FX Exposure and Regression Analysis

Introduction

Examining RS Group's foreign exposure based on their foreign operations, sourcing of raw materials and regional sales.

RS Group is a UK-based global MRO distributor, listed on FTSE 250. The firm generates 61% of their revenue from EMEA, 32% of their revenue from Americas and 7% from Asia Pacific (2024, Annual Report). Which shows company's heavy reliance on USD, EUR and other emerging market currencies. Any significant change in these currencies rate against GBP can impact RS groups revenue. However, to determine foreign currency exposure, sales cannot be only factor.

For this individual project, I have taken company's supply chain or distribution centers to determine currency for calculating company's foreign exposure which are as follows:

Supply chain distribution	Currency
United Kingdom	GBP (base currency)
Dublin	EUR
France	EUR
Germany	EUR
Milan	EUR
South Africa	ZAR
North America	USD
China	CNH (RMB offshore)
	CNY (RMB onshore)
Hong Kong	HKD
Japan	JPY
Australia	AUD

For this project, we are considering five currencies as variables for our model.

1. USD : major reserve currency with significant global influence.
2. EUR: represents the European union and is used in multiple regions.
3. JPY: Asia's largest developed economy and adds exposure to east Asian market.
4. ZAR: represents emerging market and geographical diversity.
5. CNH: capture China's growing economy while avoiding onshore trade restriction.

RS Group is listed on FTSE 250, therefore, MCX is the key performance benchmark for RS Group's performance. Hence, returns on MCX are taken as another variable for our model in this project.

For risk-free rate, Bank of England rate is inputted within the model

The equation for performance comparison integrates these factors:

$$STOCKRF_t = \beta_1 + \beta_2 MKRF_t + \beta_3 X_t + \varepsilon_t$$

$STOCKRF_t$ = stock return in excess of the risk free rate for time t

$MKRF_t$ = Market portfolio return in excess of the risk free rate for the time t

X_t= percentage change in the exchange rate factor for time t

> GBPUSDSS + GBPEURSS + GBPJPYSS + GBPZARSS + GBPCNHSS

ε_t = error term for time t

Data Assumption and transformation

All the data is sourced from Bloomberg terminal and used as single source for the data. 10-year historical data starting 1st April 2013 is taken for this research project.

Transformation is done to convert daily prices into log returns using R script. Similarly, daily exchange rate returns and market returns are also converted into log returns. Log returns is used to take compounding into effect and considers reinvesting rather taking initial investment to determine daily return on investment.

Bank of England rate is annualized rate and does not require compounding as it is constant rate throughout the year. Given it is annual rate, one must convert that into daily rate of returns. To do that, risk free rate was divided with number of trading days in financial year i.e., 252 days.

Excess returns are calculated as:

1. $STOCKRF_t = RS1P_t - (Rfr_{(bank\ of\ England)} / 252)$

$RS1P_t$ = daily stock price of RS group, $Rfr_{(bank\ of\ England)}$ = Bank of england annualized returns

2. $MKRF_t = MCXP_t - (Rfr_{(bank\ of\ England)} / 252)$

$MCXP_t$ = Daily index movements in FTSE250, $Rfr_{(bank\ of\ England)}$ = Bank of england annualized returns

Regression analysis using the CAPM model

Below is the multiple linear regression analysis where I have modelled the relationship between the dependent variable RSPEXSS (RS Group daily stock return in excess of risk-free security) and six independent variable (FTSE 250, and five foreign currency exchange rates against GBP). Arguably, these are limited variables that drive stock prices, other economic factors such as supply and demand dynamics, news or events, unsystematic risk within the firm, competitor performance, geo-political risk etc. can have much larger impact. In this research project, we are limiting model to determine firm's foreign exposure, hence, we do not expect model to have high R-squared in-fact model showing R-squared > 90% can cause overfitting or biasness.

Following is the result from regression analysis:

Variable	Estimate	Std. Error	t-value	p-value	Significance
Intercept	0.01714	0.02652	0.646	0.518	(not significant)
MCX Index (MCXEXSS)	**1.13103**	**0.02926**	**38.66**	**< 2e-16**	**(highly significant)**
GBP/USD (GBPUSDSS)	0.07738	0.09776	0.792	0.429	(not significant)
GBP/EUR (GBPEURSS)	-0.1116	0.07526	-1.483	0.138	(not significant)
GBP/JPY (GBPJPYSS)	0.01188	0.05166	0.23	0.818	(not significant)
GBP/ZAR (GBPZARSS)	-0.01776	0.03288	-0.54	0.589	(not significant)
GBP/CNH (GBPCNHSS)	-0.13392	0.10733	-1.248	0.212	(not significant)

MCX Index (MCXEXSS) has the most significant and positive relationship with RSPEXSS. And increase in MCX index will lead the large increase in RSPEXSS

The currency pair variable generally show weak or insignificant relationship with RSPEXSS, though signs vary:

GBP/USD and GBP/JPY are positively related but not significant.

