Identifying the Relationship Between Geopolitical Risk and Stock Returns: A Comparative Analysis of Traditional and Modern Forecasting Methods

Abstract

Geopolitical Risk has increased in the past decade, with events including COVID and Trump's tariffs. This article studies the predictive power of different models when forecasting the effect of Geopolitical Risk on stock returns, whilst analysing whether Geopolitical Risk has a causal effect on stock returns. Using daily returns from 2006 to 2024 across five major economies, this study employs traditional time series models whilst incorporating the random forest machine learning method to forecast and analyse the effect of Geopolitical Risk on stock returns, as measured by Baker, Bloom, and Davis (2016). Results indicate that a combination of machine learning and traditional methods outperforms a single method in out-of-sample, ex-post forecasting. The effect of Geopolitical Risk varies by nation, however, a causal relationship couldn't be identified for any nation. These findings underscore the importance of model selection and properly creating an index when analysing financial data, whilst suggesting that nonlinear dynamics improve the understanding of geopolitical shocks on financial markets.

1. Introduction

Stock market volatility has reached a level not seen since the onset of COVID-19, driven in part by the uncertainty around the United States' trade policy. President Trump's implementation of protectionist tariffs has heightened market instability. While a temporary reduction in tariffs to a baseline 10% and the provision of exemptions for tech firms offer limited respite- following a $2.4 trillion loss on April 3rd 2025- the future direction of Trump's tariffs is uncertain. The uncertainty around what policies The ambiguity around trade policy has fuelled fluctuations in Geopolitical Risk (GPR). Notably, despite Trump's tariffs being announced in advance, inefficiencies have been highlighted in the stock market. This observation has reignited the long-standing debate regarding whether the market can be beaten. Historically, this cannot be done consistently, exemplified by the rare success of Jim Simons' 'Medallion Fund'. Whilst consistent forecasts remain elusive, it is of interest to analyse how GPR can affect stock returns and see if it can provide meaningfully informed trading strategies.

Geopolitical risk is increasingly recognised as a key driver in business cycles and financial markets (Balcilar, et al., 2018). These risks are often cited by central bankers, investors and financial press as an investment determinant (Caldara and Iacoviello, 2016). The present study addresses two principal research questions, whether GPR affects stock returns, and whether there is an effect across nations of different development.

Interest in this topic has grown in the last decade, spurred by the increased ease for the public to invest, combined with intense financial scrutiny since the Global Financial Crisis. An ongoing challenge is the absence of certainty for how to measure GPR effectively. Baker, Bloom, and Davis (2016) devised the Economic Policy Uncertainty (EPU) index and Caldara and Iacoviello (2016), the Geopolitical Risk Index (GPR). Each measure utilises buzzwords, including 'economy' and 'uncertainty', in news articles to create a proxy for uncertainty.

Much of the existing literature has focused on commodities, such as oil prices, not macroeconomic conditions. While oil prices undoubtedly influence stock markets, this research examines the direct effect of Geopolitical Risk on stock returns. The question has gained urgency in light of the surge in retail investing, for example;. Ozik, Sadkha, and Shen (2021) examined a 115% quarter-on-quarter increase in traffic to Robinhood, indicating that retail investing is more prevalent now. The influx of investors has put these platforms under more pressure to have safety measures to inform investors of the risk they will incur. In parallel, JPMorgan analysts found that the market Beta had increased by 15% from 2019-2021.

The past literature has focused solely on one homogenous subset of countries. To address this gap, I will measure countries with vastly different characteristics. Past research has been unable to do this due to each author having different methods that they implemented. Choosing the US, UK, India, Brazil, and Mexico provides a plethora of differences, by extending this study to a heterogenous set of countries, this research will offer more generalisable results to be utilised.

2. Literature Review

Literature is extensive as stock returns are affected by an ‘infinite’ number of factors. No model for forecasting returns has become the overarching successor despite the research in the subject. GPR, whether potential or realised, is a useful factor for determining stock prices. Potential risk is a self-fulfilling prophecy; if investors believe prices will go down, they sell in anticipation, sending the stock price down. Even in moments where there are unpredictable shocks, such as COVID-19, we see realised uncertainty and one of the most rapid stock declines in history. If this risk is modelled, and the effect of risks on stock returns is understood, it can help identify factors behind stock movements. This review will aim to capture the developments in models which have predicted stocks and formulated a measure of geopolitical risk.

2.1 Stock Valuation Methods

To begin, Sharpe (1964) developed the Capital Asset Pricing Model (CAPM), aiming to model stock returns, deciding whether the stock is worth it relative to the market rate, as seen in (1).

$$\bar{R}_i = R_f + \beta_i\left(\bar{R}_m - R_f\right) \tag{1}$$

The return of a stock will equal the risk-free rate of interest plus the Beta coefficient multiplied by the risk premium. Beta being an index of the responsiveness of the change in returns of a stock relative to a change in the market's return- calculated using equation (2).

$$\beta_i = \frac{\sigma_{im}}{\sum_{i=1}^{n} w_i \sigma_{im}} = \frac{\sigma_{im}}{\sigma_m^2} \tag{2}$$

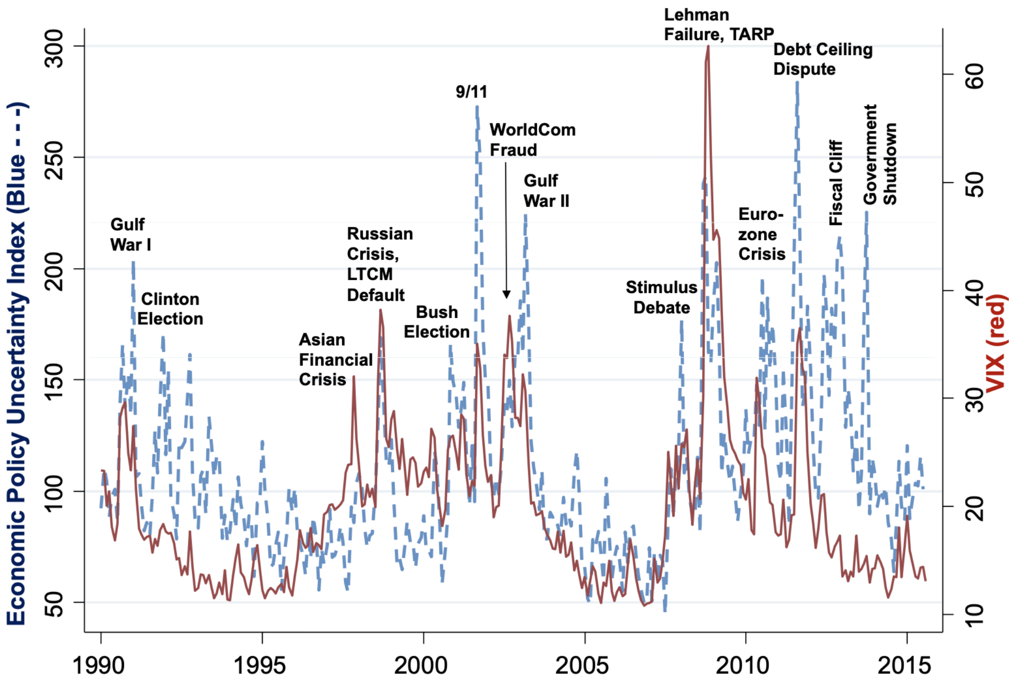
The Beta value is the covariance of the stock and the market over the variance of the market, measuring the systematic risk of the stock compared to the market. Roll's critique (1977) argues that the CAPM is flawed as it uses a proxy for the market; never encapsulating every asset in the market, hence the validity of the CAPM can not be tested. Furthermore, Fama and French (1993) concluded that Beta alone cannot explain a stock's relative performance over time, and that adding the size and value of a firm improves the relationship between risk and return. This was concluded through the study of 2000+ stocks between 1941 and 1990, compounding the conclusion that new models should be developed to analyse how stock returns are affected.

