Effect of Stock Market Movements on Foreign Exchange Rate Under Special Events

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Abstract

Have you ever noticed that when the domestic stock market rises, foreign exchange rates increase? The reason might be after the stock market's good performance, investors' confidence in the country's economy rises, which leads to an increase in demand for the domestic currency. Because the demand was up there, the value of the money went up, causing an increase in foreign exchange rates. In the study, we aim to study the fundamental reasons behind and use Granger Causality Test to test the correlation and Autoregressive Distributed Lag (ARDL) to examine the relationship between the stock market and the foreign exchange market. We chose major indices of the U.S. and European economies and stocks from the different indices to have a better understanding of this underlying relationship.

1 Introduction

In recent years, the world has observed dramatic changes in foreign exchange rates due to COVID-19 and ongoing wars between Russia and Ukraine. A country's currency appears to be an indicator of this country's current and future status. Aside from unpredictable events, multiple factors affect fluctuations in foreign exchange rates, including regulatory rules, tariffs, interest rates, and many others. However, all those factors affect people's beliefs in the economy, and the foreign exchange rate reflects those beliefs. It is also similar to stock markets because stock means company ownership. If people lose belief in our economy, the performance of stock markets is another reflection of people's level of confidence in the economy.

The purpose of the study is further to investigate the relationship between stock prices and exchange rates, as the issue still has no consensus. We choose to focus on the Euro and U.S. dollar in our research because they are one of the world's two largest economies; we focus on two global events – COVID-19 and the ongoing wars between Russia and Ukraine – because they are two most recent events that impact people's everyday life.

We consider the following below research questions to test the relationship between the stock market and foreign exchange:

1) Stock market affects the direction of the USD/EUR exchange rate. Namely, there is Granger's causality between the two variables.

2) During the global event of COVID-19 (6 months after WHO announced it as a pandemic–January 10, 2020), the effects of the stock market on the foreign exchange rate are faster reflected than the six months before this event. Specifically, the time shift variable that maximizes the correlation is lower for the period after declaration.

3) During the global event of the Ukraine War (6 months after Russia took escalated special operations in Ukraine–February 24, 2022), the effects of the stock market on the foreign exchange rate are faster reflected than the 6 months before this event. Specifically, the time shift variable that maximizes the correlation is lower for the period after declaration.

2 Literature Review

Researchers and scholars have been studying the relationship between stock price and money supply for many years (Hamburger and Kochin, 1972), (Pearce and Roley, 1983), (Urich and Wachtel, 1981), (Grossman, 1981).

Aggarwal (2003), and Soenen and Hennigar (1988) start to consider the correlation between the two variables in the area of exchange rates with the theoretical explanation. They found that a change in exchange rates would affect a firm's stock price(Tabak, 2006).

However, the empirical evidence later showed the opposite results: Aggarwal (2003) find a significant positive correlation between the US dollar and US stock prices while Soenen and Hennigar

(1988) report negative. There was not a consensus about this yet

Bahmani-Oskooee and Sohrabian (1992) later explain the direction of movement between foreign exchange rates and stock prices by adopting methods including cointegration and Granger causality in their research. While the theoretical explanation was clear, the empirical evidence appeared to be mixed again as the correlation research above. Bahmani-Oskooee and Sohrabian (1992) find out that a two-way relationship exists between the U.S. stock market and foreign exchange rates while Abdalla and Murinde (1997) discover that exchange rates Granger cause stock prices in their study in India, Korea, and Pakistan. Wu (2000) pointed out that Singapore-dollar exchange rates Granger cause stock prices while (Griffin and Stulz, 2001) suggest the impact of weekly exchange rate changes on the performance of industries was negligible.

In modern empirical studies in different regions, including Pakistan and Zambia, we found more results indicating no relationship between stock price and exchange rate (Suriani et al., 2015), (Bhattacharya and Mukherjee, 2003).

In addition to the relationship between the stock market and foreign exchange, studies about special global events, such as public health and terrorism turmoil, provide more context information under special global events, such as COVID-19 and Ukraine War we analyzed in this study. Chen and Siems (2007) argued that because of the stable financial/banking system, the U.S. capital markets have become more resilient than in the past. It also recovers sooner from special events, such as terrorist attacks, than other global capital markets.

