Financial Data Analytics Project

Code

AUTHOR
[Sahil]

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1 Introduction

1.1 Research Questions and Project Overview

This report explores how the USD/GBP exchange rate has behaved over the past decade, especially during periods of high-stress. It builds around three questions that move from exploring market behavior to modelling volatility, and finally, testing if these movements spill over into the stock market.

1. Exploratory Analysis: How has the volatility of the USD/GBP rate changed over time? We start by identifying - a) pattern in fluctuations, b) clusters of high volatility, and c) the empirical distribution of returns.

2. Time Series Modelling: What's the best GARCH model for figuring out how volatile market is? We compare family of GARCH models to identify the most effective model to handle stress periods.

3. Advanced Analysis: Can we use VAR models to see how events in one market affect other markets? Through a Vector Auto-regression (VAR) model, we examine whether currency movements spill into the UK's stock market.

These questions form a progressive investigation, starting with basic exploration, moving to formal modeling, and culminating in advanced analytical techniques.

1.2 Background

Exchange rates are barometer of economic health and key determinant of foreign investment. For the UK, two recent events shook markets: Brexit in 2016, when the pound plunged nearly 8% overnight, and the 2020 COVID crisis, which saw GBP fall to levels last seen in the 1980s. These sharp movements raise questions about how volatility builds and spread.

1.3 Research Objectives

This project aims to:

- Identify and visualise volatility clusters in the USD/GBP.
- Quantify volatility persistence using GARCH models.
- Test whether exchange rate shocks spill over to the FTSE 100 using VAR.

1.4 Literature Review

Prior work by Cont (2001) and Andersen et al. (2001) shows financial returns often cluster and have fat tails. Bollerslev (1986) introduced GARCH to model this. Sims (1980) later developed VAR models to analyse market relationships, with studies like Forbes & Rigobon (2002) and Narayan (2021) showing how crises can link markets unexpectedly.

2 Data and Methods

2.1 Data Description

Two financial time series datasets were sourced from the `tsfe` R package. The primary dataset is the USD/GBP exchange rate, originally spanning from January 2010 to mid-January 2020. To capture the increasing uncertainty during the early COVID-19 period, I extended the dataset by adding 50 daily observations from 17 January to 31 March 2020. Data expansion was crucial to present the steep depreciation of the British pound on 18 March 2020 during the global lockdown announcement.

After cleaning the exchange rate data, I transformed data into an `xts` time series to facilitate use in modeling packages like `rugarch` and `forecast`. From this cleaned dataset, log returns were calculated, for better presentation, I converted into percentage returns. Log helps to stabilize the variance and is widely adopted in financial econometrics.

Inter-market analysis in the final stage of the project is supported by the FTSE All-Share Price Index, sourced from `tsfe::indices`. After aligning the date ranges and cleaning for missing values, I calculated log returns for the FTSE index in the same manner. The final dataset includes synchronized daily log returns for both the USD/GBP exchange rate and the FTSE index, allowing for bivariate analysis using the Vector Auto-regressive (VAR) model.

Dataset	Coverage	Frequency	Variables Used
USD/GBP Exchange Rate	Jan 2010 – Mar 2020 (extended)	Business Days	Spot rate, log returns (%)
FTSE All-Share Index	Jan 2010 – Mar 2020	Business Days	Index value, log returns (%)

These datasets serve as analytical backbone for understanding volatility, modeling dynamic behavior, and evaluating shock transmission across markets.

2.2 Data Preparation

I started with converting the USD/GBP series into a tidy `tibble` structure and renaming variables. As the original dataset ended before the pandemic, I manually appended 50 new rows via `tribble()` to include data through the end of March 2020. This ensured that the dataset captured one of the most volatile scenario in recent currency history.

After merging the new and original series, duplicates were removed and the full dataset was ordered by date. Log returns were then calculated using the formula:

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \times 100, \quad \text{where } P_t \text{ is the price on day } t$$

To visualise long-term currency dynamics, I computed and plotted average annual exchange rates between 2010 and 2020. Unveiling steady pattern of depreciation, with a sharp structural break in 2016, corresponding to the Brexit referendum, and another fall in March 2020 during the COVID-19 crisis.

For the advanced analysis in Section 3, I prepared a merged dataset combining the USD/GBP and FTSE-100. After aligning dates and dropping missing values, log returns were calculated for both series. The resulting return series were employed as the underlying data for VAR estimation and subsequent shock transmission analysis.

The data preparation collectively ensured:

- Full coverage of crisis periods (Brexit, COVID-19).
- Clean and stationary return series for modeling.
- Bivariate alignment for VAR-based spillover testing.

2.3 Methodology

2.3.1 Exploratory Analysis Methods

The focus of this section was to understand the statistical properties of the USD/GBP exchange rate returns. A histogram and density plot of the log returns were used to assess normality and identify fat tails. To further explore distributional properties, a QQ plot was generated, which revealed heavy-tailed behaviour compared to the Gaussian benchmark.

Time series plots of the log returns highlighted visually distinct periods of high volatility, most notably in 2016 and 2020. To investigate volatility clustering, we computed the auto-correlation functions (ACF) of both raw returns and squared returns. While the raw return series showed little autocorrelation, the squared returns exhibited significant persistence, consistent with the presence of ARCH effects.

The results validated the need for formal volatility modeling via GARCH-family models.

2.3.2 Time Series Modeling Methods

For modeling and forecasting volatility, I estimated GARCH-family models using the `rugarch` package. The mean equation was ARMA(1,0), chosen based on AIC minimization and autocorrelation structure of returns. Three models were estimated: SGARCH(1,1), EGARCH(1,1), and GJR-GARCH(1,1).

Model selection was based on log-likelihood, Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC). Residual diagnostics included:

- Ljung-Box tests for serial correlation in residuals.
- ARCH LM tests for remaining ARCH effects.

- Sign bias tests for asymmetry in volatility.

Out-of-sample forecasts were performed using a rolling 100-day window to simulate real-world prediction. Forecast plots included conditional volatility bands, offering intuitive measures of expected uncertainty.

2.3.3 Advanced Analysis Methods

For Section 3, I used a Vector Auto-regressive (VAR) framework to investigate spillover effects from currency returns to the domestic stock market. After confirming stationarity using the Augmented Dickey-Fuller (ADF) test, I determined the optimal lag length using AIC and Schwarz Criterion (SC). The VAR model enabled:

- Granger causality testing to assess predictive relationships.
- Impulse response functions (IRF) to visualise the effect of GBP shocks on FTSE returns.
- Forecast error variance decomposition (FEVD) to determine the relative contribution of each market to future uncertainty.

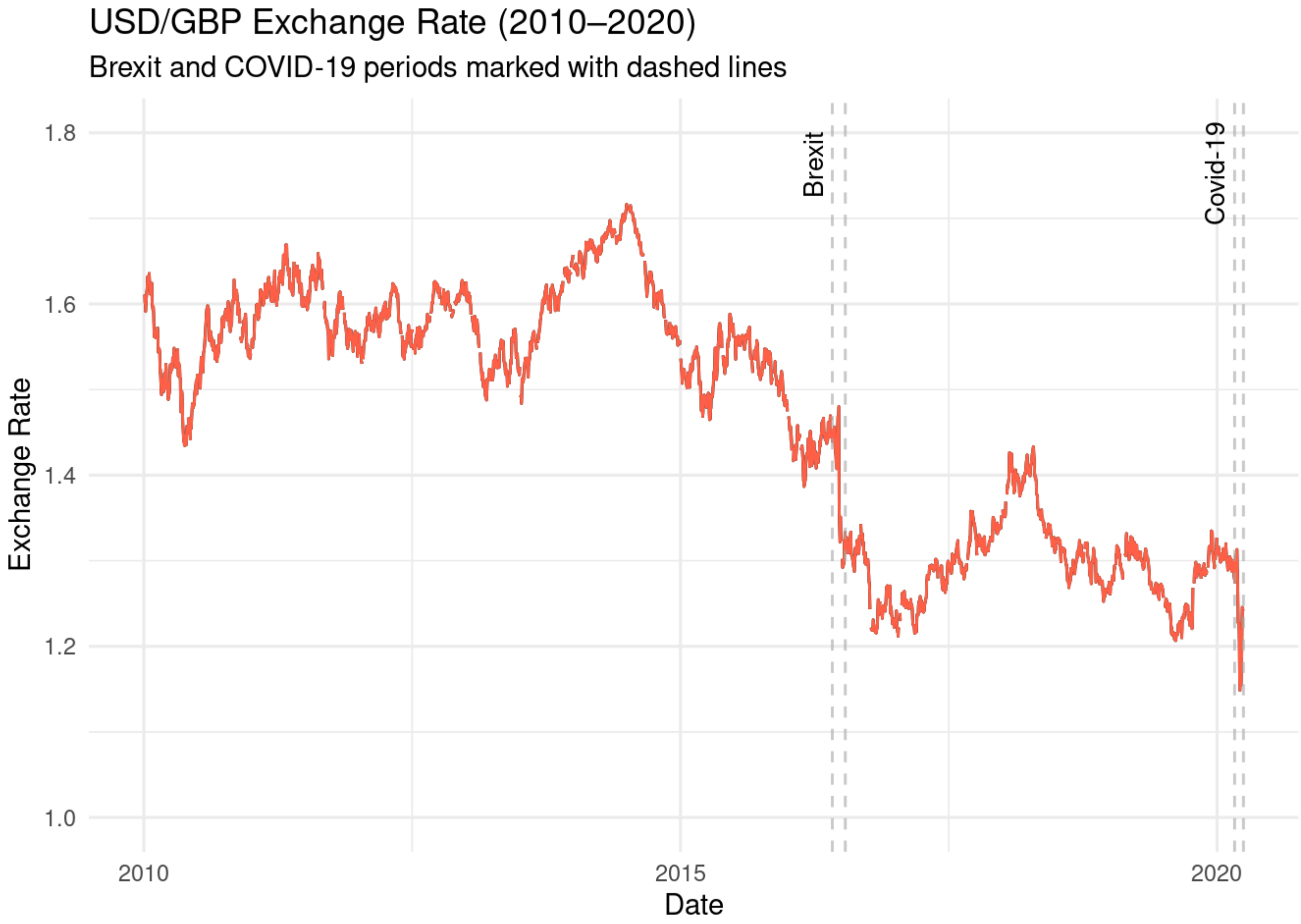
This multivariate approach provided insights into how financial shocks propagate across interconnected markets, particularly during high-stress events like Brexit and the COVID-19 pandemic.