2.2 Geopolitical Risk (GPR) Indices

Baker, Bloom and Davis (2016) theorised the Economic Policy Uncertainty (EPU) index and Caldara and Iacoviello (2016), the Geopolitical Risk (GPR) index. Both indices quantify the frequency of specific terms in newspaper articles. Although both indices are similar, this study utilises the EPU index as it closely aligns with the analytical goals of the study. The EPU index has a direct correlation with the Chicago Board Options Exchange Volatility Index (VIX), a widely used measure of stock market implied volatility. This relationship suggests the index is a proxy for geopolitical risk, with a correlation of 0.58. Nevertheless, there are some discrepancies, including the Asian Financial Crisis, WorldCom Fraud, and the Lehman Brothers collapse- events with a strong financial and stock-market connection (Baker, Bloom, and Davis, 2016). The EPU shows stronger effects when a new president is elected and political battles over taxes. The key difference is that the VIX only indicates uncertainty over equity returns, whereas the EPU is more uncertain, including equity.

Rather than employing just each nation's EPU or the global EPU, I have constructed an index to average these two values about the GDP of each nation (see (3)). Resultantly, multicollinearity when using both the VIX and risk index is avoided. The constructed index provides a more nuanced representation of geopolitical risk.

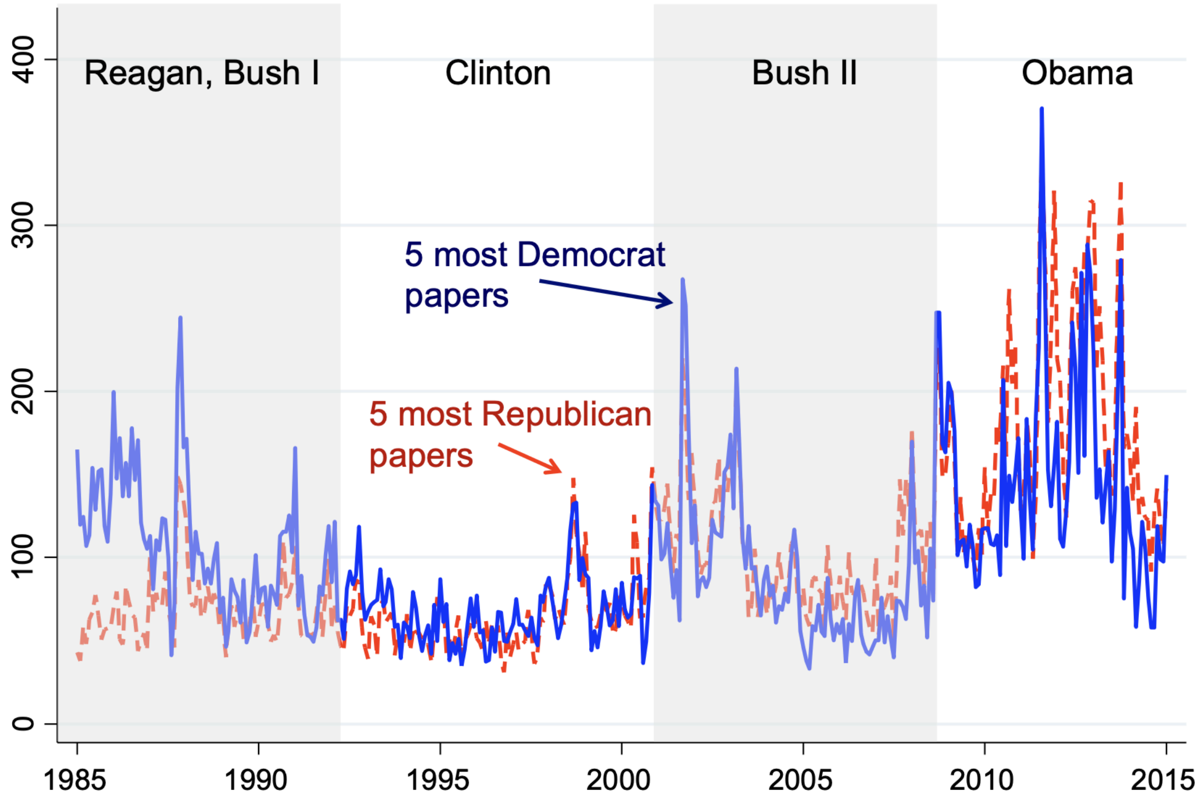
Figure 1. Relationship between the Economic Policy Uncertainty (EPU) index and the 30-day VIX



Notes: The figure shows the U.S. EPU Index from Figure 1 and the monthly average of daily values for the 30-day VIX.

A potential limitation of this index relates to the media bias in reporting certain political events. It is a well-established phenomenon that the media will provide stories and side with stories that align with their political goals. Baker, Bloom, and Davis allow for this by measuring the index using only left slanting papers and only right slanting papers, finding that the results are robust regardless of the political slant of the newspaper.

Figure 2. Comparison of EPU index results based on media political slant



Source: Papers sorted into 5 most 'Republican' and 5 most 'Democratic' groups using the media slant measure from Gentzkow and Shapiro (2010).

Moreover, the authors conducted extensive tests to validate the index. Over six months, an audit process was developed, whereby students read and coded articles drawn from eight newspapers from 1900 to 2012. Each student read several hundred newspaper articles and compared notes to develop classification criteria and an audit template. This rigorous process allowed the correct identification of newspapers to be included in the index.

2.3 Effect of Uncertainty on Stock Returns

Bouras, et al. (2018) analysed the effects of Geopolitical Risk (GPR) on emerging markets using a panel GARCH model. Their analysis employed Caldara and Iacoviello's (2016) GPR index. While the present study focuses on the EPU, the methodological similarity of the EPU to the GPR justifies comparability. Bouras, et al. (2018) found that domestic GPR has no significant effect on the returns to stock markets in each emerging country, whereas the global GPR has a significant effect, suggesting that global shocks have a greater effect on emerging economies than events purely in their nation. The authors attribute this asymmetry to emerging economies depending on larger economies, such as the US, to supply large amounts of aid. Shocks affecting multinational corporations can transmit adverse effects to their operations in emerging markets. Bouras, et al. acknowledge that the model is limiting due to the first-moment effect. They proposed a study to analyse the second-moment effect, allowing for the ability to measure volatility, besides returns.