However, other studies also show that markets seem to respond actively during special events such as terrorist attacks. TAHIR et al. (2020) found that the total number of terrorist attacks affects the Pakistan stock exchange in the long term. Research also shows that terrorism incidents make the public panic (Arin et al., 2008) and affect global financial markets such as Europe (Corbet et al., 2018) and Turkey (Aksoy, 2014).

The objective of this paper is to provide additional evidence between the foreign exchange rates and stock prices in the U.S. and Europe during a series of special world events by using a multi-feature regression analysis or the Machine Learning Classification model. In this paper, we focus on the exchange rate between the US and Europe and COVID-19 and Russian War as recent special world events.

3 Data

3.1 Data Collection

SP 500, Dow Jones Industrial Average and Nasdaq Composite indices are used as a substitute for stock prices for the following reasons:

1) The SP 500 Index tracks 500 large companies listed on stock exchanges in the U.S. This gives a good indication of movement in the U.S. market as a whole.

2) The Dow Jones Industrial Average (DJIA), one of the oldest and most frequently used indices in the world, includes the stocks of 30 of the largest and most influential companies in the United States. Similar to SP 500, it also reflects the market movement in the U.S.

3) The Nasdaq Index's movement indicates the performance of the technology industry as well as investors' attitudes toward more speculative stocks. By adopting of these three stock indices, we could use them as an indication of the market reaction.

At the same time, we also adopt three European stock indices: FTSE 100, CAC 40 and DAX 40 for the following reasons:

1) The Financial Times Stock Exchange 100 Index, known as FTSE 100 Index, is a share index of the 100 companies listed on the London Stock Exchange with the highest market capitalization. This gives a good indication of movement in the U.K. market as a whole.

2) The Cotation Assistée en Continu, known as CAC 40, is a benchmark French stock market index. The index represents a capitalization-weighted measure of the 40 most significant stocks among the 100 largest market caps on the Euronext Paris, the Paris Stock Exchange. This gives a good indication of movement in the French market as a whole.

3) The Deutscher Aktienindex, known as DAX, is a stock market index consisting of the 40 major German blue chip companies trading on the Frankfurt Stock Exchange. This gives a good indication of movement in the German market as a whole.

For individual stocks, we selected 5 representing companies from each of 8 different industries in the index (included in the appendix). For example, we chose Meta Platforms, Inc. (META), Apple Inc. (APPL), Microsoft Corporation (MSFT), Alphabet Inc. (GOOGL) and The International Business

Machines Corporation (IBM) from the technology sector. With 40 different stocks from a wide selection, this brings more diversity in our analysis, covering each single industry, which might have effects on foreign exchange rates we examined.

By the 6 of the stock indices and the 40 major stocks, this study covers both U.S. and European markets, which allows us to explore broader and further into this topic.

The data is collected through the `download` function from the `yfinance` API.

3.2 Data Preprocesings

Upon receiving data from the Yahoo Finance API, every variable consists of a set of time series. In other words, for each date, the Yahoo Finance API reports several data metrics, including the opening price, the traded volume, the closing price, and the adjusted closing price. According to Yahoo, the adjusted closing price is "the closing price after adjustments for all applicable splits and dividend distributions," and it is a better reflection of the true value than other metrics. Thus, we have used this metric as our time series data for all variables. With that established, this section focuses on two major preprocessing techniques used, namely MinMax Scalar and Upsampling.

3.2.1 Scaling

We have multiple time series variables at hand, and one of the first and most obvious problems is that they are on different scales. For example, one company's stock value can be around one hundred dollars, but another can be around one dollar, which is only a fraction of the first. Feeding this raw data into any model would likely result in a biased model because their values have different weights to start with.

To eliminate this built-in bias, a scaling technique, the MinMax Scalar, was applied individually to each variable, ensuring all variables are relatively on the same scale while preserving the trend and shape of data. The MinMax Scalar transformed every time series independently: for each variable, the max value becomes 1, the min value becomes 0, and all other data points were scaled proportionally according to their relative ratio with min and max.

