Stock Prices Analysis of MasterCard and Visa 2008-2024

```
import pandas as pd # Used for data manipulation and analysis
import numpy as np # Used for numerical operations and handling arrays
import plotly.express as px # Used for creating interactive and
        concise visualizations
import plotly.graph_objects as go # Used for detailed and customizable
        interactive visualizations
import matplotlib.pyplot as plt # Used for plotting graphs
import seaborn as sns # Adds static visualizations for correlation
        heatmaps and distribution comparisons
from scipy.stats import shapiro # Performs a Shapiro-Wilk test for
        normality on stock returns
from sklearn.preprocessing import PowerTransformer, StandardScaler #
        Apply transformations to returns to stabilize variance and
        reduce skewness
from sklearn.model_selection import train_test_split, GridSearchCV #
        Split the data and build a predictive model for future price
        predictions
from sklearn.ensemble import RandomForestRegressor # Random Forest
        algorithm for regression tasks
from sklearn.metrics import mean_squared_error, r2_score # Evaluate
        the predictive model's performance.

# Load the data
df = pd.read_csv("/content/MVR.csv")
```

Initial dataset exploration

Provides an overview of the dataset, including the shape, structure, first few rows, and summary statistics.

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4047 entries, 0 to 4046
Data columns (total 13 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   Date         4047 non-null   object
 1   Open_M       4047 non-null   float64
 2   High_M       4047 non-null   float64
 3   Low_M        4047 non-null   float64
 4   Close_M      4047 non-null   float64
 5   Adj Close_M  4047 non-null   float64
 6   Volume_M     4047 non-null   int64
 7   Open_V       4047 non-null   float64
 8   High_V       4047 non-null   float64
 9   Low_V        4047 non-null   float64
 10  Close_V      4047 non-null   float64
 11  Adj Close_V  4047 non-null   float64
 12  Volume_V     4047 non-null   int64
dtypes: float64(10), int64(2), object(1)
memory usage: 411.1+ KB
```

```
df.head()
```

	Date	Open_M	High_M	Low_M	Close_M	Adj Close_M	Volume_M	Open_V	High_V
0	2008-06-02	30.926001	32.000000	30.257000	32.000000	29.529486	50620000	21.552500	21.737499
1	2008-06-03	31.386999	31.399000	30.235001	30.740000	28.366755	93913000	21.752501	21.987499
2	2008-06-04	30.745001	30.959999	29.454000	29.740000	27.443956	66160000	21.770000	22.025000
3	2008-06-05	29.951000	30.615999	29.544001	30.615999	28.252338	45959000	21.615000	21.809999
4	2008-06-06	30.228001	30.242001	29.481001	29.573000	27.289856	29383000	21.475000	21.497499

```
df.describe()
```

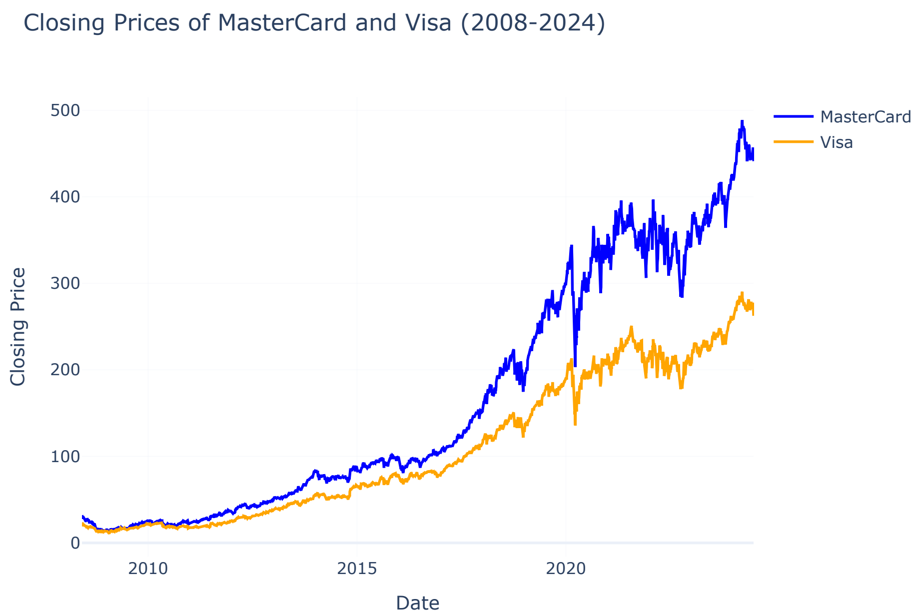
	Open_M	High_M	Low_M	Close_M	Adj Close_M	Volume_M	Open_V
count	4047.000000	4047.000000	4047.000000	4047.000000	4047.000000	4.047000e+03	4047.000000
mean	164.535600	166.170139	162.857876	164.563858	160.646182	8.249296e+06	107.988356
std	138.620480	139.946015	137.248286	138.635551	138.057771	1.140882e+07	82.319225
min	12.100000	12.736000	11.305000	11.918000	11.024753	6.411000e+05	10.672500
25%	42.459502	42.865499	42.062000	42.452500	39.624086	2.988750e+06	30.157500
50%	97.440002	98.089996	96.699997	97.599998	92.752449	4.409000e+06	78.690002
75%	304.414994	306.979995	300.304993	303.910004	297.765701	8.251500e+06	193.044998
max	488.529999	490.000000	483.640015	488.640015	487.964142	1.787220e+08	290.000000