Sharif, Aloui, and Yarovaya (2020) analysed the initial impacts of the COVID pandemic and the extent to which they would last. Their study identified that COVID significantly contributes to the GPR and EPU index. The pandemic was perceived as a persistent threat to the US economy, intensifying uncertainty over future economic indicators and the FED's response. This study focused on oil prices, finding that increased volatility has a significant, immediate impact on stock market returns. COVID led to travel restrictions and less demand due to fewer cars and planes, so demand went down. This study has concluded and proven that COVID is a geopolitical shock. The present study extends this by analysing the five years since the onset of COVID.

Agoraki, Kouretas, and Laopodis (2022) analysed 22 countries over 35 years, controlling for macroeconomic and market structure variables and the Global

Financial Crash. Their results indicate GPR negatively impacts stock returns, as does EPU. The EPU index has a slightly weaker effect, but is more closely related to the VIX. The findings indicated that the GFC had a significant prolonged impact on stock returns, and that short-term interest rates hurt stock returns. Although the study analyses a large number of countries, it sacrifices the analysis on each country. I will use only five countries, but make them diverse so the differential impacts are observed.

2.4 Models for Forecasting Returns

Box and Jenkins (1970) proposed the Autoregressive Integrated Moving Average (ARIMA) to model both persistence (AR) and shocks (MA) after adjusting for trends (I) and non-stationarity. One of the key contributions of this book was to generate first-differences of data to avoid non-stationarity, becoming a staple in modern economics. As such, ARIMAs have become the benchmark for time series modelling and forecasting.

Christopher Sims (1980) introduced the Vector Autoregressive (VAR) model as an alternative to the theory-driven structural macroeconomic models. He argued that imposing strong restrictions led to poor empirical performance and macroeconomic data should “speak for itself”. In the VAR framework, all variables are treated as endogenous, and each variable is modelled as a function of its lags and the lags of all other variables. Identification of structural shocks usually requires Cholesky decomposition, which imposes recursive ordering. This assumes that variables ordered first can contemporaneously affect variables ordered later, but not vice versa. This model avoids bias and misspecification by treating all variables as endogenous, however the identification of variables in this approach often feels arbitrary.

Bollerslev (1986) proposed the GARCH model- a continuation of Engle's (1982) ARCH model. Volatility clustering is present in many financial time series datasets, Bollerslev allows conditional variance to change over time depending on the squared residuals. The generalisation allowed for a more parsimonious representation of volatility persistence in financial and macroeconomic data.

More recently, machine learning has gained prominence in time series analysis. Breiman (2001) introduced Random Forests to build a 'forest' of decision trees, each trained on a bootstrapped subset of data and predictors at each split. This strategy reduces overfitting and captures nonlinear dynamics between variables, without imposing strong assumptions and providing a powerful model for variable identification.

3. Summary of Data

The dataset in this study comprises 4,187 daily observations of stock prices and macroeconomic indicators across five countries; the US, UK, India, Brazil, and Mexico. These countries were selected to capture a diverse range of characteristics. The US acts as a control nation, representing the market. The UK, while significantly linked to the US, displays distinct policy decisions allowing an analysis of how these differences can affect each nation's risk and thus stock returns. Brazil, India, and Mexico are classified as emerging economies, however, they have different political regimes, trade partners, and macroeconomic structures. Analysing this set of countries will provide the study with the necessary differential impacts.

The macroeconomic indicators include: interest rates, Net exports as a percentage of GDP, interest, volume, and a combination of national and global EPU to generate an overall risk value. The process of calculating risk was by taking each country's proportion of world GDP and multiplying it by global EPU, then doing 1-GDP multiplied by national EPU to generate a weighted value, as seen in (3).

$$(1 - GDP) * Log(EPU) + GDP * Log(GEPU) \tag{3}$$

Such data has been collected from the FRED, providing reliable and ethical data for analysis in this paper. The EPU values have been collected from Baker, Bloom, and Davis's website, where several indices are published. This data was simple to collect; however, merging it proved laborious, with forty files merged. The stock prices were scraped using Yahoo Finance in Python to create an already merged file for these values. Moreover, I merged all data using Python because of the increased merging functionality. To calculate returns, I used the percentage change formula on my stock prices. Returns combat the stationarity faced with prices, affecting the validity of my models.

$$Returns = \frac{New\ Price - Old\ Price}{Old\ Price} \tag{4}$$

The data can be visualised through the use of summary statistics. Table 1 shows descriptive statistics for each variable across each nation. From these results, India has the highest monthly return, however, experiences large volatility, whereas the US experiences less. The UK's stagnating economy is present, with lower returns than the US, but similar standard deviation.

Each country's stock market is reflected by one of its largest indices, the UK (FTSE100), the US (S&P 500), India (BSE Sensex), Mexico (IPC Mexico), and Brazil (IBOVESPA). Net exports as a percentage of GDP (NEXP_GDP) is calculated using trade balance and GDP data from the World Bank, then divided by GDP to compute a percentage value (4). Figure 3 shows how each country's returns vary. Each nation experiences a normal bell curve, as expected. The US has the densest returns around zero, suggesting that the returns are less volatile than other nations. Brazil is the most volatile country, indicative of its political struggles.

$$\frac{Trade\ Balance}{GDP} \tag{4}$$

Figure 4 represents the risk nations have faced over time, with the shaded areas showing recessions. The first shaded area is the Global Financial Crisis (GFC), and the second is COVID-19. From this graph, the risk profiles are relatively different, allowing the analysis of how the differences in risk will affect returns within a nation.

Table 1. Summary Statistics for Each Nation

Country	Variable	Obs	Mean	SD	Min	Max
US	Interest	4,187	1.624	1.964	0.125	5.375
	Log_volume	4,187	18.49	0.596	16.99	20.59
	NEXP_GDP	4,187	-0.375	0.0748	-0.623	-0.220
	Return	4,186	0.0534	1.278	-9.845	14.52
	Risk	4,187	4.957	0.405	3.964	6.093
UK	Interest	4,187	1.702	2.004	0.100	5.750
	Log_volume	4,186	20.61	0.395	15.94	22.05
	NEXP_GDP	4,187	-0.578	0.213	-2.476	0.492
	Return	4,186	0.0158	1.202	-10.87	10.12
	Risk	4,187	4.870	0.440	3.532	6.270
Brazil	Interest	4,187	10.20	3.434	2	17.25
	Log_volume	3,983	15.44	1.011	7.090	19.26
	NEXP_GDP	4,187	0.133	0.144	-0.234	0.563
	Return	4,186	0.0454	1.764	-14.78	18.38
	Risk	4,187	5.042	0.508	3.158	6.484
India	Interest	4,187	6.428	1.307	4	9
	Log_volume	4,181	9.569	0.722	4.605	17.28
	NEXP_GDP	4,187	-0.576	0.217	-1.316	0.0296
	Return	4,186	0.0607	1.446	-13.15	17.34
	Risk	4,187	4.473	0.470	3.256	5.624
Mexico	Interest	4,187	6.192	2.372	3	11.25
	Log_volume	4,183	18.97	0.396	14.17	21.57
	NEXP_GDP	4,187	-0.190	0.156	-0.642	0.384
	Return	4,186	0.0311	1.261	-8.472	13.42
	Risk	4,187	4.063	0.495	2.182	5.217
	Log_VIX	4,187	2.899	0.350	2.315	4.137
	VIX_Volume	4,187	0	0	0	0