3 Results

3.1 Exploratory Analysis Results

To understand the volatility of the USD/GBP exchange rate, we began with a time series plot of the exchange rate from 2010 to March 2020. This helped us visually identify structural breaks, especially around key macroeconomic events such as the Brexit referendum in June 2016 and the COVID-19 outbreak in March 2020.

▶ Code



Furthermore, the 30-day rolling volatility chart also highlights two clear spikes mid-2016 (Brexit) and early 2020, COVID-19, marking periods of heightened and sustained uncertainty in the FX market.

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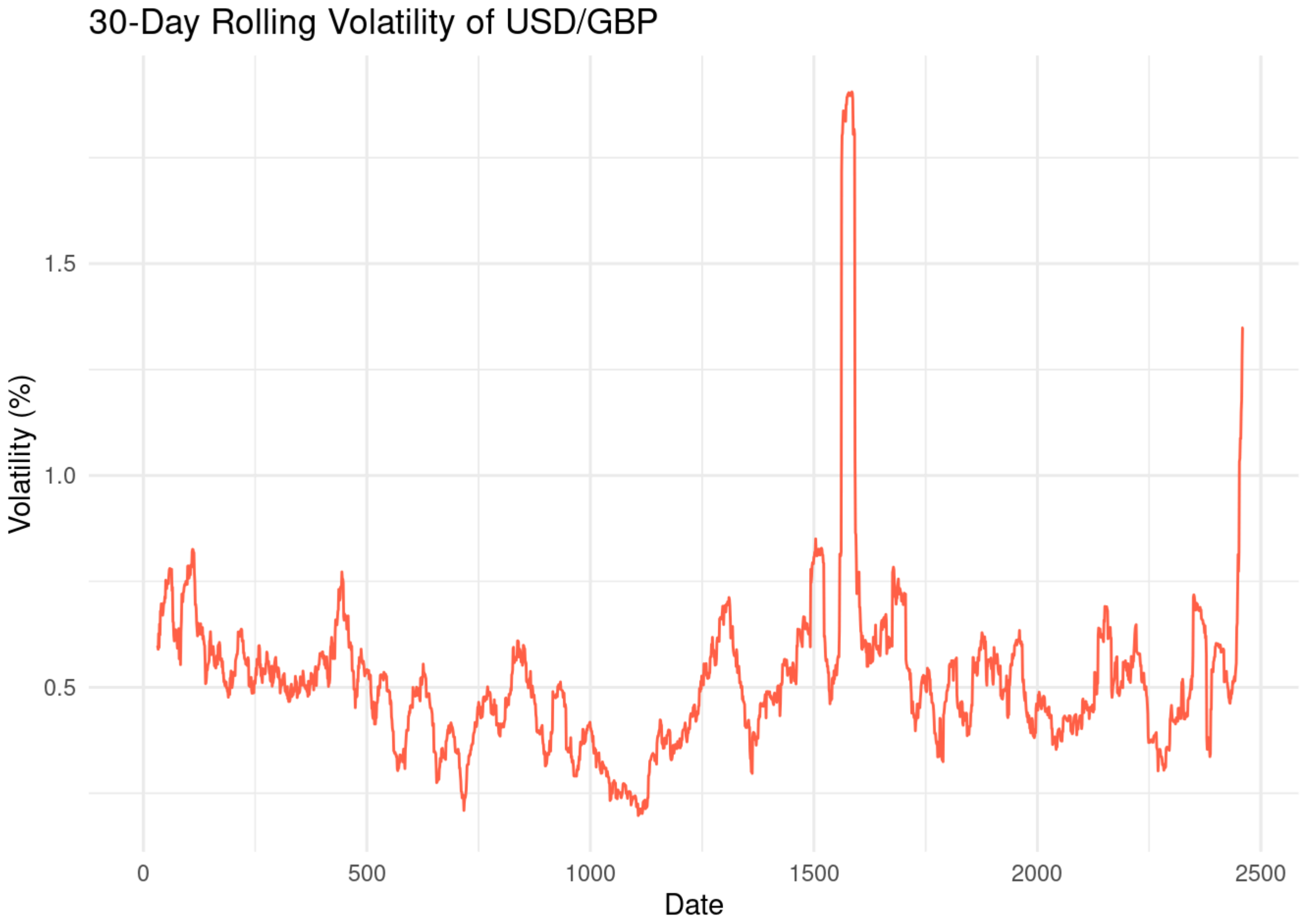

We then created a histogram of annual average exchange rates to provide a macro-level understanding of exchange rate behavior across years. The histogram shows a stable exchange rate before 2015, a steep decline in 2016 corresponding to the Brexit vote, and further weakness during 2020 as the pandemic hit.

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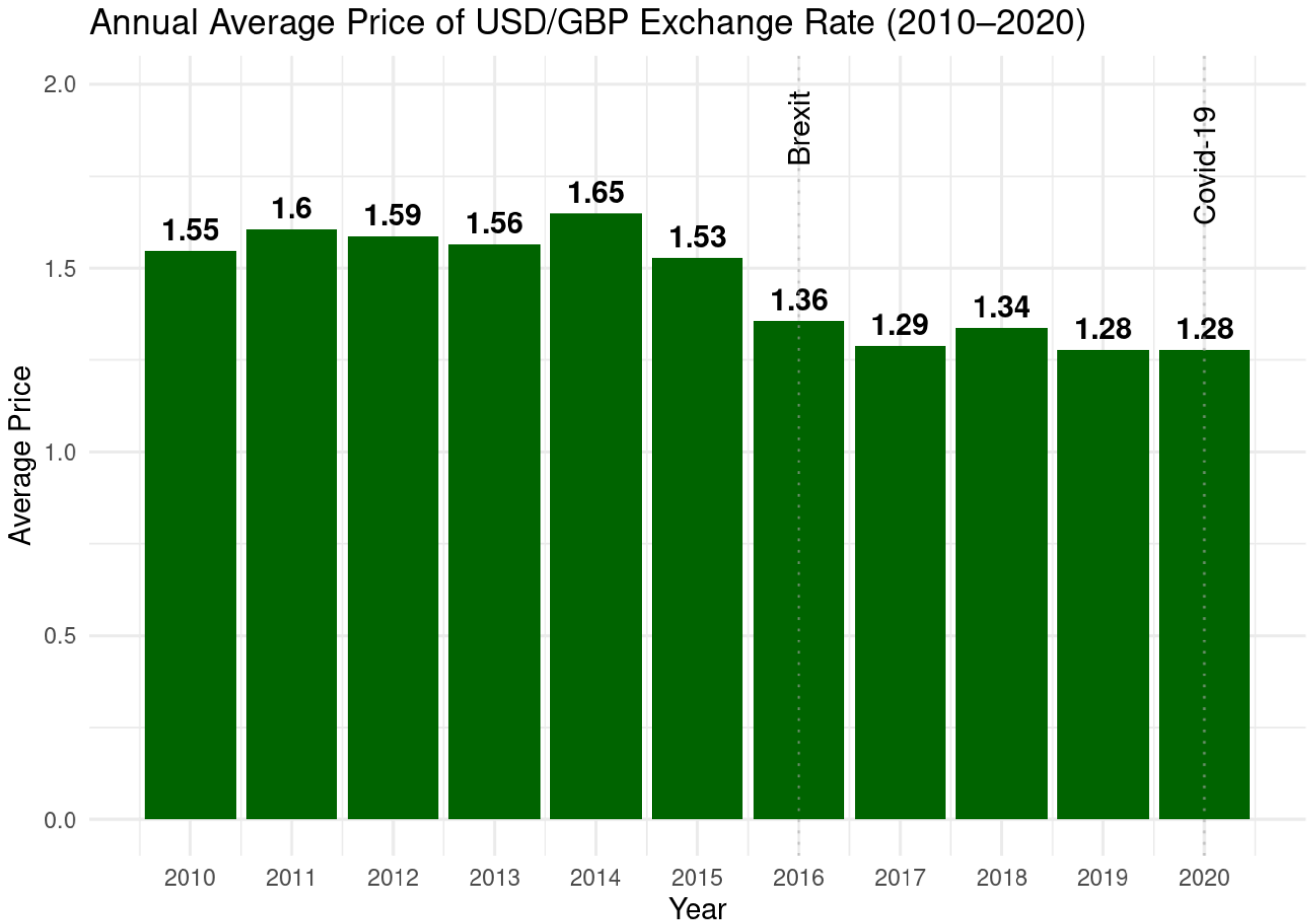