For both case studies, COVID-19 and Ukraine war, we trained the scalar separately on the corresponding time frames, which ensures the above behaviors. We used the `MinMaxScaler` from the `sklearn`'s preprocessing module to accomplish this task. The results of this scaling can be seen in Figure 5 and Figure 6.

3.2.2 Upsampling

Another important aspect of time series data is the sampling frequency. The current data is sampled at a daily frequency, which means each row represents a specific date. With the given time frame for each case study, only a limited amount of rows can be gathered from the Yahoo Finance API since it only records daily value instead of hourly or even smaller intervals.

This sampling does not cause a problem for most tests, but it would limit the ability of the Autoregressive Distributed Lag (ARDL) model. Due to the minimum requirement on the amount of data for it to regress with a higher lag parameter. As a solution to this problem, we upsampled the data by resampling the data at twice its current frequency and interpolating the missing values. This doubled the amount of data, which was time series on a daily base but is now on a 12-hours base. This goal is achieved by the built-in functions `resample` and `interpolate` of the `panda` package.

3.3 Methodology and Results

This section goes over the models and methods used for this analysis: we first looked at the correlations between every pair of time series and constructed our model by comparing lag variables. Then, we used Granger Causality Test to investigate the causality of data. Based on the results of those tests and experiments, we then used Augmented Dickey-Fuller (ADF) Test to check the stationary of each variable in the data. After all, we used the above results to select an appropriate model, autoregressive Distributed Lag (ARDL), to examine the relationships. In addition, this section also presents corresponding results for every step and model.

3.3.1 Correlations

As the first step in our analysis, the correlation coefficient was used to determine how independent variables are associated with the exchange rate. The Pearson Correlation was calculated pair-wise between every stock (independent variable) and the exchange rate. The correlation is calculated by the built-in function `corr` of the `panda` package, and the results are graphed in Figure 1 and Figure 2.

Figure 1: Pre-COVID and Post-COVID Correlations

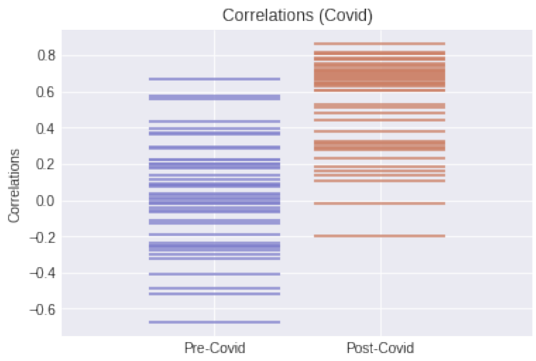
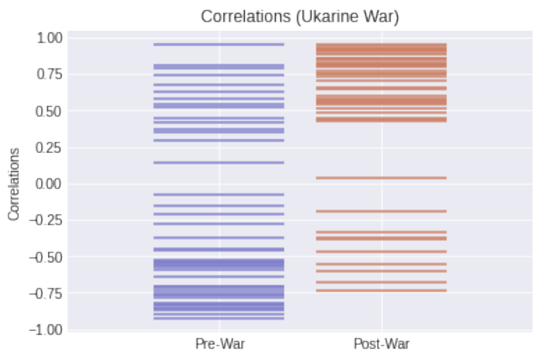


Figure 2: Pre-War and Post-War Correlations



In each above figure, every bar represents a pair-wise Pearson Correlation between a stock and the exchange rate. Thus, although these graphs do not show detailed information for each variable pair, it displays the overall trend of those relationships. This acts as a preliminary step in our study, and both figures validate our research direction by suggesting there are meaningful correlations and those values change when the two global events occur.

3.3.2 Granger Causality Test

To answer the first research question and hypothesis, also as one further step from correlations, Granger Causality Test was used to examine the causality between the independent variables and the exchange rate. Specifically, the pair-wise causality was tested. For all pair-wise Granger Causality Tests, the max lag was set to 15, which drives the test's Null hypothesis to be "the past values, within the time range from 0 to 15, of this specific stock does not contain information that can forecast exchange rate". Correspondingly, the Alternate Hypothesis then becomes the opposite, that is this specific stock granger causes the exchange rate.