GBP/EUR, GBP/ZAR, and GBP/CNH show negative relationship but are also not significant.

Most variables have a median close to 0, that indicates returns are generally centered around 0 with positive mean of RS1LNSS and MCXSS suggesting upward trends or positive relation between the two variables. Long directional movement occurs in GBPUSDSS, GBPEURSS and GBPCNHSS due to their mean closer to 0.

RS1LNSS has widest range which shows significant fluctuations in returns, possibly due to physical disruptions or supply chain breaking down in Covid period, which we will investigate further. Similarly, GBPZARSS and GBPJPYSS shows large fluctuations as well. These large differences suggests potential of outliers in the data.

RS1LN, MCXSS and GBPJPYSS are positively skewed given their high maximums compared to median. GBPUSDSS and GBPCNH shows signs of negative skewness however, less pronounced.

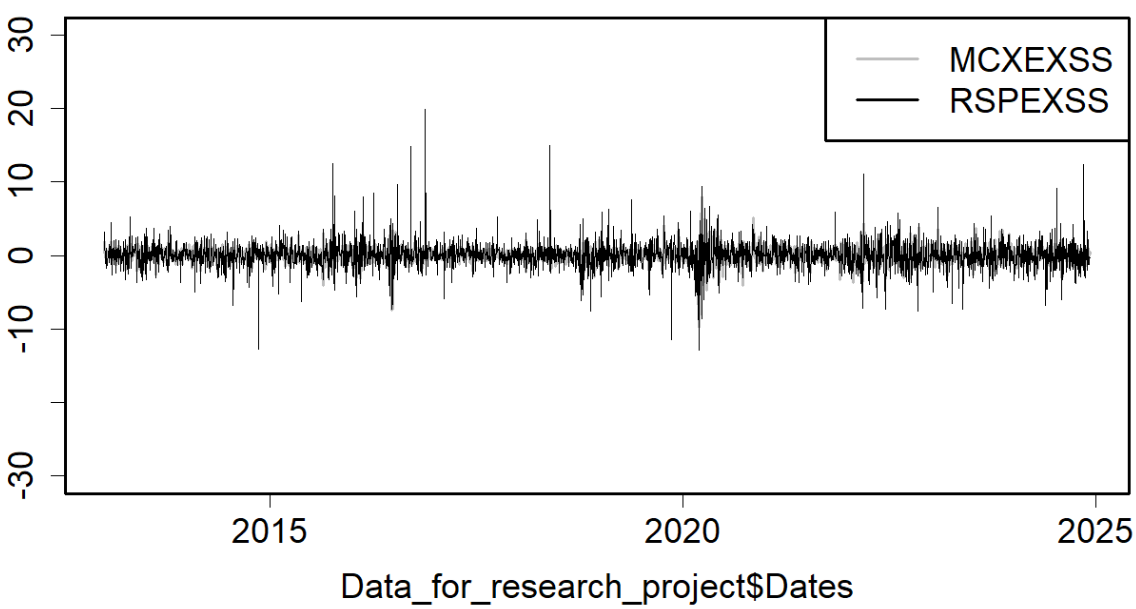
The MCX index is highly significant with a strong positive coefficient of 1.13103. other variables, currency pairs and intercept, are not statistically significant as their $p > 0.05$. however, the model is statistically significant overall with F-statistic p-value < 2.2e-16.

The R-squared and Adjusted R-squared are 0.3629 and 0.3617 respectively implied independent variables explain about 36.2% of the variance in dependent variables.

Therefore, overall model can be concluded as moderate fit which indicates neither overfitting or underfitting in the model so far.

Market returns vs stock returns: the below graph shows two time-series data plotted over the same time period. The x-axis shows the dates, from April 2013 to November 2024 and y-axis shows the value of two variables i.e., MCXEXSS (Market portfolio return in excess of the risk free rate) and RSPEXSS (stock return on RS group in excess of the risk free rate).

Gray line corresponds to MCXEXSS and black line corresponds to RSPEXSS.



Both series fluctuate significantly around the 0 mark. Variables exhibit some high variability with scale ranging from -30 to 30. Both the series present spikes with extreme drawdowns (peaks to trough) occassionally.

On comparison, two sereis overlap frequently, represents positive correlation or relatioship. However, amplitudes and timing of extreme spikes slightly differ. Simply, that suggests possible stress periods for the firm (unsystematic risk) or market (systemactic risk).