To quantify fluctuations, we calculated daily log returns and plotted them:

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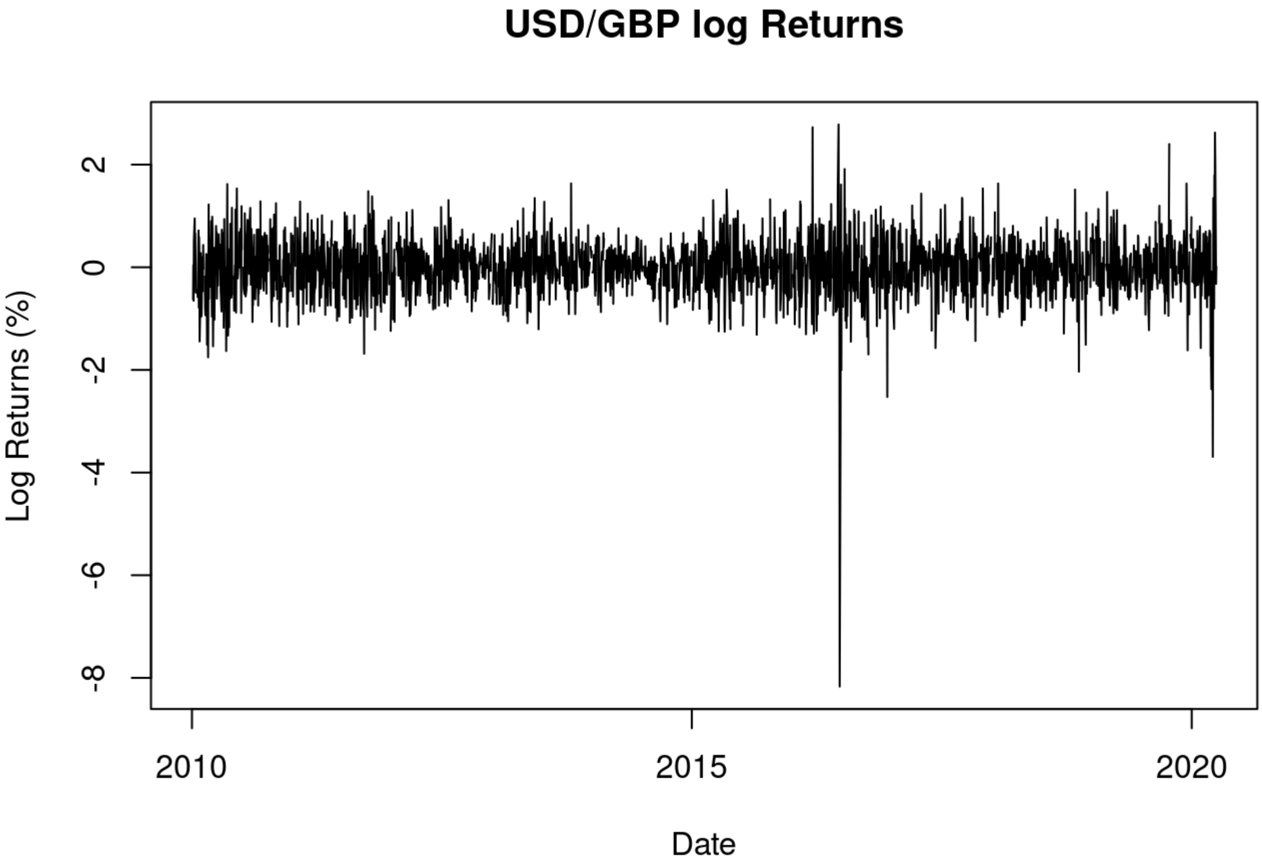

Period of sharp spike can be noticed:

We looked at those two significant stress scenarios closely by zooming in to each periods.