For this study's purpose, We used `grangercausalitytests` function with option `chi2test` in the python package `statsmodels` as the basic component. The built-in function returns a test statistic and the corresponding p-value with it. The test statistics returned are the residual sum of squares, and interpreting these values does not contribute to this study's hypothesis. Hence, we focused on interpreting the returned p-values. By setting the threshold to 0.05, causality is established with any value below the threshold. Figure 3 and Figure 4 show the overall p-value distributions from the Granger Causality Tests.

Figure 3: Pre-COVID and Post-COVID Granger Causality Test's P-value distributions

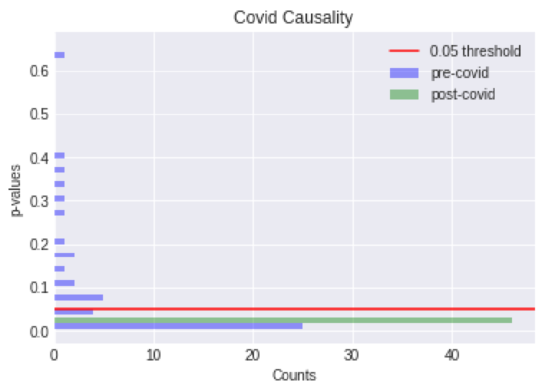
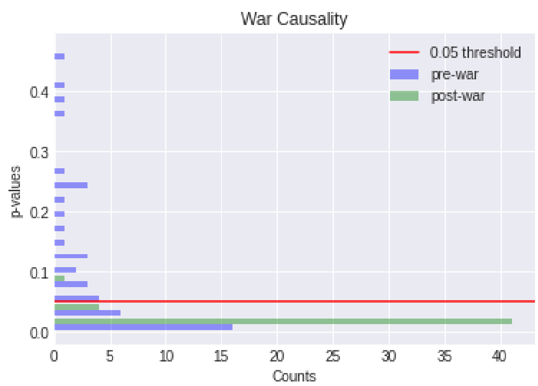


Figure 4: Pre-War and Post-War Granger Causality Test's P-value distributions



In the above figures, the x-axis represents the number of independent variables. For example, all Granger Causality Tests during the Post-COVID period have p-values less than the threshold. Thus, all selected stock Granger caused the exchange rate during the post-COVID period.

To interpret the result at a higher resolution, we examine the result of JPMorgan Chase & Co (JPM) in the COVID Case. During the Pre-COVID period, the corresponding p-value was 0.2515, above the threshold. Yet, the value was 0.0029, statistically significant. Figure 5 and Figure 6 show JPM and exchange rate during the COVID period.

Figure 5: Causality of JPM in Pre-COVID

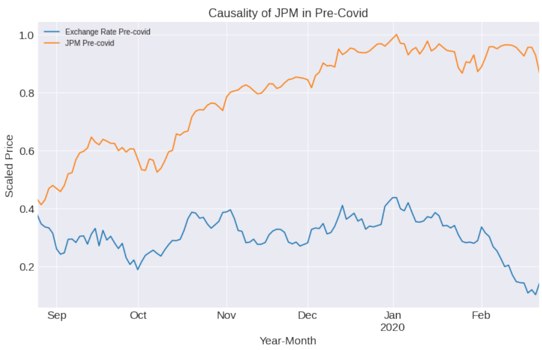
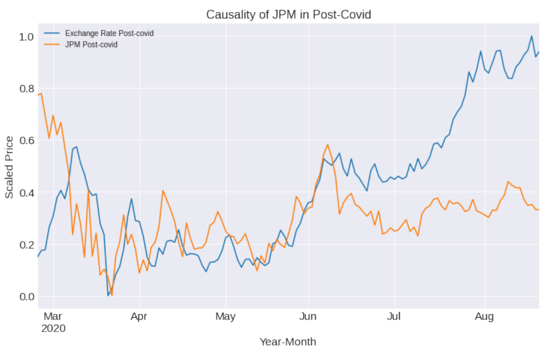


Figure 6: Causality of JPM in Post-COVID



As shown in the above graph, the two variables across time during the Pre-COVID period do not overlap nor show a similar shape. Specifically, the JPM stock is overall, whereas the exchange rate remains roughly the same. For the Post-COVID period, the two variables highly overlap and share the same shapes. Using the time period roughly from 04/2020 to 05/2020 in Figure 6, the two variables' local maximums and minimums are roughly within the exact dates, well within the 15 days for the Granger Causality Test to detect. Overall, this detailed examination confirms the validity of this study's approach to causality.