```
# Checking for null values and duplicates
# Identifies missing data and duplicate rows in the dataset.

print("\nNull values per column:")
print(df.isnull().sum())
print("\nNumber of duplicate rows:", df.duplicated().sum())
```

```
Null values per column:
Date           0
Open_M         0
High_M         0
Low_M          0
Close_M        0
Adj Close_M    0
Volume_M       0
Open_V         0
High_V         0
Low_V          0
Close_V        0
Adj Close_V    0
Volume_V       0
dtype: int64

Number of duplicate rows: 0
```

```
# Converting the 'Date' column to datetime format to enable time-
        series operations for better handling
df['Date'] = pd.to_datetime(df['Date'])
```

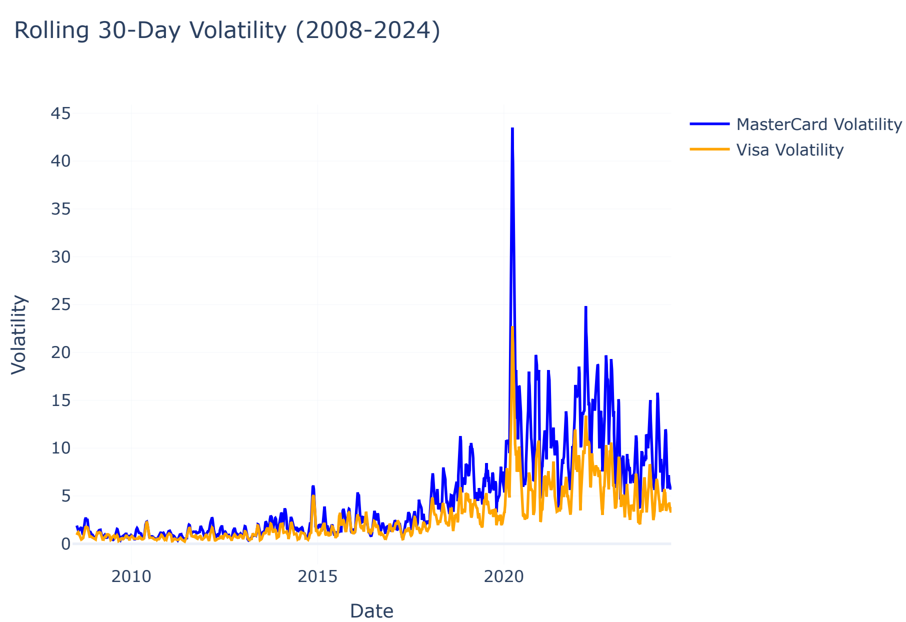
```
# Plotting closing prices over time
fig = go.Figure()
fig.add_trace(go.Scatter(x=df['Date'], y=df['Close_M'], mode='lines',
        name='MasterCard', line=dict(color='blue')))
fig.add_trace(go.Scatter(x=df['Date'], y=df['Close_V'], mode='lines',
        name='Visa', line=dict(color='orange')))
fig.update_layout(title='Closing Prices of MasterCard and Visa (2008-
        2024)',
                  xaxis_title='Date',
                  yaxis_title='Closing Price',
                  template='plotly_white')
fig.show()
```




