

A close-up, high-angle photograph of a computer keyboard. The keys are a light gray or silver color, and the image shows the perspective of looking down at the keys, with some keys in the foreground being more prominent than others in the background. The lighting creates soft shadows between the keys, emphasizing their three-dimensional shape.

Forecasting the Price of Silver

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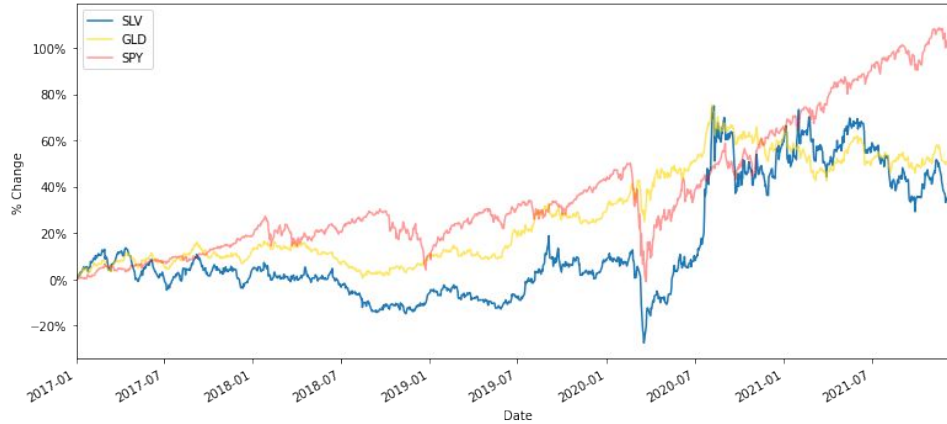
Investment Outlook



- Silver has long played a significant role in society
 - Currency
 - Precious Metal
 - Industrial Component
- Silver has also been considered a safe haven in periods of economic uncertainty
- With the emergence of cryptocurrency, does silver remain a solid investment?
- Stakeholders include private and professional investors, speculators



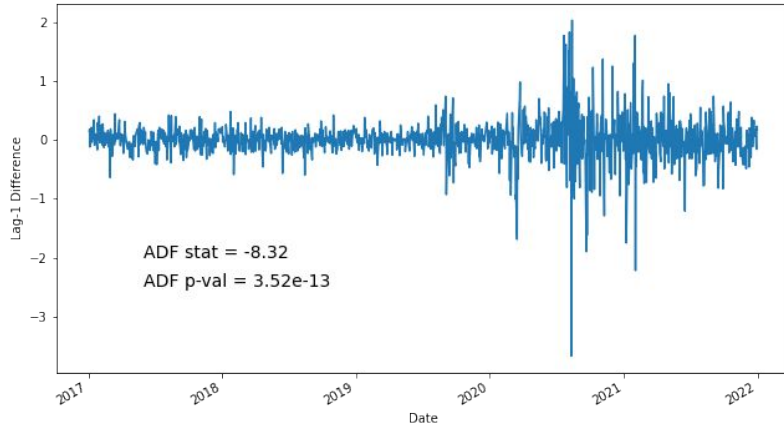
Data Overview



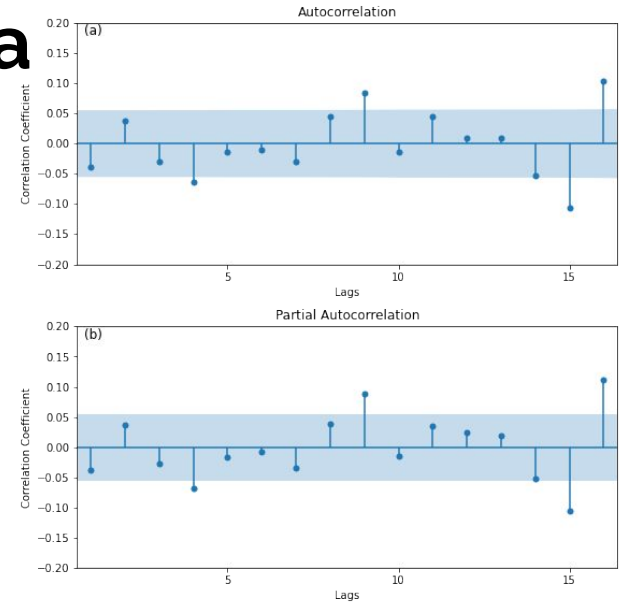
- Study uses exchange-traded fund SLV as a proxy for price of silver from 2017–2021
- SLV has traded within two ranges over the past five years
- Slightly lagging other precious metal gold (GLD) but showing more volatility
- Precious metals have trailed the broad market (SPY) in performance