Similar examinations can be drawn for all tests, but they would deviate from the topic. To conclude, this section accepts the first hypothesis, that is "Stock market overall Granger Causes the direction of the USD/EUR exchange rate."

3.3.3 Naive Model for Best Lag

In the JPM case of the previous section, we observed that it shares a similar shape across time with the exchange rate during the Post-COVID period. However, the peak values of JPM seem to come before the peaks of the exchange rate in a consistent. Thus, this leads to our second and third hypotheses on the reflection speed of the stock market on the exchange rate. This section first proposes a naive algorithm for finding the best time-shift variable, then applies the method to both case studies.

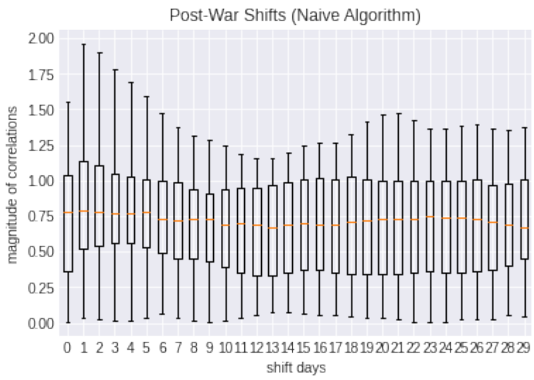
The intuition behind this algorithm is rather simple: it realigns the independent variables with the dependent variable by different lag, generates corresponding correlations, and finds the best lag that maximizes the magnitudes of correlations. In this algorithm, the T-test was used to compare the difference between two different correlation matrices, and Fisher-Z Transformation was used to relax the normality assumption of the T-test, which resulted in the transformed correlations that do not have the traditional range. The model is implemented according to the following pseudo-code:

Algorithm 1 Naive Algorithm for finding best lag

Require: data, maxlag, threshold
  $res \leftarrow 0$
  $r \leftarrow$ correlation of data
  $z \leftarrow abs(arctanh(r))$
  $t, p \leftarrow$ ttest (z, z)
  $lag \leftarrow 1$
  while $lag \neq maxlag$ **do**
    $data \leftarrow shift(lag)$ ▷ Shift dependent data by lag
    $r_{temp} \leftarrow$ correlation of shifted data
    $z_{temp} \leftarrow abs(arctanh(r_{temp}))$
    $t_{temp}, p_{temp} \leftarrow$ ttest (z, z_{temp})
    if $t < 0$ and $p >$ threshold **then**
      $res \leftarrow lag$
      $t, p \leftarrow t_{temp}, p_{temp}$
      $z \leftarrow z_{temp}$
    end if
  end while

For this analysis, the maxlag was set to 29, and the threshold was set to 0.05 again. Intuitively, this algorithm generates the below graph, Figure 7, during its process. In Figure 7 and the following graphs, each bar represents the set of correlations with the corresponding lag.

Figure 7: Example of Naive Algorithm for Post-War Period



The algorithm then compares each bar to the base–the bar with no shift (0), and uses T-tests to output lag with the highest increase that is also statistically significant. Figure 8 and Figure 9 show the results of the COVID case study.

Figure 8: Pre-COVID Shifts for Highest Fisher-Z Correlation Magnitude Mean (Naive Algorithm)

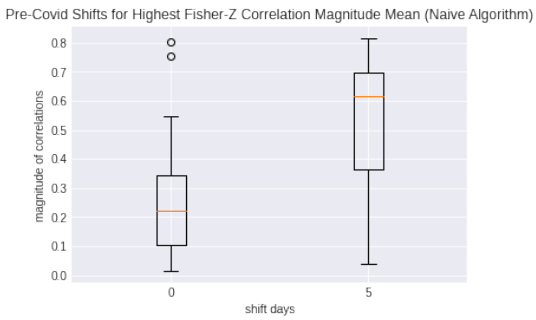
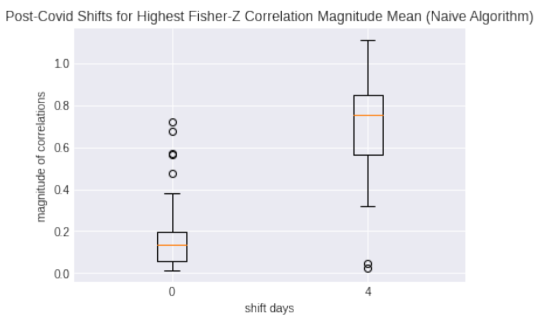