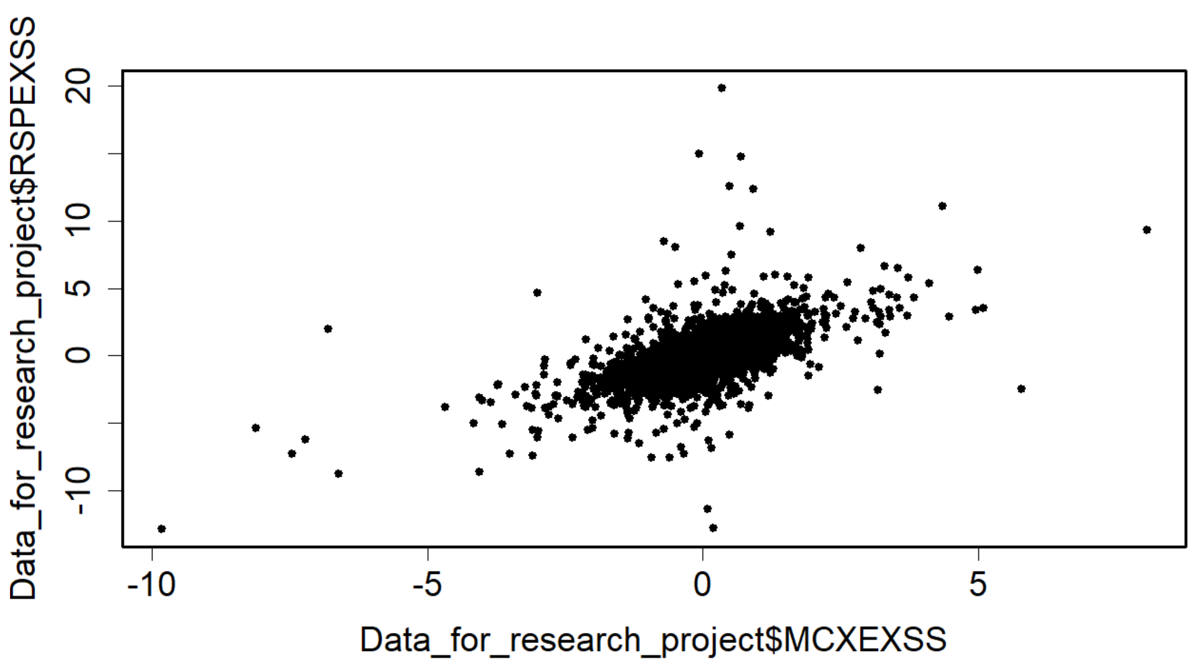
Therefore, the plot describes volatility, trends and outlier events (or possible worst case scenario, major market events).

CAPM model describes the relationship between a stock's expected return and market's expected return which are as follows:

$$STOCKRF_t = Rfr(_{\text{bank of England}}) / 252 + \beta * [MCXP_t - (Rfr(_{\text{bank of England}}) / 252)] + \varepsilon_t$$

If the CAPM holds, the excess returns on RS group should move the excess returns on FTSE 250 according to beta co-efficient. The time series graph broadly show that it returns on RS Group broadly follows the market fluctuations, suggesting the presence of positive beta. It can also be inferred with fluctuation exhibited, however, excess returns on RS group appears to have slightly higher spikes. This indicates RS group is more volatile than market.

We will examine this further with the help of scatter plot:



the scatter plot visualizes and describes similar trends as time-series plot with potential outliers, linear trend and idiosyncratic risk. Based on the spread and upward trend, the positive beta is expected.

Possible outliers exist due economic slowdown and shocks: major events highlighted between 2015 to 2022 which shows how return on RS group was impacted. The group was majorly impacted by Chinese stock market turbulence in 2015-2016 (Hsu, n.d.) that impacted MRO industry and China as virtue of major supplier of global manufacturing product. Furthermore, COVID-19, which impacted global supply chain and impacted physical disruptions across the globe. However, the volatility are not limited to these two events but these have certainly impacted the returns of RS group the most with the nature of and segment of business as global distributor.

Regression analysis: Hypothesis testing

Circling back to regression results, only one variable is statistically significant i.e., MCX Index, however, there are number of other variables (currency pairs) which are not significant, different from zero. In this hypothesis test we will determine whether that all of the slope parameters are jointly zero. We will set null hypothesis and an alternative hypothesis on "lm_returns" i.e., our regression model.