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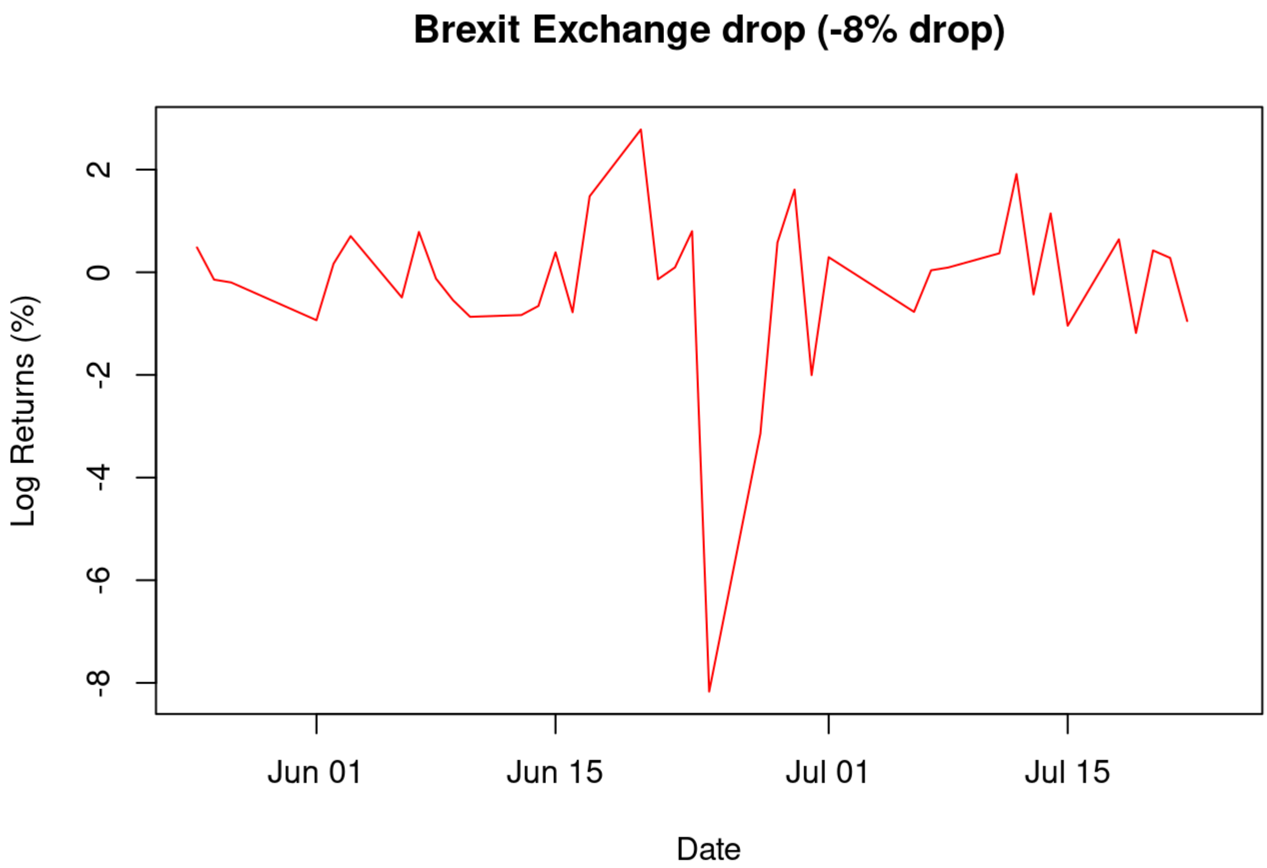
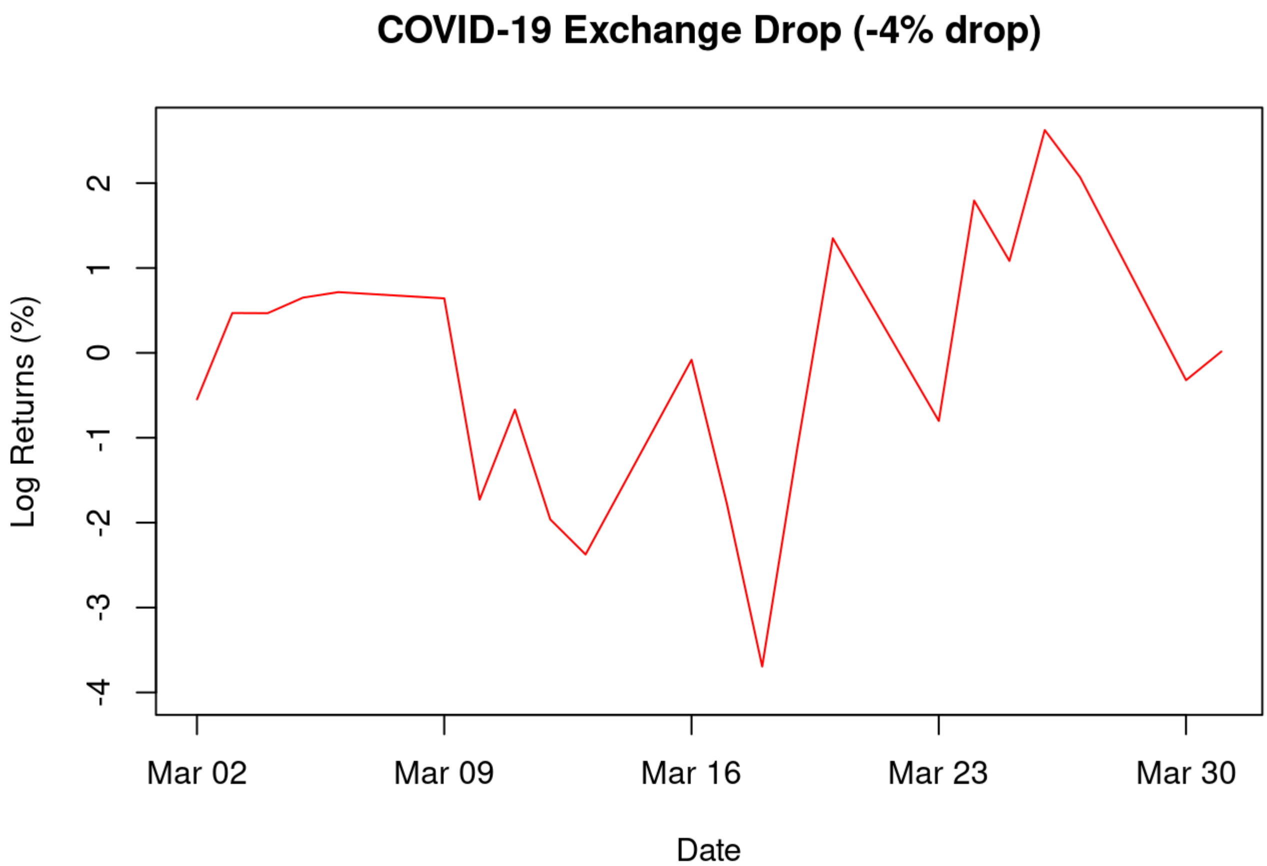

Brexit Exchange drop (-8% drop)
Log Returns (%)
2
0
-2
-4
-6
-8
Jun 01
Jun 15
Jul 01
Jul 15
Date

▶ Code


COVID-19 Exchange Drop (-4% drop)
Log Returns (%)
2
1
0
-1
-2
-3
-4
Mar 02
Mar 09
Mar 16
Mar 23
Mar 30
Date

During Brexit, the pound lost its largest one-day value in over 30 years, declining by over 8% against the USD (Treanor et al., 2016). Similarly, in March 2020, the COVID-19 outbreak triggered a sharp depreciation as international markets reacted to lockdowns and emergency policy reactions (Islam, 2020). They were not isolated market reactions - they were coordinated with the UK's largest current account deficits in decades. In 2016, for instance, the UK's trade deficit was 5.4% of GDP, in part because it relied on EU imports for roughly 40% of its total import volume. The shift from tariff-free trade inside the EU to tariff-imposed trade after Brexit also put additional pressure on the balance of payments.

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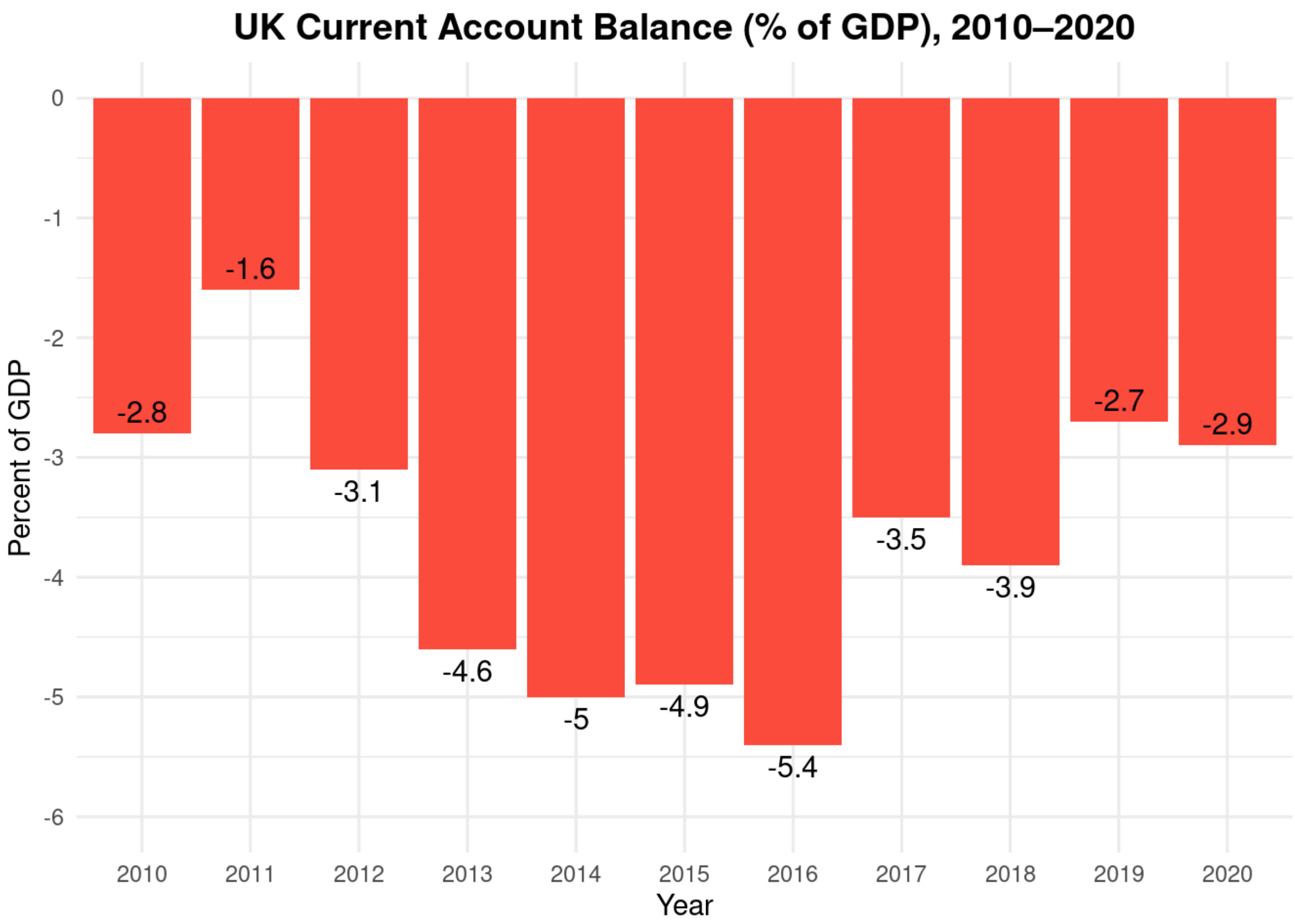

Before choosing the correct model for volatility, we checked if returns are normally distributed. If they are not, standard models will reduce the probability of large changes in the market.