Figure 3. Kernel Density of Returns by Country

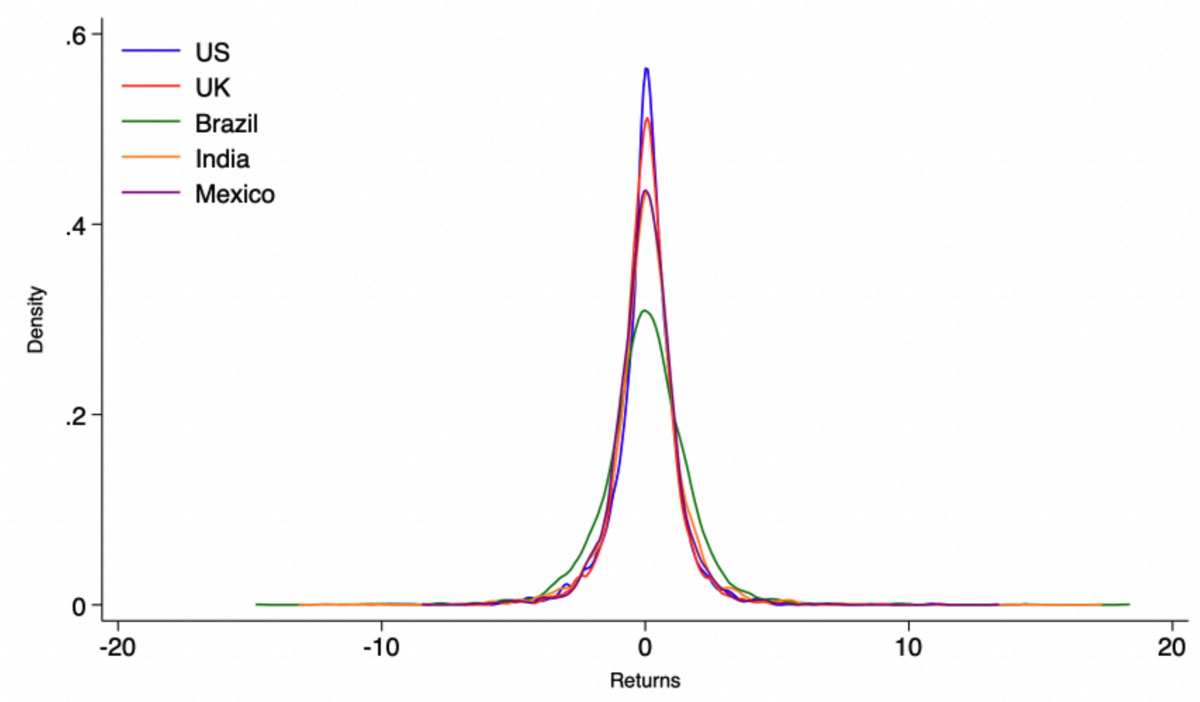
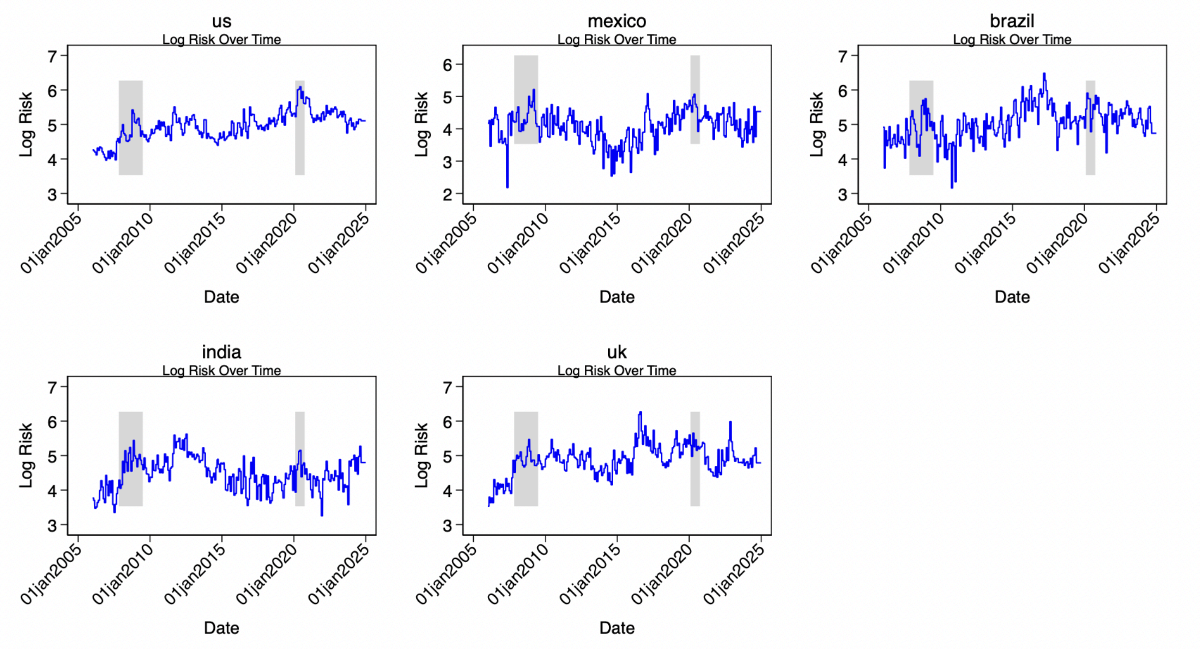


Figure 4. Risk Profile for Each Nation



4. Framework

A VAR model effectively measures the relationship between multiple time series variables, capturing how they affect each other over time. It relates current observations of a variable with past values of itself and other variables in the system.

$$Y_t = A_0 + \sum_{i=1}^{p} A_i Y_{t-i} + e_t \tag{5}$$

Where:

- Y is a 6x1 vector of our endogenous variables: return, log(risk), log(volume), log(VIX), net exports as a percentage of GDP (NEXP_GDP), and interest.
- Y is also a vector for each country: UK, US, India, Brazil, Mexico, so they each have their own equation.
- A_i are the autoregressive coefficient matrices at i.

The model shows how each of the variables, organised in a 6x1 vertical vector [return, log(risk), log(volume), log(VIX), net exports as a percentage of GDP (NEXP_GDP), and interest], affects each of the other variables in the vector. This is measured by A, our coefficient of the effect. This output allows the analysis of the causality between the variables and for forecasting.

The next procedure calculates Granger Causality, presented by Granger (1969), testing whether one time series can provide statistically significant information about the future values of another. It is based on predictive content rather than true causality. The test denotes two time series, X_t, Y_t. so X granger causes Y if past values of X help predict future values of Y better than just using past values of Y. This is useful to identify the causal links between a set of independent variables on a dependent variable, however it is worth noting that it isn't true causality.

Another typical financial model is the Autoregressive Integrated Moving Average (ARIMA) model, initially proposed by Box and Jenkins (1970). It is commonly used to provide a systematic framework to model temporal patterns in data which exhibit trend, seasonality, or autocorrelation. The flexibility of the model makes it popular in academic research and institutional forecasts in finance.

The Autoregressive component represents the relationship between the current observation and its past values.