Exploring the Data



- Lag-1 differencing produces highly stationary dataset
- Low ADF p-value indicates second-differencing unnecessary



- ACF plot show significant autocorrelation at lags 4, 9, 15, 16 - perhaps weekly periodicity
- PACF plot shows almost identical autocorrelations - mixture of AR, MA



ARIMA Modeling

SLV Modeling Procedure

- Data is chronologically split 80/20
 - Training Set: 2017–2020
 - Test Set: 2021
- Model is trained via training set
- Models are chosen by grid search based on AIC/BIC score
- Predictions are generated over the test set and models are evaluated over MAE/RMSE metrics
- Selected model is used to generate 2022 forecast

Model-Order Fitting

- Grid search of first-differenced ($d=1$) ARIMA models is conducted over p (AR) and q (MA) orders
- ARIMA(3,1,2) model shows lowest BIC, 2nd lowest AIC
Log-transformation is performed to reduce heteroscedasticity
- Here, ARIMA(3,1,2), (2,1,3) show nearly identical AIC/BIC
- ARIMA(3,1,2) is selected as the chosen model



Seasonality (SARIMA)

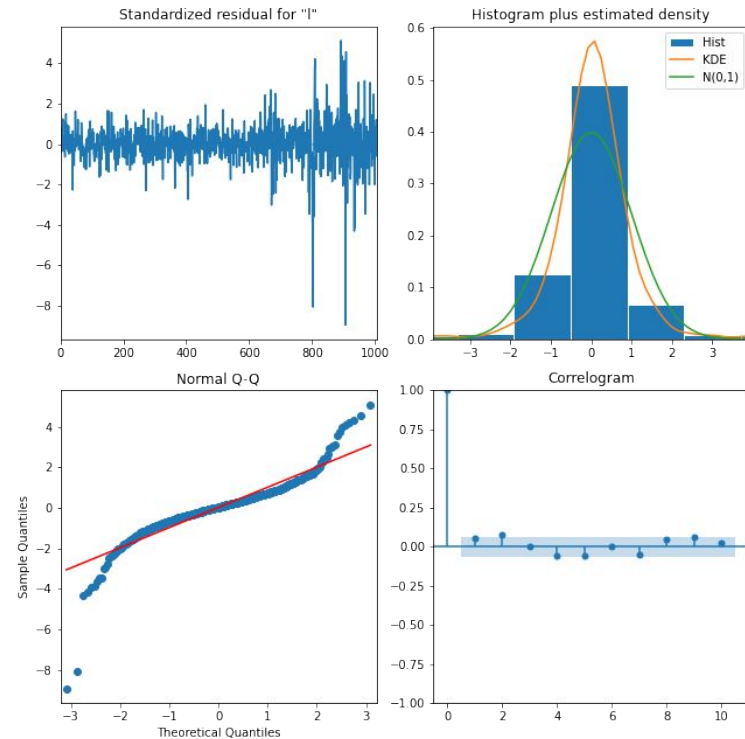
- Autocorrelation suggests some type of seasonality
- Grid search of Seasonal ARIMA (SARIMA) models reveal SARIMA(0,1,0)(2,0,2)[3] as having the lowest AIC/BIC scores - lower than ARIMA(3,1,2)

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SARIMAX Results
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Dep. Variable:          Close      No. Observations:      1007
Model:                ARIMA(0, 1, 0)x(2, 0, [1, 2], 3)  Log Likelihood        2703.794
Date:                  Mon, 10 Jan 2022                AIC                  -5397.589
Time:                  07:26:39                        BIC                  -5373.020
Sample:                0                                HQIC                 -5388.254
Sample:                - 1007
Covariance Type:      opg
=====
              coef    std err          z      P>|z|      [0.025    0.975]
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ar.S.L3      -1.0081     0.015    -69.397     0.000    -1.037    -0.980
ar.S.L6      -0.9748     0.016    -61.977     0.000    -1.006    -0.944
ma.S.L3       1.0380     0.016     64.222     0.000     1.006     1.070
ma.S.L6       0.9634     0.019     50.706     0.000     0.926     1.001
sigma2        0.0003    4.68e-06    58.217     0.000     0.000     0.000
=====
Ljung-Box (L1) (Q):           3.15   Jarque-Bera (JB):           8267.02
Prob(Q):                      0.08   Prob(JB):                  0.00
Heteroskedasticity (H):       5.44   Skew:                      -1.04
Prob(H) (two-sided):          0.00   Kurtosis:                   16.89
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SARIMA Model