To explore this, I used a Q-Q plot and a histogram. The Q-Q plot shows how real USD/GBP returns relate to a normal distribution. We can see significant deviations from the red reference line at both tails - especially at the extremes. This shows that large losses and gains happen more often than a normal model would expect.

The left tail indicates that large losses occur with higher frequency. We experienced it in Brexit and the COVID-19 crash. Such trend is Leptokurtic.

▶ Code

The histogram of USD/GBP log returns also show a steep central peak and long left tail, suggesting returns are tightly clustered around the mean but with occasional sharp losses. This asymmetry, not easily seen in the QQ plot, reflects a negative skew - where extreme downside movements occur more frequently than gains.

Such return behaviour reinforces the need for models that account for asymmetry and tail risk, like EGARCH, especially in stress periods like Brexit and COVID-19.

Egan (2007) and Hatem et al. (2022) found similar patterns in other markets, noting that extreme price movements occur more frequently than the normal distribution predicts. This holds true for USD/GBP returns as well. Together, the QQ plot and histogram confirm that the distribution is not normal - it exhibits fat tails, negative skew, and frequent extreme values, particularly during crisis periods like Brexit and COVID-19.

These characteristics highlight the need for more flexible models such as GARCH to better capture the true nature of volatility.

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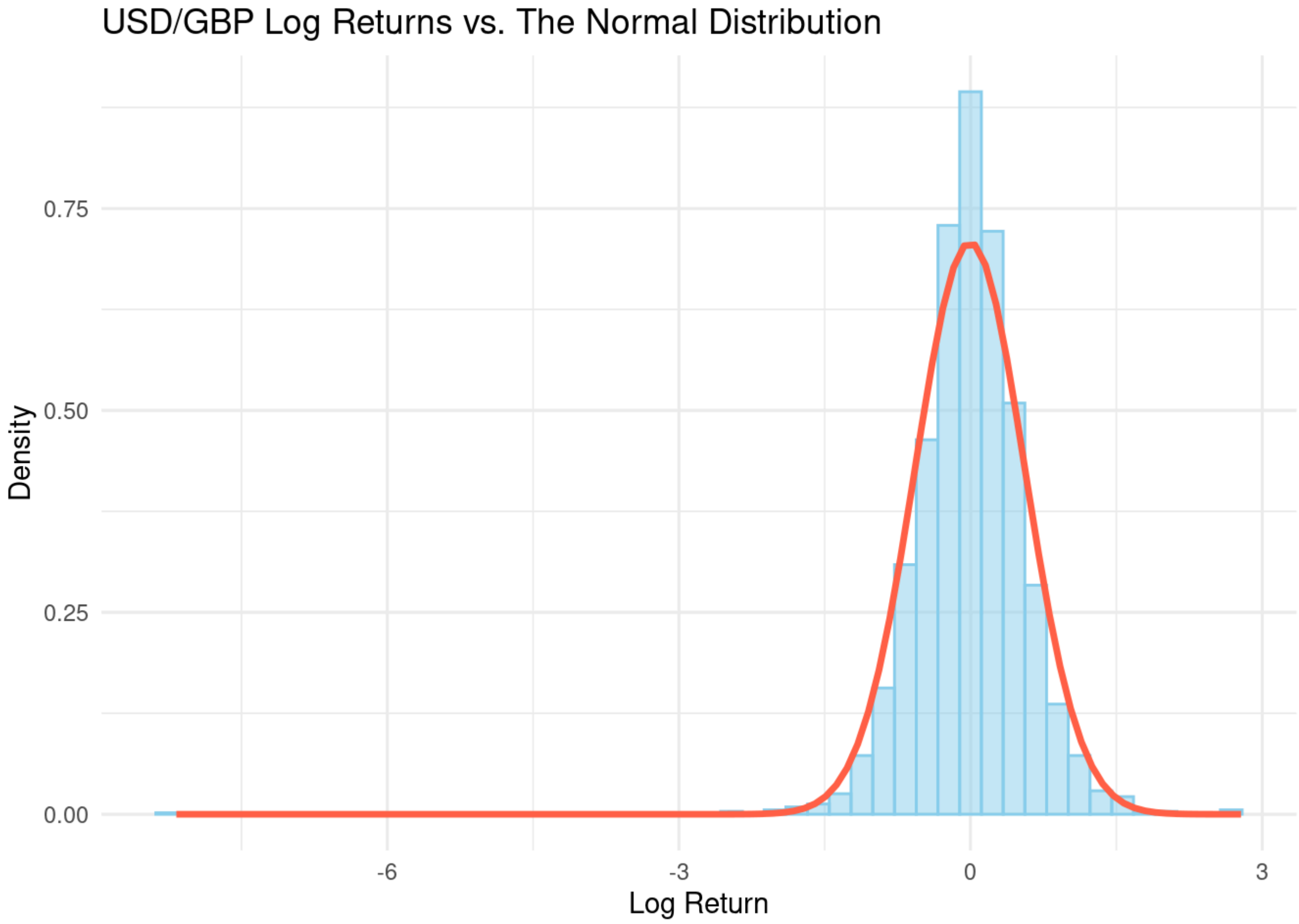

But prior to that, we need to examine the auto-correlation function (ACF). The ACF of raw returns had little serial correlation, but the ACF of squared returns had high persistence, particularly at lag 1. This is textbook evidence of volatility clustering (where high volatility periods are followed by high volatility periods) one of the primary characteristics of financial time series.

Our findings are closely aligned with Niswatul Qona'ah (2023), who predicted and simulated USD/GBP volatility through ARIMA and GARCH modeling. The article concluded that EGARCH(1,1) was a better model than other models at modeling asymmetric and non-linear behavior, especially during volatile periods. Stationarity and clustering of volatility were highlighted by the article as the key features of good modeling.

Collectively, our ACF test and existing research (e.g., Bollerslev, 1986) justifies the application of GARCH-type models.

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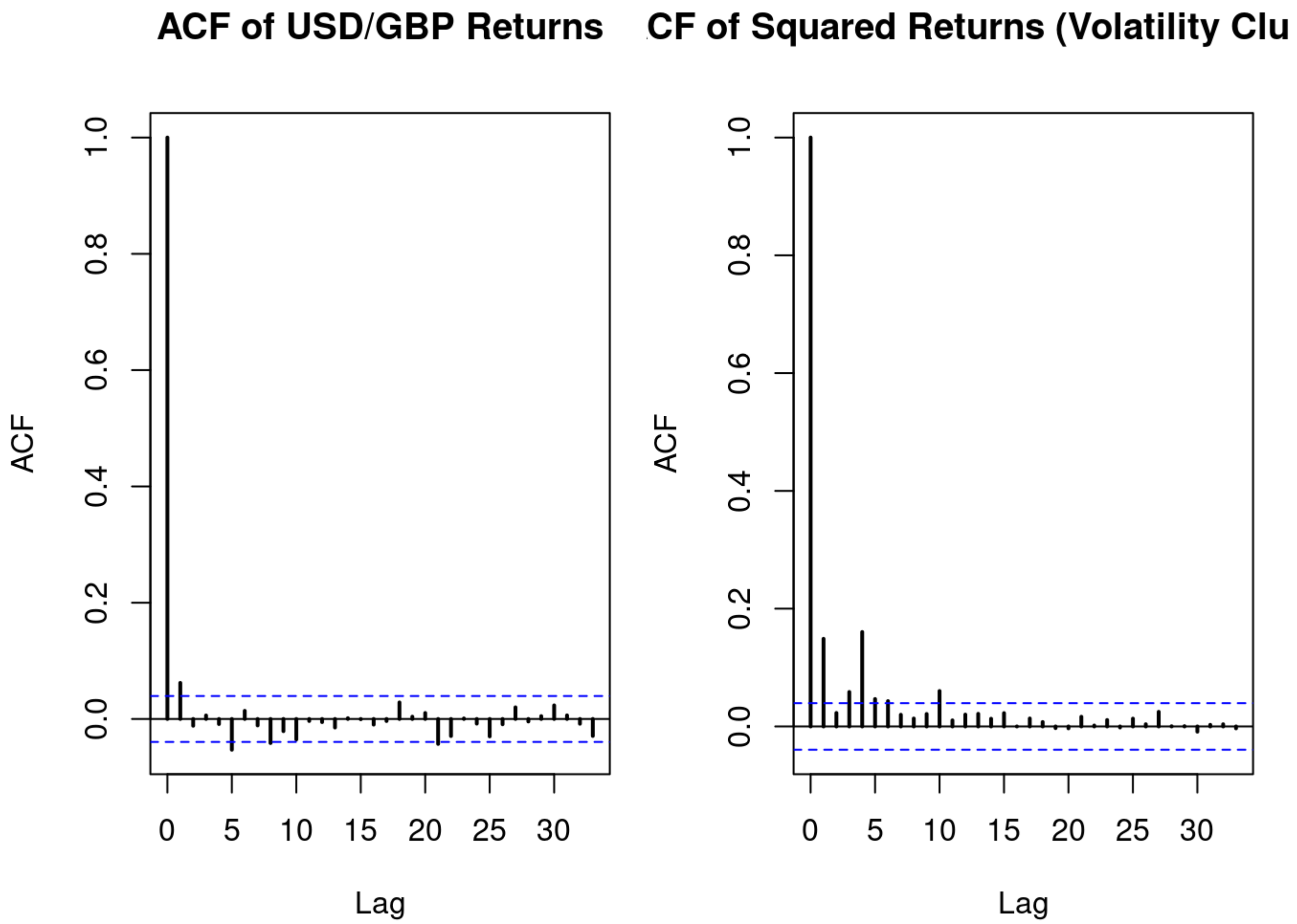