```
# Plotting the distribution of closing prices
plt.figure(figsize=(14, 7))
sns.histplot(df['Close_M'], kde=True, color='blue',
        label='MasterCard')
sns.histplot(df['Close_V'], kde=True, color='orange', label='Visa')
plt.title('Distribution of Closing Prices')
plt.xlabel('Close Price')
plt.ylabel('Frequency')
plt.legend()
plt.show()
```

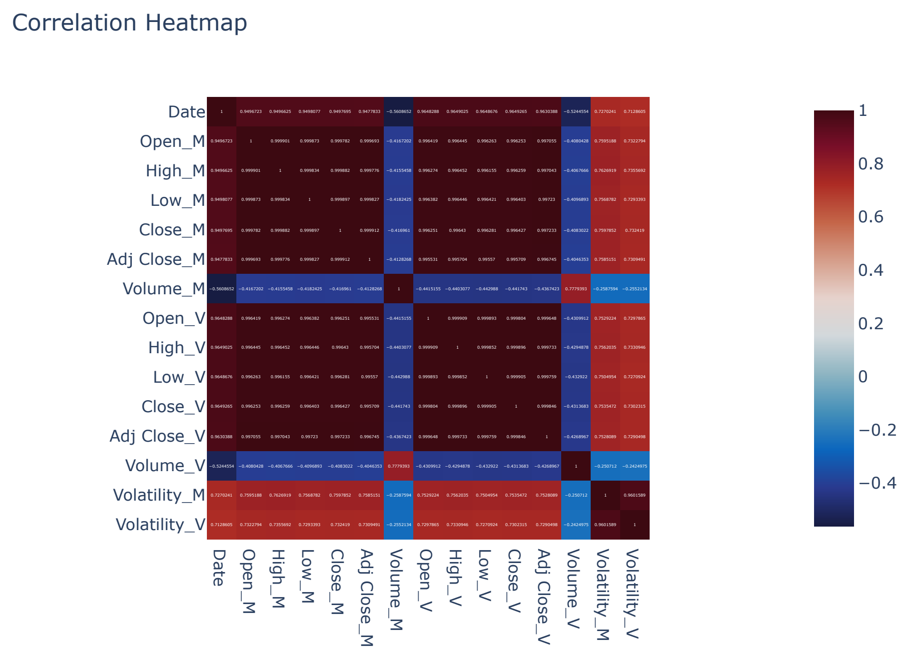
```
# KDE plot for closing prices
fig = px.density_contour(df, x='Close_M', y='Close_V',
        marginal_x="histogram", marginal_y="histogram",
                        title='KDE Plot: MasterCard vs Visa Closing
        Prices')
fig.update_layout(xaxis_title='MasterCard Close Price',
        yaxis_title='Visa Close Price')
fig.show()
```


```
# Add volatility metrics (rolling standard deviation)
# Computes 30-day rolling volatility as a measure of price
        fluctuations.


df['Volatility_M'] = df['Close_M'].rolling(window=30).std()
df['Volatility_V'] = df['Close_V'].rolling(window=30).std()

# Plotting rolling volatility over time
fig = go.Figure()
fig.add_trace(go.Scatter(x=df['Date'], y=df['Volatility_M'],
        mode='lines', name='MasterCard Volatility',
        line=dict(color='blue')))
fig.add_trace(go.Scatter(x=df['Date'], y=df['Volatility_V'],
        mode='lines', name='Visa Volatility',
        line=dict(color='orange')))
fig.update_layout(title='Rolling 30-Day Volatility (2008-2024)',
                  xaxis_title='Date',
                  yaxis_title='Volatility',
                  template='plotly_white')
fig.show()
```