Null hypothesis (H_0: lm_returns) = 0, lm_returns are not significantly different from 0

Alternative hypothesis (H_a: lm_returns) $\neq$ 0, lm_returns are significantly different from 0

```
> linear Hypothesis(lm_returns,
c("MCXEXSS=0","GBPUSDSS=0","GBPEURSS=0","GBPJPYSS=0","GBPZARSS=0","GBPCNHSS=0"))

Linear hypothesis test:
MCXEXSS = 0
GBPUSDSS = 0
GBPEURSS = 0
GBPJPYSS = 0
GBPZARSS = 0
GBPCNHSS = 0

Model 1: restricted model
Model 2: RSPEXSS ~ MCXEXSS + GBPUSDSS + GBPEURSS + GBPJPYSS + GBPZARSS +
   GBPCNHSS

  Res.Df     RSS Df Sum of Sq      F    Pr(>F)
1   3109 10638.9
2   3103  6777.7  6    3861.2 294.63 < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The resulting F-test statistic follows an F(6, 3103) distribution as there are 6 restrictions, 3115 usable observations and 6 parameters to estimate unrestricted regression. The F-statistic value is 294.63 with p-value < 2.2e-16, suggesting that null hypothesis can be rejected.

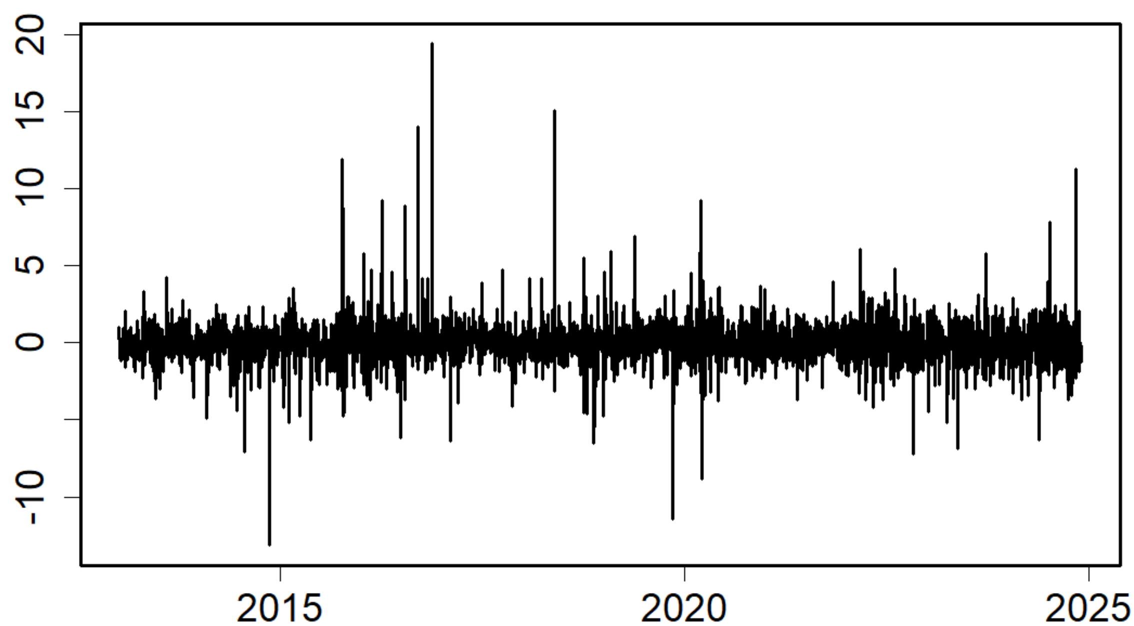
Given the results of hypothesis, we will be prioritizing diagnostic testing. These tests will help us to identify improvements in the model, ensuring assumptions are met, and that model performance is reliable and robust.

Diagnostic testing

<u>Heteroscedasticity testing:</u>

Heteroscedasticity occurs when variance of residuals in not constant across observations, violating one of the key assumptions of Ordinary least squares (OLS) regression.

The linear regression model lm_returns has saved the residuals in the variable residuals. To get a clear view, we will plot residuals from regression to the times series plot as a part of our heteroscedasticity diagnostic test:



The above graph shows residuals over time to examine the existence of heteroscedasticity. A constant spread indicates homoscedasticity and varying spread suggests heteroscedasticity.

However, its difficult to describe any clear pattern from the graph (noting increase in volatility in and after 2015).

Therefore, to confirm visible clustering and spikes, that may indicate periods of high variance, require formal testing named Breusch-Pagan. The results are as follows:

```
> bptest(formula(lm_returns), data = Data_for_research_project,
studentize = FALSE)