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3.2 Time Series Modeling Results

Before fitting any time series model, we need to ensure the data is stationary. The Augmented Dickey-Fuller (ADF) test confirms that the USD/GBP return series is stationary (Dickey-Fuller = –14.33, p < 0.01), meaning its statistical properties remain stable over time.

▶ Code

```
	Augmented Dickey-Fuller Test

data:  usuk_merged_clean$log_returns
Dickey-Fuller = -14.334, Lag order = 13, p-value = 0.01
alternative hypothesis: stationary
```

After confirming stationarity, we tested for ARCH effects to check if volatility changes over time. The ARCH LM test strongly rejected the null hypothesis (Chi-squared = 124.7, p < 0.001). This supports our decision to use GARCH models, which are designed to capture these time-varying patterns in exchange rate volatility.

▶ Code

```
	ARCH LM-test; Null hypothesis: no ARCH effects
```

```
data:  usuk_merged_clean$log_returns
Chi-squared = 124.7, df = 12, p-value < 2.2e-16
```

We began by estimating a standard GARCH(1,1) with AR(1) mean. The results were no surprise: both short-run shocks ($Alpha_1$= 0.084) and long-run persistence ($Beta_1$ = 0.903) were significant, and omega = 0.00547 is capturing the steady-state volatility. Since alpha + beta < 1, the process is stable but very persistent - shocks like Brexit or COVID-19 do not wear off quickly.

Model diagnostics preferred a good fit. Ljung-Box tests confirmed there was no residual auto-correlation, and the Sign Bias test indicated there was no asymmetry, so a symmetric GARCH specification was required. There was no residual ARCH effect either.

Practically, this confirms that while USD/GBP returns are hard to predict directionally, their volatility is anything but random. This underlines the need for risk management instruments responding to volatility instead of returns. These findings validate our modeling approach and open the door to exploring more flexible GARCH models and spillover dynamics in the following sections.

▶ Code

```
*---------------------------------*
*          GARCH Model Fit        *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model : sGARCH(1,1)
Mean Model  : ARFIMA(1,0,0)
Distribution    : norm

Optimal Parameters
------------------------------------
        Estimate  Std. Error  t value Pr(>|t|)
mu     -0.002969    0.009900 -0.29988 0.764269
ar1     0.021408    0.021482  0.99655 0.318983
omega   0.005470    0.002218  2.46595 0.013665
alpha1  0.083852    0.012197  6.87473 0.000000
beta1   0.903402    0.016288 55.46394 0.000000

Robust Standard Errors:
        Estimate  Std. Error  t value Pr(>|t|)
mu     -0.002969    0.010426 -0.28475 0.775838
ar1     0.021408    0.020981  1.02036 0.307559
omega   0.005470    0.003838  1.42524 0.154087
alpha1  0.083852    0.034101  2.45894 0.013935
beta1   0.903402    0.037021 24.40225 0.000000

LogLikelihood : -1886.38

Information Criteria
------------------------------------

Akaike       1.5371
```

```
Bayes        1.5489
Shibata      1.5371
Hannan-Quinn 1.5414

Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                        statistic p-value
Lag[1]                     0.2845  0.5938
Lag[2*(p+q)+(p+q)-1][2]    0.3200  0.9927
Lag[4*(p+q)+(p+q)-1][5]    0.7042  0.9811
d.o.f=1
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                        statistic p-value
Lag[1]                     0.4174 0.51823
Lag[2*(p+q)+(p+q)-1][5]    5.8786 0.09605
Lag[4*(p+q)+(p+q)-1][9]    9.7184 0.05759
d.o.f=2

Weighted ARCH LM Tests
------------------------------------
            Statistic Shape Scale  P-Value
ARCH Lag[3]    0.6691 0.500 2.000 0.413350
ARCH Lag[5]   10.4967 1.440 1.667 0.004970
ARCH Lag[7]   11.6623 2.315 1.543 0.007473

Nyblom stability test
------------------------------------
Joint Statistic:  1.4521
Individual Statistics:
mu     0.1847
ar1    0.1241
omega  0.4428
alpha1 0.1837
beta1  0.1833

Asymptotic Critical Values (10% 5% 1%)
Joint Statistic:         1.28 1.47 1.88
Individual Statistic:    0.35 0.47 0.75

Sign Bias Test
------------------------------------
                   t-value   prob sig
Sign Bias           1.1824 0.2371
Negative Sign Bias  0.7073 0.4795
Positive Sign Bias  0.6847 0.4936
Joint Effect        1.4370 0.6969


Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
```

```
1    20     31.39      0.03653
2    30     42.77      0.04775
3    40     45.38      0.22335
4    50     54.75      0.26568


 Elapsed time : 0.3669333
```

While the GARCH(1,1) model captured volatility clustering well, it assumes that markets react the same way to good and bad news. To test for asymmetry (where negative shocks have a bigger impact) we estimated EGARCH(1,1) and GJR-GARCH(1,1) models. These extensions allow us to capture the so-called leverage effect often observed in financial markets.

▶ Code

Both EGARCH and GJR-GARCH models showed a better fit (lower AIC/BIC) and captured asymmetries in volatility, making them more suitable for modeling USD/GBP returns.

▶ Code

```
      Model      AIC      BIC
1     GARCH 1.537083 1.548883
2    EGARCH 1.487367 1.503888
3 GJR-GARCH 1.495367 1.511888
```

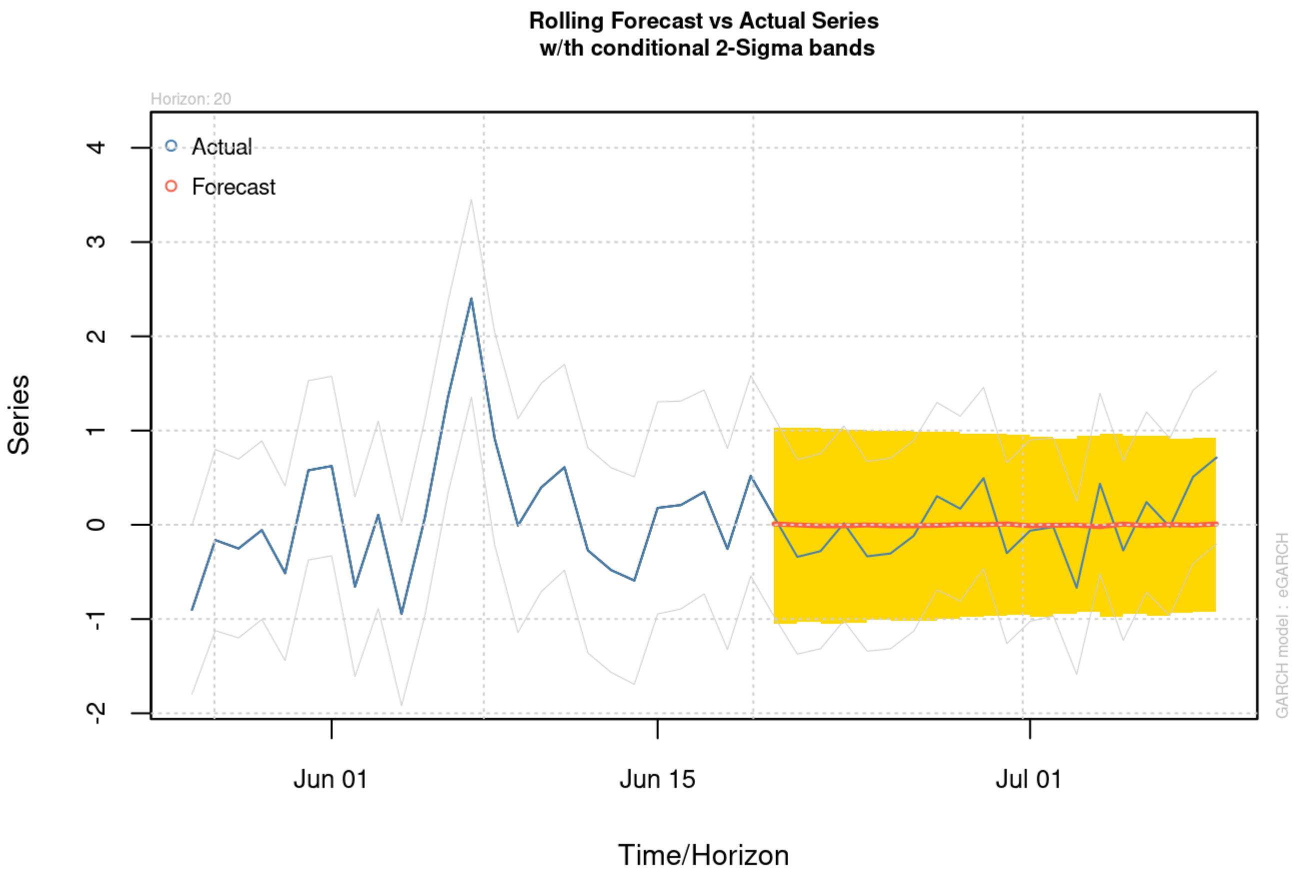
Both EGARCH and GJR-GARCH were better than the baseline GARCH model based on AIC and BIC but both models better described the asymmetric characteristic of financial volatility. I used the EGARCH-t model for forecasting as it was more flexible and a better fit.