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + ... + \phi_p Y_{t-p} + \varepsilon_t \quad (6)$$

The integrated component reflects the differencing needed to ensure stationarity.

$$Y_t' = Y_t - Y_{t-1} \quad (7)$$

The moving average component models the dependency between an observation and the residual error from a moving average model applied to lagged residuals.

$$Y_t = \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + ... + \theta_q \varepsilon_{t-q} \quad (8)$$

The components can be identified using autocorrelation plots and partial autocorrelation plots. Once identified, we can model and forecast future values.

While ARIMA models are useful for meddling returns directly, capturing volatility dynamics requires further tools. The Generalised Autoregressive Conditional Heteroskedasticity (GARCH) model, proposed by Bollerslev (1986), is useful for capturing volatility in financial markets. In particular, it models volatility clustering, whereby large shocks in returns tend to be followed by further large shocks and vice versa. Letting r_t represent the return of a financial asset at time t, which is modelled as:

$$r_t = \mu + \varepsilon_t,\ \varepsilon_t = \sigma_t z_t \tag{9}$$

Where:

- μ is the conditional mean
- ε_t is the shock at time t
- σ_t^2 is the conditional variance of ε_t
- $z_t \sim i.i.d.\ N(0, 1)$ or another distribution which allows for heavy tails

The conditional variance σ_t^2 follows a GARCH(p,q) process

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-1}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \tag{11}$$

Where:

- $\omega > 0, \alpha_i \geq 0, \beta_j \geq 0$ are parameters to be estimated
- α_i captures the impact of past squared residuals (our ARCH term)

- β_j captures the persistence of past conditional variances (our GARCH term)

A high value of $\alpha + \beta$ (close to 1) implies strong volatility persistence. We can incorporate the forecasts of this model into our next model, the Random Forest, to enhance predictive performance by accounting for time-varying volatility.

Random Forests provide an effective means for identifying the most important predictors for improving model forecast accuracy. A Random Forest is particularly suited to handling large datasets with nonlinear effects, as there are no heavy assumptions about the data structure; as such, it captures complex interactions among predictors.

Random forest aggregates multiple decision trees and trains each tree on a random subset of the data with bootstrapping. At each decision node, a random subset of features is considered for splitting. The final output is an average of the individual tree predictions, to prevent overfitting and potentially utilise nonlinear relationships.

Hyperparameter tuning is critical for optimising Random Forest performance. To ensure the correct parameters, we can find the out-of-bag errors (OOB) by running different interactive processes with varying numbers of trees and variables to be considered before each tree split. In this study, I implemented the forecasts of variance from the GARCH and lagged returns into the Random Forest to mimic the temporal order of a VAR, however, it is worth noting that the deterioration of the model's predictiveness occurs when lags of the control variables are added, likely due to overfitting.

Suppose we observe data $D = \{(X_i, Y_i)\}_{i=1}^{n}$ where $X_i \in R^p$ are predictors and Y_i are responses, which are continuous for regression. The Random Forest algorithm proceeds as follows:

1. Bootstrap sampling- For each $b = 1,\ldots\ldots, B$ where B is the number of trees. A bootstrap sample D_b is drawn of size n from D.

2. Decision Trees- The model grows a decision tree T_b on D_b. Each split there is a random subset of predictors $M \subset \{1,\ldots\ldots, p\}$ of size $m << p$. This stage chooses the best split of among the m variables to grow the tree fully without pruning.

3. Prediction Aggregation- For a new observation $x \in R^p$, each tree provides a prediction $\widehat{f}_b(x)$. The Random Forest prediction $\widehat{f}_{RF}(x)$ aggregates across trees, for regression it provides:

$$\widehat{f}_{RF}(x) = \frac{1}{B}\sum_{b=1}^{B} \widehat{f}_b(x) \qquad (12)$$

To avoid data leakage, I generated a 'train' dummy variable at the 3500th observation. The test data was set at the 4000th observation to ensure that the model cannot observe any future data. This training split ensures we have 84% for training, a 10% gap and 6% for testing. Having this training split ensures the model can predict values effectively, regardless of shocks, such as COVID-19 or GFC. Moreover, a defined training period ensures data leakage does not affect the results. If this period were not defined, there would be biased predictions, inadvertently trained on the values observed in the dataset, especially important in ex-post out-of-sample prediction, where models are tested against values already observed but explicitly excluded during model training. This setup allows a comparison of actual returns to the predicted returns. After completing ex-post forecasting, I will also aim to provide an ex-ante forecast, whereby the model is trained on all available historical data to predict unseen data.

To evaluate which model is most effective, I will use the Diebold-Mariano test introduced by Diebold and Mariano (1995). The test aims to see if two models have significantly different forecasting power, and if they do, which one is better. Let's consider a situation where $\{y_t\}$ denotes the time series and $\{\widehat{y_{1,t}}\}$ and $\{\widehat{y_{2,t}}\}$ represent the forecasted values of models 1 and 2 and the residuals are $\{e_{i,t}\}$, i.e $\{e_{i,t}\} = y_t - \widehat{y_{i,t}}$. The loss differential at each point can be defined as:

$$d_t = g\{e_{1,t}\} - g\{e_{2,t}\} \qquad (13)$$

g is a loss function, e.g. $g(.) = (.)^2$. The null hypothesis of this test states that we have equal predictive accuracy, so the loss differential is zero. The alternative hypothesis states that one model is more accurate.

$$H_0: E[d_t] = 0 \qquad (14)$$

$$H_1: E[d_t] \neq 0 \qquad (15)$$

The test statistic the Diebold-Mariano test is given by:

$$DM = \frac{\bar{d}}{\sqrt{\widehat{V}(\bar{d})}} \tag{16}$$

Where:

- $\overline{d} = \frac{1}{T}\sum_{t=1}^{T} d_t$ is the sample mean of the loss differential.
- $\widehat{V}(\overline{d_t})$ is a consistent estimator of the variance of $\overline{d}$, which accounts for potential autocorrelation in the loss differential.

5. Results

5.1 Vector Autoregressive Model (VAR)

This data requires a model which can capture effects better than an Ordinary Least Squares (OLS). The two choices are a Vector Autoregressive (VAR) model or a Vector Error Correction Model (VECM). To decide which model to use, we perform a Dickey-Fuller test on each of our variables to test whether each variable is stationary. The results highlight that all our variables are stationary, as expected.

The US displays varying responses to different shocks. In response to a shock in GPR, returns exhibit little movement, persistently hovering around the baseline rate over the next 30 trading days. This result is counterintuitive; higher risk typically dampens returns. One explanation for the effect is that returns do fall with increased risk; however, investors demand exacerbated returns, thus providing a reactionary effect and cancelling each other out, providing a zero net effect.

Volatility shocks, measured by the VIX, see a negative shock to returns, consistent with financial literature. As the volatility of a stock increases, returns will typically fall. A persistent shortcoming is observed, explained by the past returns (implied volatility) affecting the VIX value, so when returns fall, the VIX rises, and as the VIX rises, we see returns fall in a cyclical pattern.

When interest increases in the US, it yields a surprising rise in returns. Classical economic theory states that interest rates should cause stock prices to fall by encouraging shifts in investments to fixed-income securities (hot money flows). In the period of this study, the FED often used interest rates as guidance for economic strength. Particularly in the GFC and COVID-19 recovery periods, historically low interest rates meant increases were associated with the economy strengthening, rather than monetary tightening.