```
# Correlation heatmap
import plotly.express as px

correlation_matrix = df.corr()
```

```python
# Use a valid diverging colorscale (e.g., 'balance')
fig = px.imshow(
    correlation_matrix,
    text_auto=True,
    color_continuous_scale=px.colors.diverging.balance,
    title='Correlation Heatmap'
)

fig.show()
```




```python
# Cap outliers in closing prices using IQR
# Caps outliers using the interquartile range method.
# The interquartile range (IQR) method is a way to calculate the
        spread of data by identifying the middle 50% of values and
        finding the difference between the upper and lower quartiles.

for col in ['Close_M', 'Close_V']:
    Q1 = df[col].quantile(0.25)
    Q3 = df[col].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    df[col] = np.clip(df[col], lower_bound, upper_bound)

# Shapiro-Wilk test for normality
# Tests if stock prices follow a normal distribution.

for col in ['Close_M', 'Close_V']:
    stat, p = shapiro(df[col])
    print(f"Shapiro-Wilk Test for {col}: Statistics={stat:.3f}, p=
        {p:.3f}")
```

```
Shapiro-Wilk Test for Close_M: Statistics=0.862, p=0.000
Shapiro-Wilk Test for Close_V: Statistics=0.885, p=0.000
```

```python
# Apply PowerTransformer if data is not normal
# Transforms data to stabilize variance and reduce skewness.

pt = PowerTransformer()
df[['Close_M', 'Close_V']] = pt.fit_transform(df[['Close_M',
        'Close_V']])
```

```
# Prepare data for regression modeling
X = df[['Open_M', 'High_M', 'Low_M', 'Volume_M', 'Open_V', 'High_V',
        'Low_V', 'Volume_V']]
y_M = df['Close_M']
y_V = df['Close_V']
X_train_M, X_test_M, y_train_M, y_test_M = train_test_split(X, y_M,
        test_size=0.2, random_state=42)
X_train_V, X_test_V, y_train_V, y_test_V = train_test_split(X, y_V,
        test_size=0.2, random_state=42)

# Training a RandomForestRegressor with hyperparameter tuning using
        GridSearchCV.


param_grid = {
    'n_estimators': [100, 200],
    'max_depth': [10, 20, None],
    'min_samples_split': [2, 5],
    'min_samples_leaf': [1, 2]
}


grid_search_M = GridSearchCV(RandomForestRegressor(random_state=42),
        param_grid, cv=3, n_jobs=-1)
grid_search_V = GridSearchCV(RandomForestRegressor(random_state=42),
        param_grid, cv=3, n_jobs=-1)


grid_search_M.fit(X_train_M, y_train_M)
grid_search_V.fit(X_train_V, y_train_V)


# Retrieve best estimators
model_M = grid_search_M.best_estimator_
model_V = grid_search_V.best_estimator_

# Best parameters for each model
print("Best parameters for MasterCard:", grid_search_M.best_params_)
print("Best parameters for Visa:", grid_search_V.best_params_)
```

```
Best parameters for MasterCard: {'max_depth': 20, 'min_samples_leaf':
2, 'min_samples_split': 2, 'n_estimators': 100}
Best parameters for Visa: {'max_depth': 20, 'min_samples_leaf': 2,
'min_samples_split': 5, 'n_estimators': 200}
```

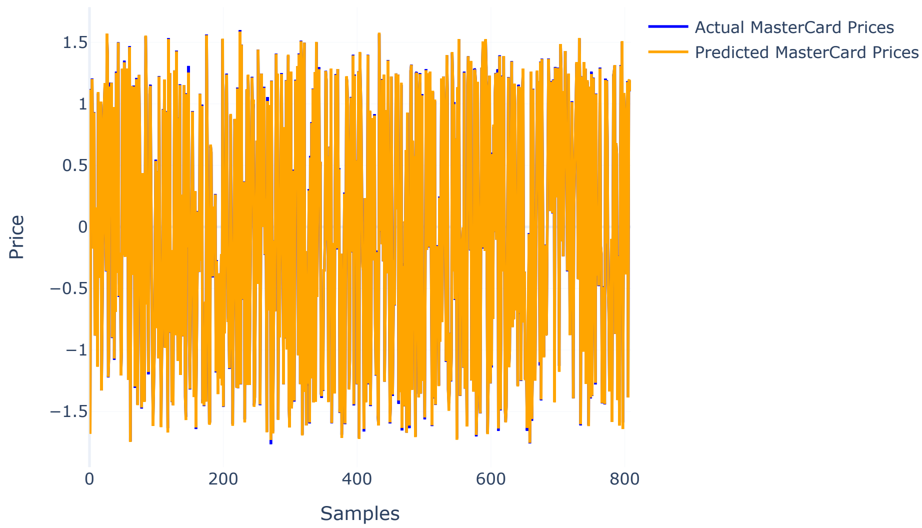
```
# Predictions and evaluation
# Evaluating the model's performance using metrics like MSE and R2
        Score.


