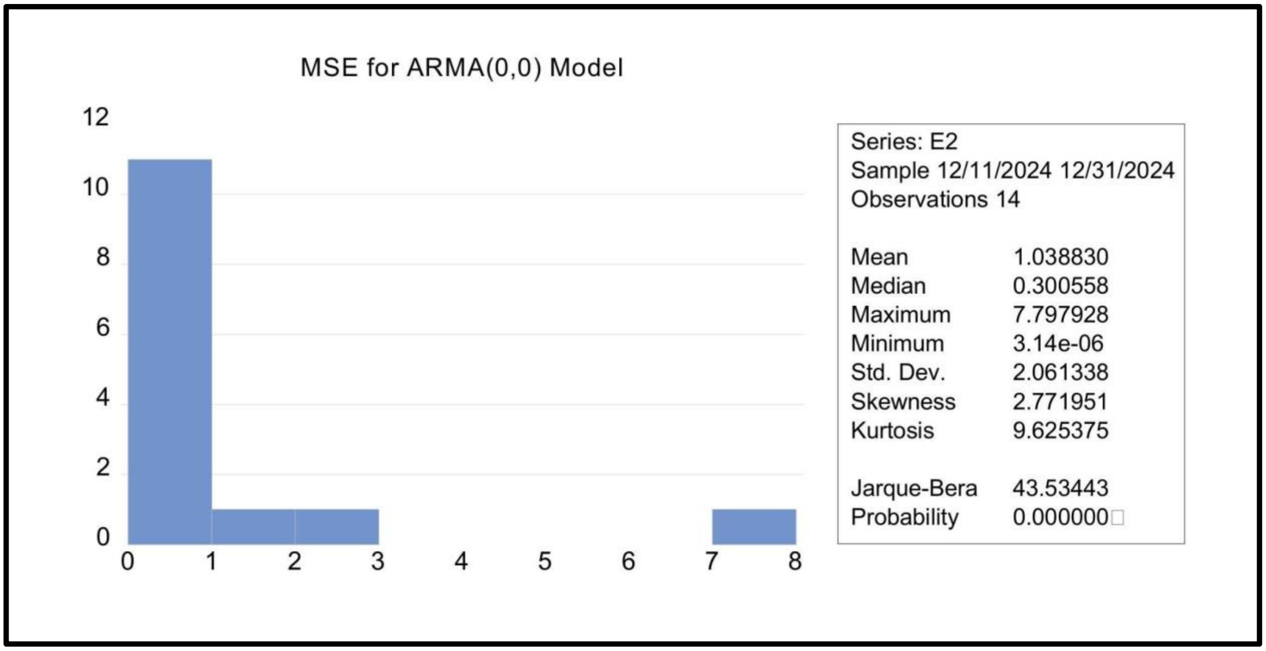
Using the optimal model, I conducted a forecasting exercise for the out-of-sample period from December 11 to December 31, 2024, using a fixed sampling scheme. The predictions from this model show very limited responsiveness, with virtually no variation in the forecasted values. This is expected, as we are using an ARMA(0,0) model, which assumes that daily returns are white noise and not influenced by past values or error terms.