Volume has an immediate effect on returns. An increase in volume traded sees a persistent fall in stock returns, and over the next 30 trading days, does not recover to the baseline rate.

Table 3. Augmented Dickey-Fuller Test

Country	Variable	P value	No. of lags
US	Return	0.0000***	1
	Risk	0.0005***	1
	NEXP/GDP	0.0000***	2
	Volume	0.0000***	6
UK	Return	0.0000***	1
	Risk	0.0000***	0
	NEXP/GDP	0.0000***	3
	Volume	0.0000***	1
Brazil	Return	0.0000***	1
	Risk	0.0000***	2
	NEXP/GDP	0.0000***	2
	Volume	0.0011***	2
India	Return	0.0000***	1
	Risk	0.0000***	1
	NEXP/GDP	0.0000***	3
	Volume	0.0000***	1
Mexico	Return	0.0000***	1
	Risk	0.0000***	1
	NEXP/GDP	0.0000***	3
	Volume	0.0057***	3
	VIX	0.0057***	2

The UK responds similarly to the US. Risk has a prolonged positive impact on returns, recovering to the baseline rate within 30 trading days, consistent with a risk-averse response. Volatility shocks also negatively affect returns. However, interest shows no statistically significant effect, with the 95% confidence interval encompassing both positive and negative returns. The muted response may reflect the UK's use of quantitative easing (QE), totalling £895 billion (Bank of England, 2024). QE was implemented after negative interest rates were considered impossible. The interest rates in the UK remained low, and their responsiveness to them was depressed. Volume traded in the UK has a similar effect to the US, albeit not as large.

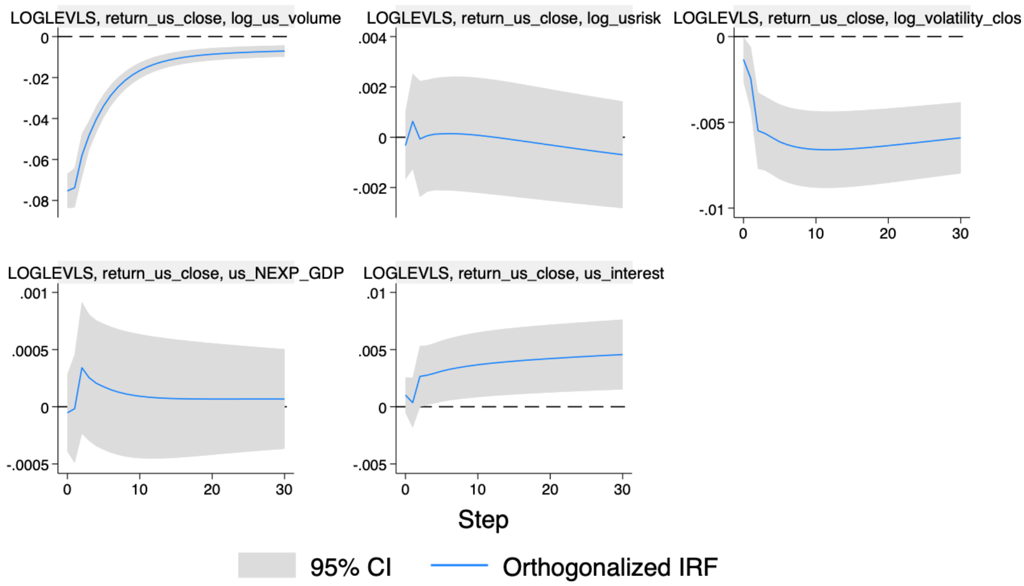
Figure 7 shows the VAR analysis in India. Here, the model predicts differing magnitudes of results. The risk variable produces immediate positive effects, followed by a swift return to the baseline. The VIX dampens returns again; however, the effect is smaller than in the US. The VIX measures implied volatility in US stocks, so the information will not translate directly to India. The effect is still felt due to the sheer size of the US economy. Interest in India reduces returns. The magnitude of the effect is similar to the US; however, they have different characteristics. The US had near-zero interest rates for a long time, whereas India has consistently utilised interest rates, suggesting that the effect of interest could be due to the demography of the nation, so India and the US have risk-loving populations. Volume traded has little effect on stock returns in the US, with a shock quickly trending back to the baseline rate.

Mexico experiences modest effects on stock returns- the results for risk and the volatility index follow the same trend as other nations, with volatility causing stock returns to fall and have a slow recovery. Our risk sees a sharp increase, after the first period, in stock returns, but a quick return to the baseline. The initial effect of zero can highlight the lag effect of markets to factor in geopolitical risk, potentially presenting an opportunity to inform trading strategies. Mexico also has a positive effect on returns when interest increases. This effect takes two periods to show, potentially a result of the central bank using rising interest rates as a strong signal for the economy; however, people are hesitant whether the market is as strong as the central bank indicates. NEXP_GDP provides different results. We see little effect on returns. The intuitive reasoning is that when net exports rise, the country moves closer to being a net exporter, which is generally seen as a positive for an economy, especially if it is a developing country. This effect is not prolonged and falls quickly to the baseline rate; hence, it is only a short-run shock.

Brazil's NEXP_GDP has little effect on its returns; despite Brazil being a net exporter, it does not provide significantly different results to other nations. The interest rate has little effect on stock returns, potentially reflecting reduced investor confidence after years of corruption. Brazil's increasing risk has an immediate effect on stock returns, unlike other nations. This effect is attributed to investors being more wary of the political risk in the nation. Furthermore, the economy is not strong enough for investors to look past certain political decisions.

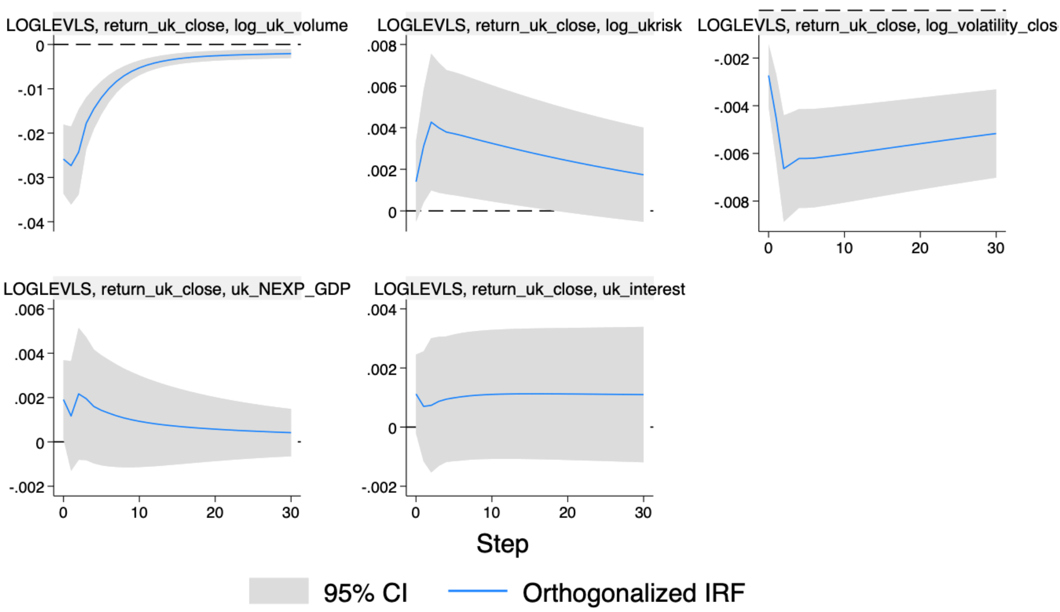
In summary, whilst common patterns are observed among the nations, such as the negative impact of volatility on stock returns, there are also important differences. The interpretation of interest rates varies substantially depending on each country's monetary history and institutional credibility. Volume shocks are seen to generally depress returns, but with varying magnitudes. These findings highlight the importance of accounting for country-specific factors when assessing the transmission of macro shocks to stock markets, suggesting that stock markets are mediated by local factors and investor sentiment.