        Breusch-Pagan test

data:  formula(lm_returns)
BP = 76.081, df = 6, p-value = 2.298e-14

> bptest(formula = (lm_returns), data = Data_for_research_project,
studentize = TRUE)

        studentized Breusch-Pagan test

data:  (lm_returns)
BP = 5.6741, df = 6, p-value = 0.4607
```

Above results are from the Breusch-Pagan (BP) test which we are using to detect heteroscedasticity in lm_returns regression model.

The result can be interpreted in two categories 1. Standard BP test (unstudentized) and 2. Studentized BP test.

1. Standard BP test (unstudentized): BP statistic = 76.081, degrees of freedom = 6 i.e., number of independent variables in the model, p-values 2.298e-14.

The result shows that variance of residuals is constant in BP test for null hypothesis which indicates homoscedasticity. And a very low p-value strongly suggests that we reject null hypothesis. Which indicates that residual exhibit heteroscedasticity.

2. Studentized BP test: BP statistic = 5.6741, degrees of freedom = 6, p-values = 0.4607

Residual are studentized in this test to reduce the influence of extreme values. P-value more than 0.05 indicates null hypothesis cannot be rejected. This suggests that there is no strong evidence of heteroscedasticity.

All these discrepancies suggests the presence of mild heteroscedasticity in the model. To further address heteroscedasticity, White's modified standard error estimate approach is taken.

<u>White's Modified Standard Error Estimates</u>

A statistical test to determine whether the variance of errors in regression model is constant, known as homoscedasticity.

The results of White's test is as follows:

t test of coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	0.02	0.03	0.65	0.52	
MCXEXSS	1.13	0.04	26.68	<2e-16	***
GBPUSDSS	0.08	0.10	0.75	0.45	
GBPEURSS	-0.11	0.08	-1.37	0.17	
GBPJPYSS	0.01	0.05	0.22	0.83	
GBPZARSS	-0.02	0.03	-0.52	0.60	
GBPCNHSS	-0.13	0.11	-1.26	0.21	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

The initial BP test results underweighted regression (non-robust) which indicated the presence of heteroscedasticity. After applying studentized weights and adjustments, the non-significant results suggested that heteroscedasticity is no longer was a concern.

By using White's standard error, heteroscedasticity is effectively controlled.

Significance of co-efficient is determined by their t-values and p-values, both of which depend on the standard errors. If heteroscedasticity were present and unaddressed, result might have been unreliable.

MCXEXSS remains highly significant (p<0.0001) which indicates the strong and positive relationship with dependent variable. All other variable has p-values less that 0.05 indicates that currency pairs are not significant predictors.

Some other factors may also cause lack of significance for other predictors such as autocorrelation or multicollinearity.

<u>Autocorrelation and Dynamic Models</u>

The degree of similarity of a variable between two time series and lagged version of itself over successive time intervals is called autocorrelation. Durbin and Watson is most widely used test to detect autocorrelation. In addition, Breusch-Godfrey test is performed to detect autocorrelation. Results are as follows:

```
> dwtest(lm_returns)


	Durbin-Watson test
```

```
data:  lm_returns
DW = 2.0597, p-value = 0.952
alternative hypothesis: true autocorrelation is greater than 0
```

Durbin-Watson statistic is 2.0597, suggests no significant autocorrelation in residuals. P-value is high which is much higher than standard significance level i.e., 0.05 which indicates that we fail to reject the null hypothesis.

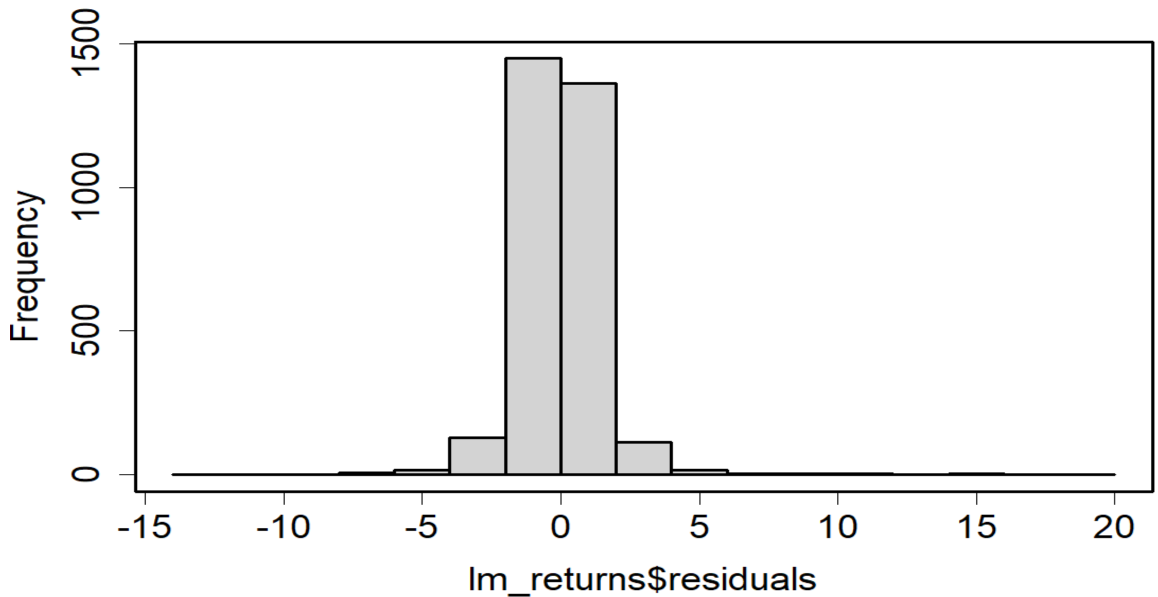
```
> bgtest(lm_returns)