The out-of-sample forecast kept a close correspondence with realized volatility, with most of the observations staying within the 2-sigma bands. This is particularly relevant to FX markets, where abrupt, event-driven movements like Brexit and COVID-19 are common.

The model confirms what we have observed thus far: volatility is elevated and responds vigorously to shocks in the market. That it is capable of replicating asymmetry and fat tails renders EGARCH highly suitable for obtaining the actual risk dynamics of the USD/GBP exchange rate.

Therefore, EGARCH(1,1) with Student-t distribution is the best-fitting model.

▶ Code



3.3 Advanced Analysis Results

Before estimating the VAR model, we confirmed that both USD/GBP and FTSE 100 return series were stationary using the ADF test. Both tests returned highly negative statistics (−14.69 and −14.89) with p-values < 0.01, allowing us to reject the null of non-stationarity.

▶ Code

```
	Augmented Dickey-Fuller Test

data:  df$gbp_return
Dickey-Fuller = -14.688, Lag order = 13, p-value = 0.01
alternative hypothesis: stationary
```

▶ Code

```
	Augmented Dickey-Fuller Test

data:  df$ftse_return
Dickey-Fuller = -14.886, Lag order = 13, p-value = 0.01
alternative hypothesis: stationary
```

To explore the interaction between currency and equity markets, we fitted a Vector Auto-regression (VAR) model using the two stationary return series. Although AIC and FPE suggested a lag of 4, we opted for a more stable VAR(2) specification.

The results show that GBP returns exhibit short-term autocorrelation - lag 2 was significant (p = 0.002). However, FTSE returns showed only weak auto-correlation at lag 1 (p = 0.041), and there was no statistically significant spillover from GBP to FTSE or vice versa.

This was confirmed by the forecast error variance decomposition (FEVD), which showed that both GBP and FTSE returns are mostly driven by their own past shocks over a 10-day horizon.

- GBP returns: Significant own-lag effect at lag 2 (p = 0.002), indicating short-term persistence.
- FTSE returns: Mild auto-correlation at lag 1 (p = 0.042), no impact from GBP.
- Spillovers: No strong evidence of predictive influence between markets.

These findings suggest that, during stress periods like Brexit and COVID-19, GBP volatility did not meaningfully spill into UK equities.

▶ Code

```
AIC(n)  HQ(n)  SC(n) FPE(n) 
     4      1      1      4 
```

▶ Code

```

VAR Estimation Results:
========================= 
Endogenous variables: gbp_return, ftse_return 
Deterministic variables: const 
Sample size: 2623 
Log Likelihood: -5553.251 
Roots of the characteristic polynomial:
0.2426 0.2426 0.1731 0.1731
Call:
VAR(y = ts_data, p = 2, type = "const")


Estimation results for equation gbp_return: 
=========================================== 
gbp_return = gbp_return.l1 + ftse_return.l1 + gbp_return.l2 + ftse_return.l2 + const 

                Estimate Std. Error t value Pr(>|t|)   
gbp_return.l1   0.014951   0.019675   0.760  0.44738   
ftse_return.l1 -0.001257   0.012548  -0.100  0.92019   
gbp_return.l2  -0.060202   0.019676  -3.060  0.00224 **
ftse_return.l2  0.001730   0.012539   0.138  0.89031   
const          -0.008175   0.010929  -0.748  0.45455   
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1


Residual standard error: 0.5594 on 2618 degrees of freedom
Multiple R-Squared: 0.003789,   Adjusted R-squared: 0.002267 
```

```
F-statistic: 2.489 on 4 and 2618 DF,  p-value: 0.04141


Estimation results for equation ftse_return:
============================================
ftse_return = gbp_return.l1 + ftse_return.l1 + gbp_return.l2 + ftse_return.l2 + const

               Estimate Std. Error t value Pr(>|t|)
gbp_return.l1   0.02306    0.03090   0.746   0.4555
ftse_return.l1  0.04016    0.01971   2.038   0.0417 *
gbp_return.l2  -0.02850    0.03090  -0.922   0.3564
ftse_return.l2 -0.02846    0.01969  -1.445   0.1486
const           0.01513    0.01716   0.882   0.3781
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

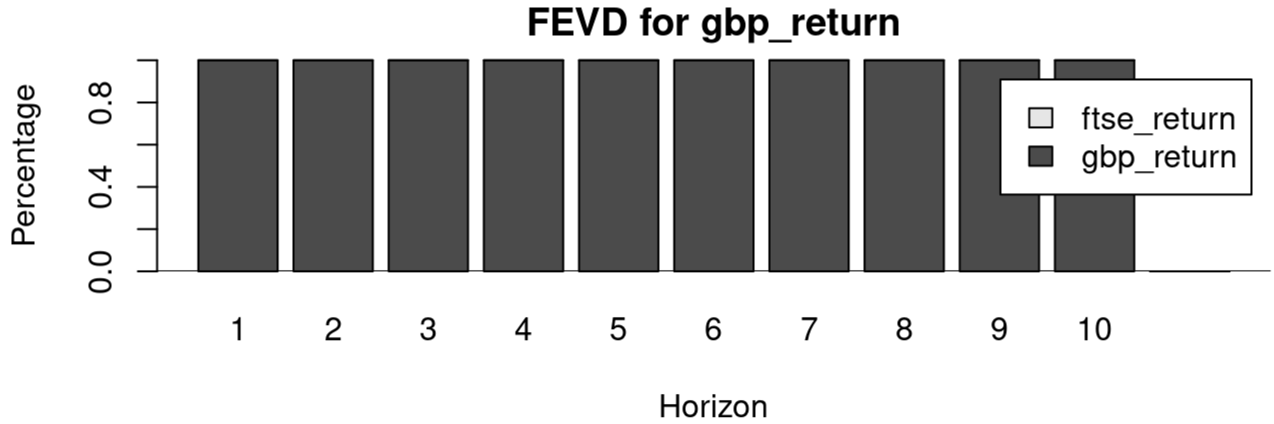

Residual standard error: 0.8786 on 2618 degrees of freedom
Multiple R-Squared: 0.003128,   Adjusted R-squared: 0.001605
F-statistic: 2.054 on 4 and 2618 DF,  p-value: 0.08436

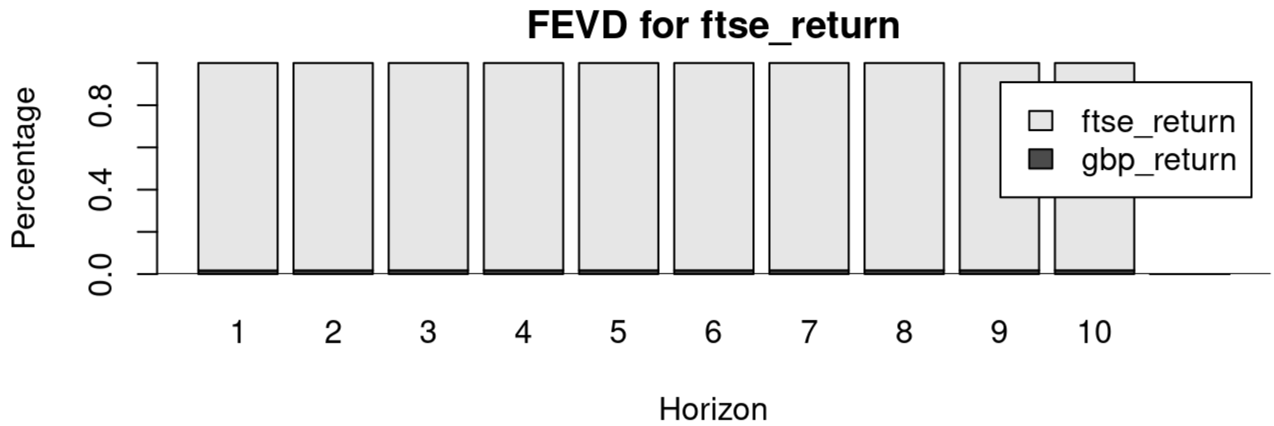


Covariance matrix of residuals:
            gbp_return ftse_return
gbp_return       0.313      0.0640
ftse_return      0.064      0.7719

Correlation matrix of residuals:
            gbp_return ftse_return
gbp_return      1.0000      0.1302
ftse_return     0.1302      1.0000
```