Figure 5. VAR Analysis of the US on returns



Graphs by irfname, impulse variable, and response variable

Figure 6. VAR Analysis of the UK on returns



Graphs by irfname, impulse variable, and response variable

Figure 7. VAR Analysis of India on returns

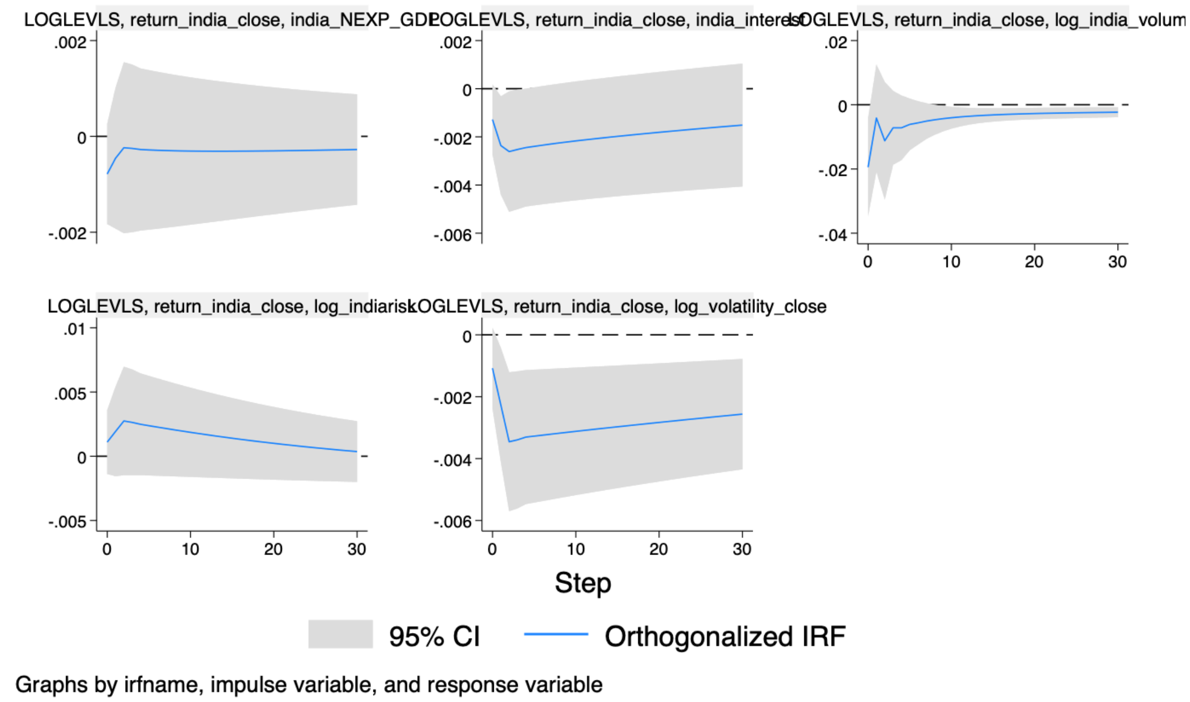


Figure 8. VAR Analysis of Mexico on returns

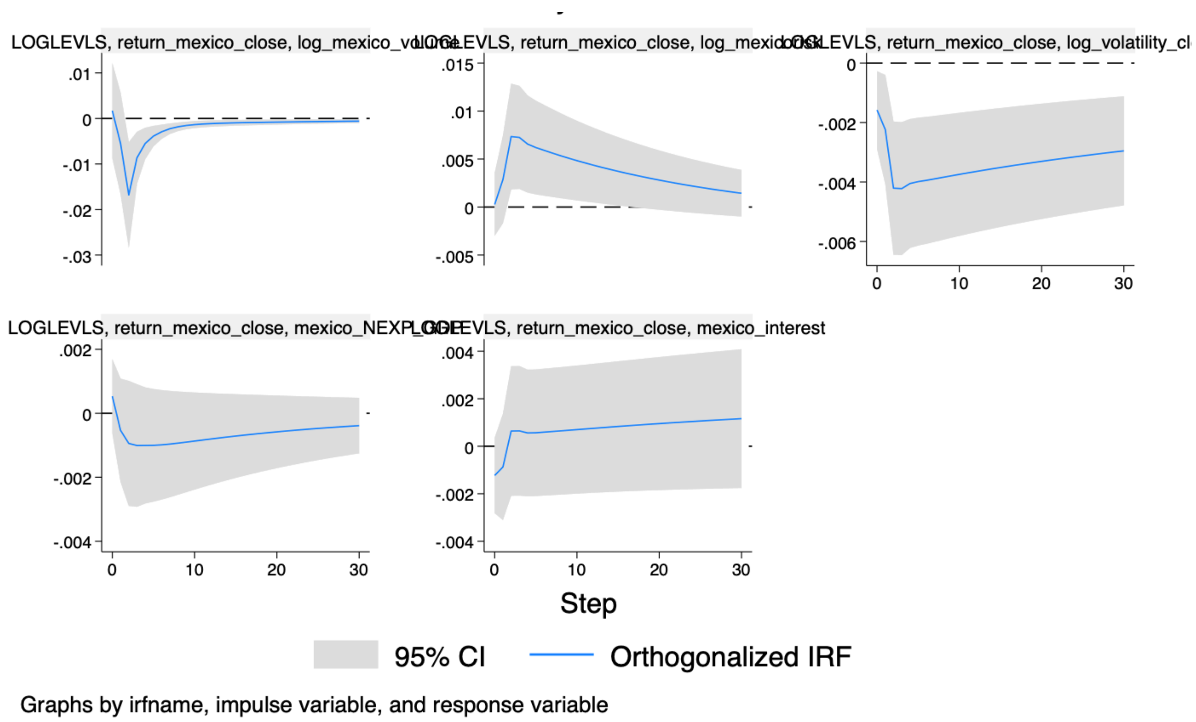
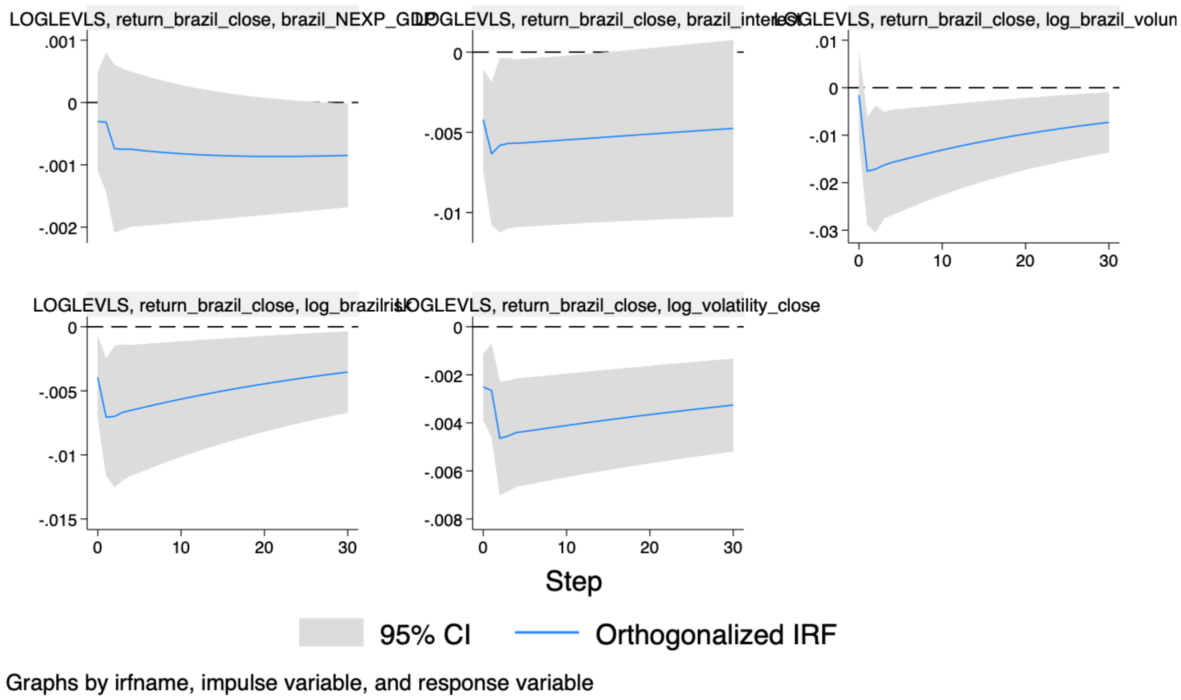