	Breusch-Godfrey test for serial correlation of order up to 1

data:  lm_returns
LM test = 2.8049, df = 1, p-value = 0.09398
```

Based on the mode residuals and lagged residuals, LM test was calculated 2.8049 in Breusch-Godfrey test. Potential autocorrelation can be detected with higher value, however, significance of the value is dependent on the associated p-value (0.09398) which is higher than common significance threshold.

Therefore, there is no strong evidence of autocorrelation which indicates residuals are uncorrelated.

Testing for non-normality

Non-normality test is conducted to check whether the distribution of the residuals from regression model significantly deviates from a normal distribution. Also called as assumption of normality.



With skewness of ~1.43 and kurtosis of ~27.82, the residuals deviate significantly from normality. Positive skewness indicates asymmetry distribution with long right tail and high kurtosis depicts high tails and a sharp central peak which is much higher than normal distribution (kurtosis = 3). Histogram shape also shows extreme outliers and a distribution is not bell shaped.

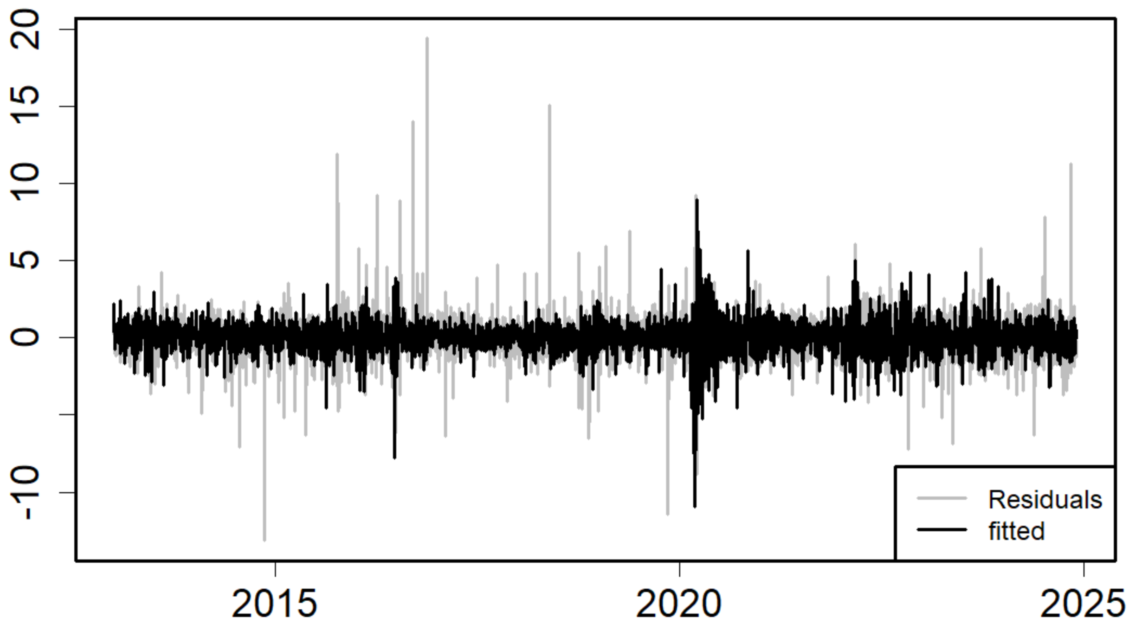
Therefore, the residuals are not normally distributed, violating assumption of normality required in regression model.

We further tested the normality assumption more formally with Jarque-Bera test and D'Agostino skewness test. Results suggest that the residuals do not follow normal distribution and are skewed. The issue pertains due to presence of outliers

We will address the outliers with constructing dummy variable and fitted vs residual value plot.

<u>Dummy variable construction</u>

To identify outliers, we will plot time series graph to show residuals from lm_returns regression model, alongside fitted values



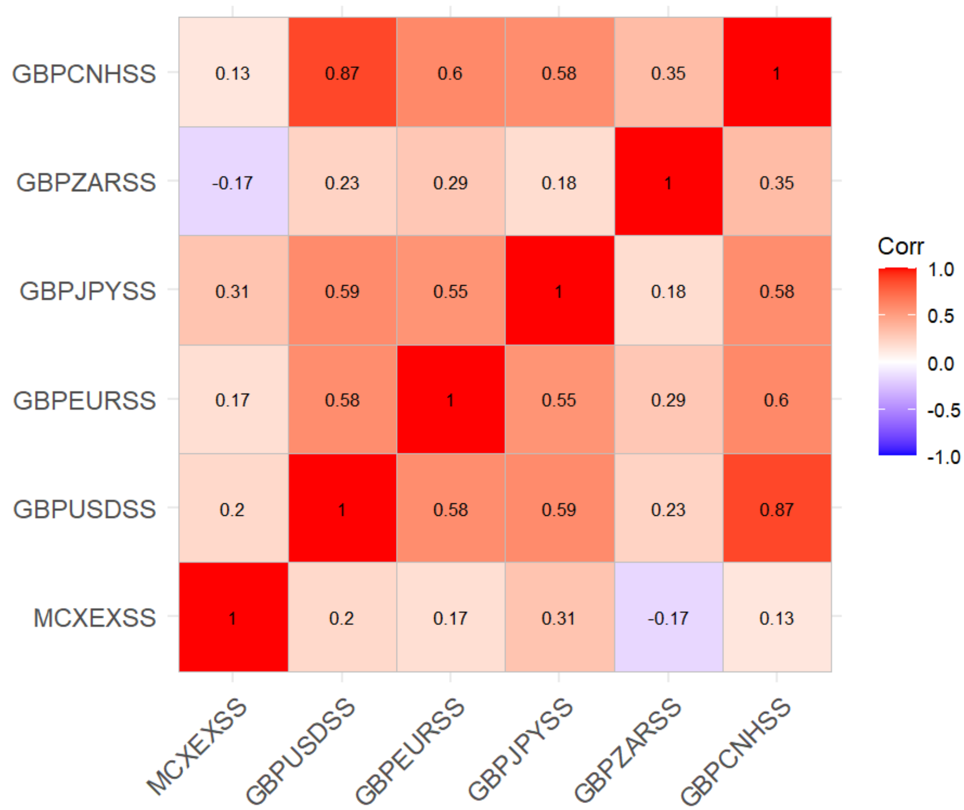
The residual oscillate around zero which is expected. However, there can be noted a visible patterns and period of high variability. The high variability around 2018 – 2020 indicates volatility clustering. Another observation that can be made is outliers exceeding +/-10 and +/-15 indicates several extreme events which are not well explained by model.