- Reduced but persistent heteroscedasticity in residual plot
- Extreme values veer from normal line in quantile-quantile plot
- Correlogram indicates no significant autocorrelation in residuals
- Plots similar to those of ARIMA(3,1,2)



Prediction & Forecasting

In-Sample Prediction

- One-step-ahead predictions of the test set are generated
 - Model is trained on training data
 - Prediction of first test data point
 - Actual value is added to training set
 - Model is retrained on new training set
 - Prediction of next data point
 - Steps 3–5 are repeated

Out-Of-Sample (OOS) Forecast

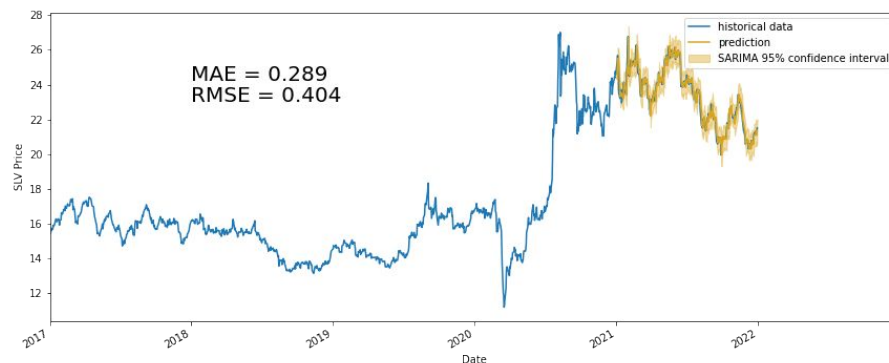
- Selected model is used to generate forecast for 2022
 - Model is trained on entire dataset
 - Forecast of first OOS data point
 - Forecasted value is added to training set
 - Model is retrained on new training set
 - Forecast of next OOS data point
 - Steps 3–5 are repeated



Prediction Results

- Both base and log-transformed ARIMA(3,1,2) and SARIMA(0,1,0)(2,0,2)[3] models are evaluated against baseline
- Baseline: today's price = tomorrow's
- Metrics
 - MAE - mean absolute error
 - RMSE - root-mean-square error
- Log-transformed models consistently exhibit worse metrics
- Only base SARIMA outperforms baseline but insignificantly ($p=0.86$)

Model	Training Set	Test Set
Base ARIMA(3,1,2)	MAE: 0.1848 RMSE: 0.3132	MAE: 0.2997 RMSE: 0.4126
Log-transformed ARIMA(3,1,2)	MAE: 0.1843 RMSE: 0.3155	MAE: 0.3000 RMSE: 0.4157
Base SARIMA(0,1,0)(2,0,2)3	MAE: 0.1854 RMSE: 0.3110	MAE: 0.2886 RMSE: 0.4041
Log-transformed SARIMA(0,1,0)(2,0,2)3	MAE: 0.1835 RMSE: 0.3162	MAE: 0.2914 RMSE: 0.4057
Baseline	MAE: 0.1830 RMSE: 0.3184	MAE: 0.2895 RMSE: 0.4054



Forecast



- Base SARIMA model is the selected model
- Generates a 2022 SLV forecast of 6.0% appreciation
- Price projected to fall within interval of (12.56, 33.42) by the end of 2022 with 95% probability



Conclusions

- SLV price is made stationary by lag-1 first-order differencing
- Significant autocorrelation evident at lags 4, 9, 15, suggesting weekly seasonality
- Best models to describe SLV price are non-seasonal ARIMA(3,1,2) and seasonal SARIMA(0,1,0)(2,0,2)[3] with lag-3 seasonality
- SLV data show significant heteroscedasticity, which is not resolved by log-transformation
- SARIMA model barely outclasses baseline model, which predicts next-day value as equal to present-day value
- Selected SARIMA models forecasts a 6.0% appreciation in price of silver for 2022
- Results may be improved by coupling selected SARIMA model with GARCH model, which models volatility