for model, X_test, y_test, label in zip([model_M, model_V], [X_test_M,
        X_test_V], [y_test_M, y_test_V], ['MasterCard', 'Visa']):
    y_pred = model.predict(X_test)
    print(f"{label} - Mean Squared Error: {mean_squared_error(y_test,
        y_pred):.2f}")
    print(f"{label} - R2 Score: {r2_score(y_test, y_pred):.2f}")
```

```
MasterCard - Mean Squared Error: 0.00
MasterCard - R2 Score: 1.00
Visa - Mean Squared Error: 0.00
Visa - R2 Score: 1.00
```

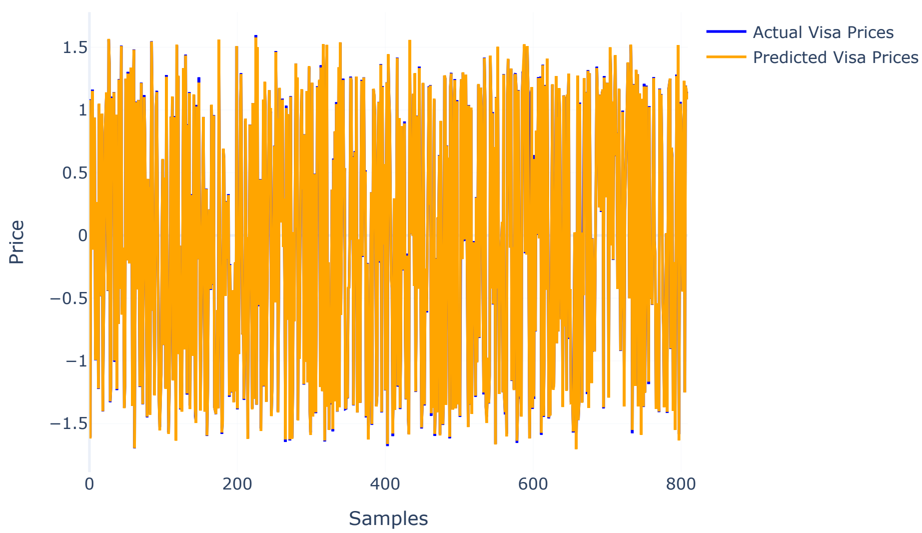
```
# Interactive plots for actual vs predicted prices
for y_test, y_pred, label in zip([y_test_M, y_test_V],
        [model_M.predict(X_test_M), model_V.predict(X_test_V)],
        ['MasterCard', 'Visa']):
    fig = go.Figure()
    fig.add_trace(go.Scatter(y=y_test.values, mode='lines',
        name=f'Actual {label} Prices', line=dict(color='blue')))
    fig.add_trace(go.Scatter(y=y_pred, mode='lines', name=f'Predicted
        {label} Prices', line=dict(color='orange')))
    fig.update_layout(title=f'Actual vs Predicted {label} Prices',
                      xaxis_title='Samples',
                      yaxis_title='Price',
```

```
                    template='plotly_white')
fig.show()
```

Actual vs Predicted MasterCard Prices



Actual vs Predicted Visa Prices



The plots compare the actual stock prices (blue line) with the predicted prices (orange line) for MasterCard and Visa. The near-perfect overlap between the two lines indicates that the Random Forest model has captured the underlying patterns in the data very well, achieving high accuracy. This suggests the model has learned the relationship between the input features and target variable effectively.

However, the tight fit could also point to potential overfitting, where the model performs exceptionally well on the training data but might not generalize to unseen data. This observation underscores the importance of validating the model on an entirely separate dataset to ensure its robustness and reliability. If the model's performance remains consistent across validation sets, it could serve as a reliable tool for short-term price forecasting of these stocks.