Figure 9: Post-COVID Shifts for Highest Fisher-Z Correlation Magnitude Mean (Naive Algorithm)



Specifically, the p-value of the t-test during Pre-COVID is 3.53e-09, and 1.58e-20 for Post-COVID. As shown in the above results, the best lag for the Pre-COVID period is 5 days, but 4 days for the Post-COVID period, and we accept the second hypothesis that "During the global event of COVID-19 (6 months after WHO announced it as a pandemic–January 10, 2020), the time shift variable that maximizes the correlation is lower for the Post-COVID period." Similarly, Figure 10 and Figure 11 show the results of the COVID case study.

Figure 10: Pre-War Shifts for Highest Fisher-Z Correlation Magnitude Mean (Naive Algorithm)

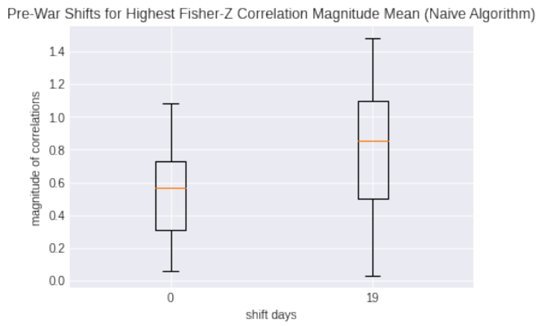
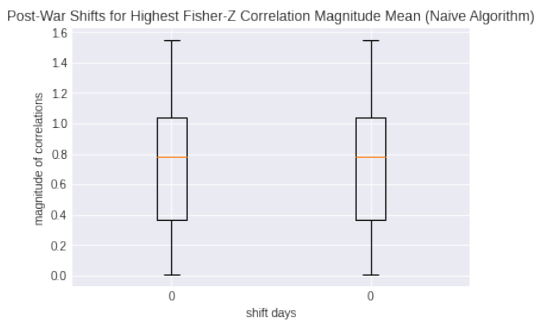


Figure 11: Post-War Shifts for Highest Fisher-Z Correlation Magnitude Mean (Naive Algorithm)



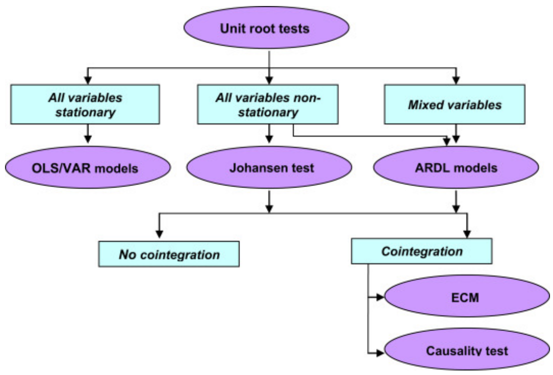
For the Ukraine War study, the p-value of the t-test during Pre-War is 0.001 and non-significant for all shifts during Post-COVID. As shown in the above results, the best lag for the Pre-COVID period is 19 days, but 0 for the Post-COVID period, and we accept the second hypothesis that "During the global event of the Ukraine War (6 months after Russia took escalated special operations in Ukraine–February 24, 2022), the time shift variable that maximizes the correlation is lower for the Post-War period."

3.3.4 Augmented Dickey-Fuller (ADF) Test

The previous sections have answered and accepted all the hypotheses. However, those approaches are naive, and this study requires a more established and classic model to validate the statements from the above sections. Selecting a model from all the published models, including the ones mentioned in Section 2, is not an easy task. To accomplish this, this section follows the selection methodology proposed in a previously published study (Shrestha and Bhatta, 2018).