▶ Code





Impulse Response Function (IRF):

A one-unit shock in returns in GBP produced a small, temporary rise in FTSE 100 returns, peaking quickly and vanishing by day three. The initial effect crosses the 95% confidence band momentarily but turns statistically insignificant soon after.

This suggests that the FTSE index reacts to GBP shocks, but neither intensively nor over a long period. This can also be seen in our FEVD exercise, which had suggested both markets to be predominantly self-driven with not much cross-predictive strength.

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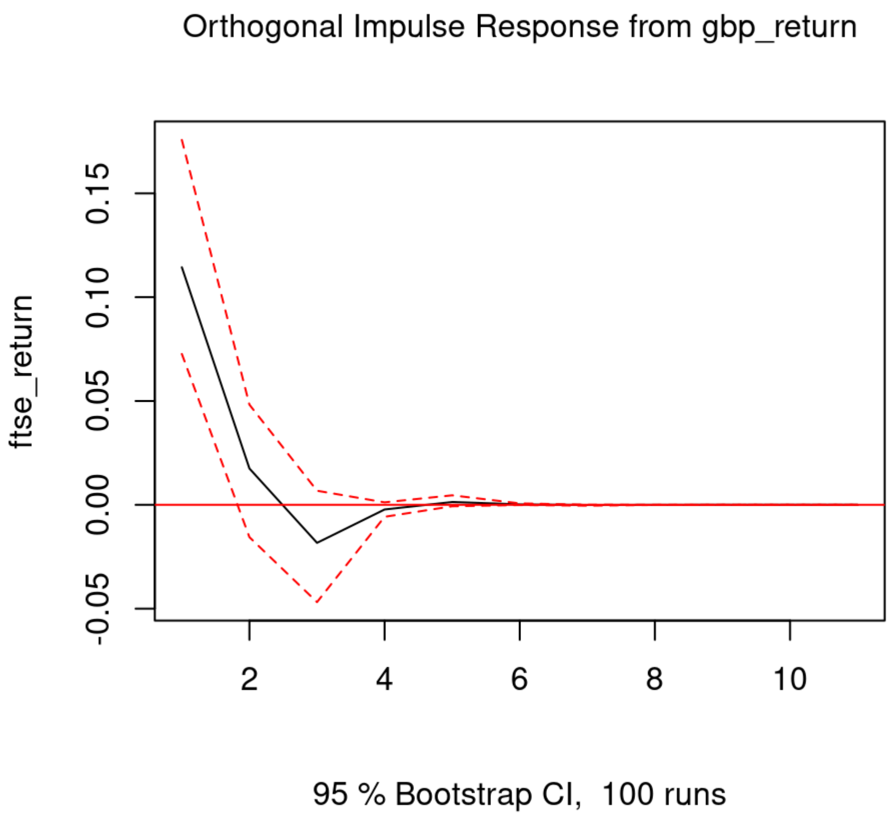

In order to test for predictability, we carried out a Granger causality test. This was not statistically significant (F = 0.695, p = 0.498), suggesting that GBP returns do not Granger-cause FTSE returns. The instantaneous causality test was extremely highly significant (Chi-squared = 43.7, p < 0.001), suggesting the two markets are moving together to shared shocks.

In simple words, contemporaneous relation is high but future influence is low.

▶ Code

```
$Granger

    Granger causality H0: gbp_return do not Granger-cause ftse_return

data:  VAR object model_var
F-Test = 0.69538, df1 = 2, df2 = 5236, p-value = 0.4989


$Instant

    H0: No instantaneous causality between: gbp_return and ftse_return

data:  VAR object model_var
Chi-squared = 43.732, df = 1, p-value = 3.765e-11
```

Therefore, Granger causality was not significant (p = 0.4989), but strong instantaneous causality (p < 0.001) suggests GBP and FTSE returns react simultaneously to common shocks.

4 Discussion

4.1 Integration of Findings

USD/GBP stress behavior and whether it spillovers on UK equities were differentiated in this project. Rolling standard deviations and ACF plots exploratory techniques picked up notable volatility clustering around Brexit and the COVID-19 crash - two of the most confounding events in recent financial history.

Time series analysis confirmed that volatility was not just noise. EGARCH(1,1) with Student-t distribution totally dominated, capturing the persistence and asymmetry of volatility in response to shocks - volatility responded more to bad news than to good.

The VAR model extended this, examining the influence of currency market shocks on equity markets. Though Granger causality was non-existent, the instantaneous spillovers were massive i.e., both GBP and FTSE 100 returns react in real time to other news, such as announcements by central banks or global risk occurrences.

Every test naturally evolved from the last one. They collectively establish USD/GBP volatility to be long-run stable, asymmetric, and part of a general real-time system of market reactions.

4.2 Practical Implications

The findings are pertinent to policymakers and risk managers. Volatility doesn't drop off suddenly models need to keep this persistence or else they end up underpriced risk. The EGARCH model's responsiveness to asymmetry is invaluable in stress tests and crisis management. The VAR outputs capture the way markets coordinate their response to shared shocks, although they do not forecast one another. To policymakers, that means looking to the broader world (primarily FX markets) for direction. To investors, it provides room for policy responses to converge in periods of global unease.

4.3 Limitations

This study utilized daily returns, which are strong but brief market movements. However, intraday returns (capturing price within same day) can provide more precise insights into the volatility spikes or flash crashes.

I did not encompass other such variables such as interest rates, inflation, or world indices in VAR - which could conceivably affect both markets.

As with all models, outcomes of our models are sensitive to assumptions, probability distributions, lag length and sample horizons.

4.4 Future Research

We can expand our scope to multiple other time-series through DCC-GARCH models and identify how market correlations (for multiple assets) change over time (Engle, 2002).

In this report we examined USD/GBP rate and UK stock market. Brexit rightly points out affects in exchange but COVID impacted highly impacted commodities market (e.g., Oil and Metals). In future, these model should be extended to capture more macro-economic linkages so that concerned investors or traders are informed timely.

Machine learning models like LSTMs could also be explored (Moghar and Hamiche, 2020).

4.5 Concluding Remarks

This research chronicled the USD/GBP volatility story through two major stress events (COVID-19 and Brexit) and monitored its UK equity market correlations. We found compelling evidence of clustering, asymmetry, and real-time cross-market reactions. Our findings vindicate why volatility can never be lonely - and why adaptive, multi-layer models are needed to untangle markets today.

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5.1 AI Usage Statement

In accordance with course requirements, I disclose the following AI tool usage:

- **Tools Used:** ChatGPT (OpenAI)
- **How They Were Used:**

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-    Assisted with brainstorming ideas for research framing.

-   Generated and refined R code snippets for statistical analysis and data visualization,
including time series modeling, plotting, and interpreting diagnostics.

**Example Prompts:**

-   *"Which companies use GARCH and VAR models and how it assists them in decision making"*

-   *"How EGARCH(1,1) helps to determine volatility asymmetry?"*

-    *"Can I add annotations in graph?"*
```

- **Verification Process:**

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-    All AI-generated codes were verified with lecture slides and tutorials.

-    Results were reviewed manually for factual correctness, academic papers and articles were
utilzeed for independent review.
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