On looking into data, the outliers are term 488, 1791 and 1884 i.e., 13th November 2014, 12th November 2019 and 20th March 2020 respectively. To better explain the model we will replace these datapoints with dummy variables i.e., NOV14dumSS, NOV19dumSS and MAR20dumSS and then rerun the regression with new variables “lm_returns_dummy”. On comparing new regression model, it is identified that R-squared has been risen to 39.9% with all three new variables being highly significant along with MCXEXSS. Co-efficient variable has also changed a bit.

However, re-examining the normality test results of the results, it is observed that skewness and kurtosis still strongly reject test results for normality. That’s probably there might still be some large outliers but generating dummy variable for each outlier would be extremely challenging and manual.

<u>Multicollinearity</u>

Let’s say the reason for low r-squared is where independent variables are highly correlated. the existence of such relationships are called multicollinearity.



Above heatmap represents correlation matrix. The correlation matrix describes presence of moderate to strong positive correlations. GBPUSD and GBPCNH indicates a significant linear relationship with correlation of 0.87. afterwards, GBPUSD and GBPEUR shows moderate correlations with 0.58. These relationship potentially suggest issues with multicollinearity.

There are negative correlation between MCXEXSS and GBPZAR (-0.17) which is weak inverse relationship.

Rest of variables do not show major or concerning multicollinearity.

To further investigate multicollinearity, Variance inflation factor was used, none variable has VIF > 5 with noting that there is no severe multicollinearity among all the variables as per the heatmap. The highest VIF is GBPUSD (4.38) and GBPCNH (4.67).

The RESET test for functional form

The RESET test stands for “regression equation specification error test” which is a diagnostic test used to check whether the model is correctly specified in terms of presence of omitted variables, incorrect functional form or interaction that are not included in the model. To test RESET, we will set null hypothesis and an alternative hypothesis.

Null hypothesis (H_0): the model is correctly specified

Alternative hypothesis *(H_a)*: the model is mis-specified

The results are as follows:

```
RESET test

data:  lm_returns

RESET = 4.1518, df1 = 3, df2 = 3100, p-value = 0.00604
```

RESET = 4.1518: F-statistic from RESET test, which is calculated by comparing residual sum of squares from restricted model. The higher F-statistic generally suggest that the additional terms explain a significant amount of variation which was not captured by the model.

Df1 = 3: the degree of freedom associated with numerator. Three corresponds to the power of fitted values $\hat{y}^2$, $\hat{y}^3$ and $\hat{y}^4$ were added to model.

Df2 = 3100: the degree of freedom associated with denominator. With 3100, the test has a large sample size which increases reliability of the result.

p-value = 0.00604: p-value for the test indicates the probability that the observed F-statistic would occur if the null hypothesis were true. A low p-value suggests that we reject null hypothesis.

Since p-value is high, we can reject the null hypothesis. The evidence suggests that there might be mis-specification in model.

<u>Stability test</u>

Stability test is conducted to further examine whether model is consistent overtime.

We have 3,111 observations in our dataset and variable Fstats has 2,179 entries. We are finding index for May 11, 2018. Which is almost middle of our dataset. After running the Wald test of whether coefficients in the regression vary between two subperiod i.e., before and after May 11, 2018. Observed p-value of 0.0168 which is less than the threshold of significance which provides evidence of structural break in the relationship on May 11, 2018. suggests that model parameters might have changed at this point in time.

Conclusion

Based on comprehensive analysis conducted throughout the research project, below is summary of key findings:

Model Diagnostics (Multicollinearity, VIF, and RESET Test):

Multicollinearity: The correlation matrix revealed moderate to low correlations among the independent variables, indicating that multicollinearity may not be a major issue in the model. The VIF results did not exceed the threshold. Suggests no evidence of multicollinearity.

RESET Test: The RESET test showed a significant result (p-value = 0.00604), indicating that there might be nonlinearity in the relationship modeled. This suggests that the linear specification of the model might not fully capture the complexities of the data, and further model refinement could be required to account for possible higher-order relationships.

Structural Breaks (Chow Test):

The Chow test indicated a significant structural break in the data at May 11, 2018, with a p-value of 0.0168. This suggests that there was a significant change in the underlying relationship at this point in time. It could be a reflection of an external event or market shift, such as a policy change, geopolitical event, or financial crisis, which may have affected the forex market.

Stability of the Model:

Using stability tests, we found evidence of structural breaks, which might call for a reassessment of the model at certain points in time. It implies that any forecasts or estimates based on this model need to account for potential changes in the relationships over time.

Forex Exposure Relationship:

The focus of the research was exploring the relationship between foreign exchange exposure and the model's variables, particularly how different currency pairs relate to each other and to a central market indicator. Forex exposure can be described as the risk a company or entity faces due to volatility in foreign exchange rates. In the model, we have examined the impact of exchange rate movements between various currency pairs (e.g., GBP/USD, GBP/EUR, GBP/JPY, etc.) on financial returns or market behavior.

The correlation matrix for the currency pairs shows the interrelationships between various pairs:

The GBP/USD and GBP/CNH pairs show the highest correlation (0.87), indicating that the GBP to Chinese Yuan exchange rate moves in a similar manner to the GBP to USD exchange rate.

Currency pairs like GBP/JPY and GBP/ZAR have moderate correlations with others (e.g., GBP/USD), suggesting that they follow similar trends but with less strength.

There is a negative correlation between MCXEXSS and GBP/ZAR, indicating that as one increases, the other tends to decrease.

Implications for Forex Exposure:

GBP-based Exposure: The high correlation between GBP/USD and GBP/CNH suggests that changes in GBP/USD are likely to have a substantial impact on GBP/CNH exposure. Any fluctuations in GBP/USD may amplify the exposure to Chinese market conditions.

Cross-Currency Relationships: The positive correlations between GBP/USD, GBP/EUR, and GBP/JPY suggest that changes in one currency pair could have a ripple effect on other pairs, which could amplify forex exposure in a broader market context.

Currency Risk Management: The structural break detected on May 11, 2018, suggests that changes in global markets or economic policies could have influenced forex markets. This emphasizes the need for dynamic risk management practices that take into account sudden shifts in exchange rates.

Structural Breaks and Forex Exposure:

The detection of a structural break on May 11, 2018 suggests that the relationship between these currency pairs may have been significantly altered during this time, potentially due to market events like Brexit developments, monetary policy changes, or other geopolitical events. Such shifts could affect a firm's exposure to foreign exchange risk, necessitating adjustments in hedging or risk management strategies.

Reference:

Hsu, S. (n.d.). *China's Stock Market Crash: One Year Later*. [online] Forbes. Available at: https://www.forbes.com/sites/sarahsu/2016/07/13/chinas-stock-market-crash-one-year-later/.

Annual Report 2024 (year ended 31 March 2024)

https://www.rsgroup.com/investors/results-reports-and-presentations/

Supply chain Report

https://assets.rs-online.com/image/upload/v1655907536/MKT/pdf/Fact%20Sheets/fs_rsgroup_RSGroup.pdf