Using the Augmented Dickey-Fuller (ADF) Test as a Unit Root Test for stationarity, the results show the independent variables (stock market) are a mix of stationary and non-stationary time series. Again, the specific results from the ADF tests are not important to this study, but this overall property of the independent variables decides the model used in the next section. Figure 12 shows the selection methodology.

Figure 12: Method selection for time series data (Shrestha and Bhatta, 2018)



To find the stationarity, we used `adfuller` function in the python package `statsmodels` to test for all stock variables.

3.3.5 Autoregressive Distributed Lag(ARDL)

As a result of the previous section, Autoregressive Distributed Lag (ARDL) model was selected to re-examine the relationships between the stock market and the exchange rate. This section first introduces the model and challenges, then also provides the results from the model. We used `ARDL` model directly from the python package `statsmodels` as the ARDL model.

Instead of considering a universal lag across the independent variables, the ARDL model accounts for different lags on different independent variables, hence "Distributed Lag." However, because of this powerful nature, this model requires more data than the current amount for it to regress properly. To maintain consistency throughout this study, we decided not to specify a new time frame but used the upsampling trick in section 3.2.2. Although this trick makes the model regress properly, it only could support a limited maxlag–2 days. In essence, this model can only consider the values of today, yesterday, and the day before yesterday. Figure 13 shows an example output of the ARDL model on Apple Inc.

Figure 13: ARDL model outputs for AAPL during the Pre-Covid Period

	coef	std err	z	P>|z|	[0.025	0.975]
const	1.1041	0.468	2.362	0.020	0.180	2.028
AAPL.L0	0.7633	0.293	2.606	0.010	0.184	1.343
AAPL.L1	-0.0013	0.210	-0.006	0.995	-0.417	0.414
AAPL.L2	-1.2216	0.309	-3.952	0.000	-1.833	-0.610
AAPL.L3	0.0474	0.213	0.223	0.824	-0.373	0.468
AAPL.L4	-0.2605	0.335	-0.778	0.438	-0.923	0.402

Using the above figure as an example, we can interpret the model in the following way. Data points for "AAPL.L1" and "AAPL.L3" were interpolated data from the upsampling trick, and they always have high P-values due to their interpolated nature. This study only considers "AAPL.L0", "AAPL.L2" and "AAPL.L4" as they represent today, yesterday, and the day before yesterday. Similar to the naive algorithm, the coefficients do not contribute to this study because they represent how the time series interact with itself, but not what lag is significant. Again, this work directs attention to their corresponding p-values because they entail information on the significance of the lag. Using the same p-value threshold of 0.05, Apple has a meaningful lag of 0 and 1, which means only today's and yesterday's values of apple can help predict the exchange rate during the Pre-Covid Period. Figure 14 and Figure 15 display the overall result from the ARDL model.

Figure 14: Covid ARDL P-value results

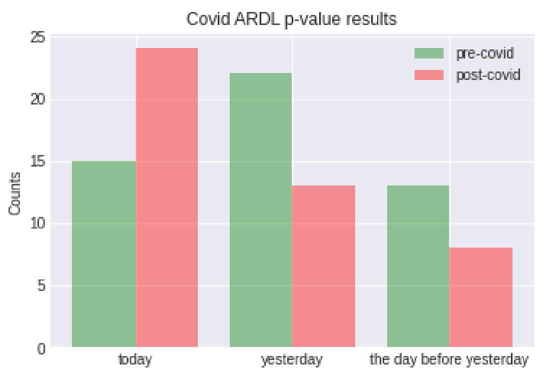
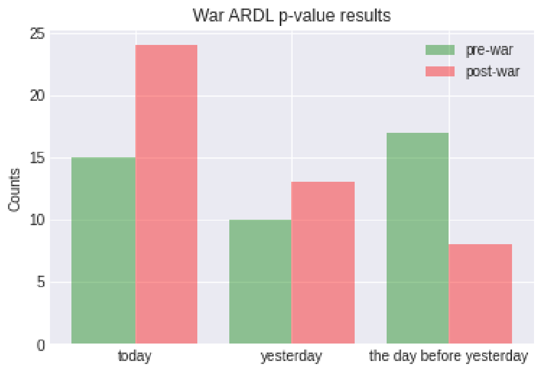


Figure 15: War ARDL P-value results



Using Figure 14, today's value of 15 stocks can help predict the exchange rate during the Pre-Covid period, but 24 for the Post-Covid period. However, yesterday's value of 22 stocks can help predict the exchange rate during the Post-Covid period, but 13 for the Post-Covid period. Using the same manner, we can interpret the rest of Figure 14 and Figure 15. Overall, this model does not provide results that can directly help us to validate our hypothesis, partially due to data limitations. However, if only focusing on today's value, this model shows there are more independent variables during the post-event period that can be used for predicting, which is probably due to a faster reflection speed.