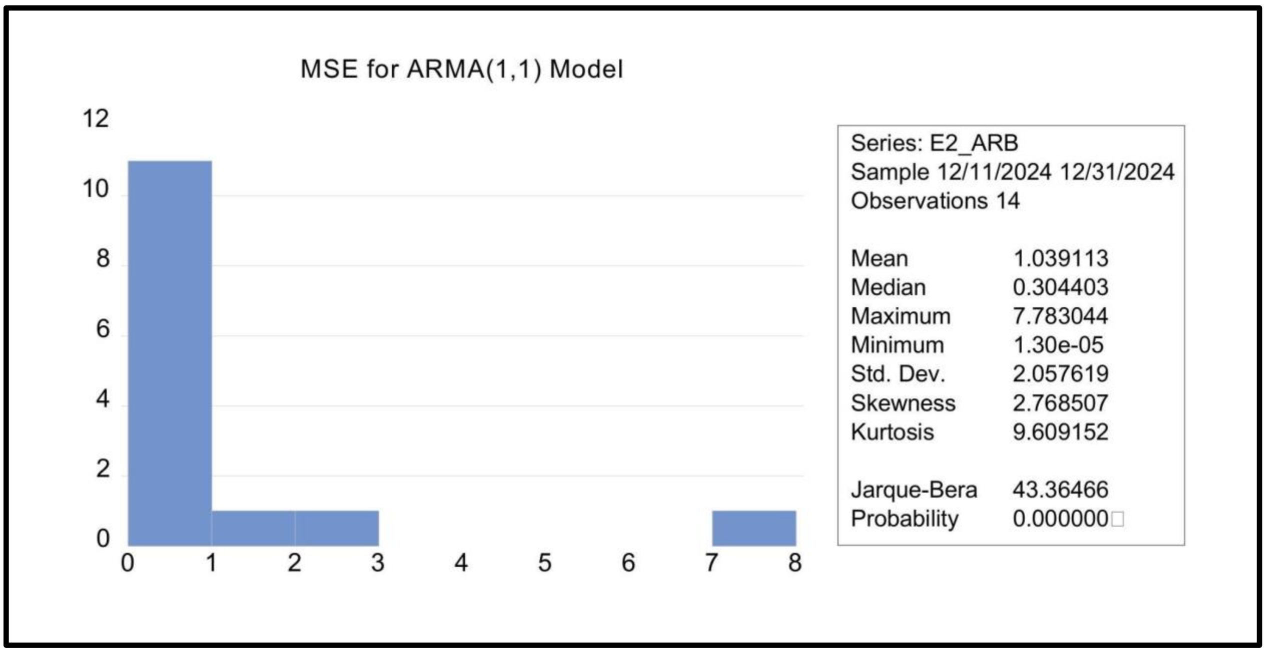
Figure 6. Fixed Sampling Forecast



As seen, the prediction is essentially flat, which differs significantly from the actual observed values. The Mean Squared Error (MSE) for this forecast was calculated to be 1.038830. To assess the accuracy of this model, I ran the same forecast exercise using an ARMA(1,1) model as an arbitrary comparison. It's important to note that this model was not optimal based on SIC, with an MSE of about 3.06, placing it in the mid-range compared to all the models tested. This suggests that better-fitting models exist, according to SIC.

Figures 6 & 7. MSE Results for ARMA(0,0) and ARMA(1,1)





Based on the MSE, the optimal model is technically more accurate, though the difference is minimal. A simple rounding to the third decimal would make both models appear equally accurate, as the MSE for the ARMA(1,1) model was calculated at 1.039113. The key takeaway here is that while SIC helps select the most efficient model using in-sample data, it isn't always the best indicator for out-of-sample forecasting accuracy.

7. Rolling Sampling Scheme

To further evaluate the optimal model, I will repeat the exercise using a rolling sampling scheme. Starting with the same initial sample period — January 3rd through December 10th — I will continue training the model using a rolling window, advancing forward until December 30th, 2024. Forecasts will be made one step ahead and recorded separately in an Excel spreadsheet. At the conclusion of the exercise, I will calculate the MSE in the same manner as above. My expectation is that this approach will yield more accurate results than the fixed sampling scheme. My results are as follows, noting ***y*** denotes actual values and ***yf*** denotes forecasts:

Figure 8. Rolling Sample Scheme Results

Date	y	yf	residual squared
12/11/2025	0.450358	0.07928	0.137698882
12/12/2025	0.140123	0.080839	0.003514593
12/13/2025	0.16217	0.081088	0.006574291
12/16/2025	0.364715	0.081425	0.080253224
12/17/2025	0.760028	0.082601	0.45890734
12/18/2025	-2.713197	0.0854	7.832145168
12/19/2025	1.632925	0.073883	2.430611958
12/20/2025	0.89474	0.080273	0.663356494
12/23/2025	-0.154348	0.083597	0.056617823
12/24/2025	1.075465	0.08263	0.985721337
12/26/2025	0.081052	0.086649	3.13264E-05
12/27/2025	-0.703601	0.086627	0.624460292
12/30/2025	-1.056842	0.083453	1.300272687
12/31/2025	0.231251	0.078892	0.023213265

MSE: 1.043098477

Based on the results of the rolling sampling process, the MSE was actually higher than that of the fixed sample. This outcome is somewhat surprising, as my understanding is that rolling processes generally have the potential to be more accurate, given that they continuously incorporate new data into the estimation window. In contrast, fixed sampling uses a stationary in-sample period and doesn’t adapt to new information.

This result may suggest that, in this case, the model is not sensitive enough to benefit from the newly added data, or that the white noise nature of the returns limits the value of re-estimating the model each time. Since the ARMA(0,0) model assumes no dependence on past values, frequently updating the estimation window likely has little to no impact on forecast accuracy.

8. Conclusion

For this assessment, I used ARMA models to estimate and forecast daily returns for Visa Inc. The exercise provided a practical look at how these time series models perform when applied to real financial data. While ARMA models are widely used in econometrics, this exercise reinforced their limitations—particularly when it comes to modeling stock returns, which are known to be notoriously difficult to predict.

The residuals from the optimal ARMA(0,0) model did not follow a normal distribution, as confirmed by the Jarque-Bera test, and showed signs of excess kurtosis. This raises concerns about the underlying assumptions of the model. More importantly, the fact that the best-fitting model implies returns are simply white noise suggests that there is little to no dependence on past values or error terms. The near-flat forecasts and minimal differences in MSE across models support this idea, indicating that past returns offer very limited insight into future performance in this case.

Additionally, incorporating a rolling sampling scheme—despite its potential advantages in adaptive modeling—did not improve forecast accuracy. This outcome further supports the notion that, for this dataset and modeling approach, daily returns lack predictable structure.