4 Discussions and Conclusions

4.1 Summary

In this paper, we have examined the effects of stock market performance, using stock indices and representing stocks of the U.S. and European markets as indicators, on the USD/EUR exchange rate.

We began our analysis by adopting 6 major stocks and 40 representing stocks from Yahoo Finance API, and used MinMax Scalr to eliminate the build-in bias of the variables we had and upsampled them to a 12-hour frequency from the default data. During the testing process, we first validated our research direction after examining the correlations between every pair of time series. This leads to the Granger Causality Test between the independent variables and the exchange rate, which shows that the Stock market overall Granger Causes the direction of the USD/EUR exchange rate. Through the naive model, we accept the second and third hypotheses by identifying the time shift variable that maximizes the correlations is lower for the Post-event period. Finally, the ARDL model provides additional insights into the study but failed to validate previous results.

4.2 Discussions

As the world witnessed the stock market show volatile movements when the pandemic hit the world and Russia invaded Ukraine, this study was designed to explore those global events from an analytical perspective. For this study, the goal is to investigate further and provide a broader framework for understanding the relationship between stock markets and foreign exchange rates.

We start the discussion of this study by emphasizing that although this work finds evidence and significant results that support our hypotheses, the validity of the naive model was not confirmed on other data sets. In other words, while the naive model generates promising results for this study, there is a lack of evidence to support the model overall as a correct algorithm. Specifically, the observed p-values are extremely small and 19 days for the Pre-War period seems too large, which adds doubts to this algorithm.

Taking the results with a grain of salt, the overall results are still very convincing. An implicit difference between the two global events – COVID-19 and Ukraine War – is that Ukraine War should be considered as a more dramatic event. A global pandemic is a gradual process that occurs over months or even years, and its impact on the financial markets is also subtle at a given timestamp. On the other hand, the Kremlin announced a war is more disruptive and effective to the market. Therefore, this difference explains the small gap in the pandemic case–5 days and 4 days, where they are 19 and 0 for the war case.

Moreover, the Stock Market is more complex than the selected individual stocks and indexes. Although the attempt was made to include all kinds of industries, it may still fall short in generalizing the overall market. As an example, there could be stocks that behave in the opposite direction than suggested, but they are not included in the data, and thus become potential confounds to the study.

One of the most unexpected challenges was the ARDL model was not satisfied with the available data. Luckily, a programming trick was applied for the model to properly regress. Due to this limitation, we failed to explore higher lags in this model, and its result only partially validates the conclusions without statistically significant measures.

Regardless, we hope that this study could provide some new analytical insights into financial systems during dramatic global events.

5 Future Works

As mentioned in the previous discussion, one future complementary study is validating the correctness of the naive algorithm proposed in this study. A possible approach can be running this algorithm on additional similar data and checking the results. For example, one can investigate the relationships before and after the September 11 Attacks.

In the future, we can also explore more data sets such as different economies in the world instead of limiting ourselves to the U.S. and European markets. More stocks and indices could be included if we have the capabilities. Exploring how different industry stocks affect foreign exchange rates and which industry has the largest impact on foreign exchange markets are also directions we can consider.

Possible improvements in the choice of global events could also be made in the future of this study. Instead of choosing a gradual process like the COVID-19 pandemic, we could conduct future research with our model on events that happens more suddenly, such as terrorism incidents or natural disasters.

In addition, this study deviates from the major research direction in this field – prediction, but rather focuses on analyzing events. Thus, another automatic research direction would be creating a prediction model that incorporates the probabilistic nature of global events. This field of research can enable many possibilities such as event-driven automated stock/foreign exchange (FX) trading systems.

6 Appendix

See the Notebook and the reference folder submitted on Coursework.

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