Figure 9. VAR Analysis of Brazil on returns



5.3 Granger Causality

Granger Causality is a powerful statistical tool to test how one time series can predict another time series more powerfully than using only its lags. Hence, it measures whether including past values of one variable increases the forecasting accuracy of another variable. The outputs of the test are shown in Table 4, and more information is shown in Appendix A.

The Granger causality test for the US suggests that Net exports as a percentage of GDP (NEXP_GDP), VIX and risk all Granger cause US stock returns. Specifically, past values of each contain information that helps predict returns beyond what the returns' past values can tell us. These results support the idea that macroeconomic conditions and market risk sentiment are important drivers of equity performance.

Table 4. Granger Causality

Country	Dependent	Excluded	P value
US	Return	log_usrisk	0.0980*
	Return	log_volatility_close	4.61482146469985E-08***
	Return	us_NEXP_GDP	0.0941*
	Return	us_interest	0.8407
	Return	log_us_volume	0.6766
UK	Return	log_ukrisk	0.7158
	Return	log_volatility_close	0.0056***
	Return	uk_NEXP_GDP	0.8638
	Return	uk_interest	0.4859
	Return	log_uk_volume	0.3818
Brazil	Return	log_brazilrisk	0.1241
	Return	log_volatility_close	0.0039***
	Return	brazil_NEXP_GDP	0.6572
	Return	brazil_interest	0.5895
	Return	log_brazil_volume	0.3438
India	Return	log_indiarisk	0.4671
	Return	log_volatility_close	0.0089***
	Return	india_NEXP_GDP	0.0199**
	Return	india_interest	0.1292
	Return	log_india_volume	0.3237
Mexico	Return	log_mexicorisk	0.8030
	Return	log_volatility_close	0.0013***
	Return	mexico_NEXP_GDP	0.1704
	Return	mexico_interest	0.0546*
	Return	log_mexico_volume	0.8048

In Brazil, the VIX Granger causes stock returns, meaning past values of the VIX can be used to predict future values of stock returns in Brazil. Risk not Granger causing stock returns goes against the hypothesis, and would not be expected due to the political regime. One explanation could be that markets have always priced in the risk, especially in Brazil, where this risk is present often through the political tensions that are ever present.

India sees NEXP_GDP and the VIX affecting returns. In India, export strength reflects the overall economic competitiveness and demand for Indian goods. If NEXP_GDP improves, it indicates stronger global demand and higher productivity, boosting future returns. Moreover, the Rupee benefits from a better trade balance, making it more attractive to foreign investment. VIX affecting Indian returns highlights the strength of the US and that the US stock market can be used as a proxy for the international market. The interest rate is significant at the 5% level, further consolidating the hypothesis that these nations are more responsive to interest than the US and UK.

Mexico has only Granger causality present for VIX, indicating that other factors affect stock returns in Mexico. This may be a result of more efficient markets, so there is no price opportunity, or investor behaviour is less macroeconomic driven.

The UK experiences the same outcome as Mexico, indicating potentially efficient markets. To test the validity of our VAR model and how much predictive power the model has, I will forecast values and compare them to the realised values. If the model provides values similar to the actual values, then we can support the conclusion that the model is effective.

5.4 Forecasts

The initial forecast of the VAR model, using a dynamic forecast for 205 trading days ahead from February 2024, highlights significant limitations with the model. The model can be concluded to have little predictive power for stock returns as there was little movement in the prediction and it failed to resemble actual returns, indicating a fundamental issue with the model (see figure 10).

A GARCH model, by itself, does not forecast stock returns; it forecasts volatility. Nevertheless, this model of volatility is very powerful if fed into the random forest or ARIMA model to act as a measure of volatility. Volatility is time-varying, not incorporated into just the ARIMA or random forest. This distinction will provide the necessary response to changing macroeconomic conditions. The GARCH model was run on returns; when doing a multivariate GARCH analysis, the results are the same, inundating it. The lack of movement of the forecast model would indicate that the decisions being made for the choice of variables and number of lags for each model are not optimal.

An initial ARIMA model was created for each country, on bivariate and multivariate components. The order of the ARIMA was dependent on the output from the 'arimasoc' command. The bivariate only utilised the relationship between past values of returns. This initial model showed poor predictive power, as seen in Figure 11.

However, controlling for the exogenous variables does improve the prediction, but we still have poor predictions in Figure 12.

The evolved version of our forecast shows how combining all these models into a machine learning framework can significantly improve the model, and potentially provide an edge in the market. To utilise this analysis, I will compare the effect of the random forest model with only the GARCH and ARIMA effects against a random forest model which uses these and controls for the exogenous variables, such as risk.

Moreover, I will compare it to an ARIMA forecast using the multivariate controls and the GARCH terms, the output of which is seen in Figure 14. The results from this model are not predictive, so they show relatively little information.

The initial results graphs show a much greater forecast accuracy when using the random forest with GARCH effects (for more detail see Appendices B and C). However, there is no visible difference between the effect with and without control variables. To decide which model is better, I will later perform the Diebold-Mariano test.

Table 5 shows the relative importance of features in our random forest model. For most nations, the VIX is the most important, whereas for the US and India, it is the volume traded of stocks. Notably, risk is one of the least important variables in determining returns; however, it is still relatively strong, highlighting the potential effectiveness of this model.

Figure 10.Forecasts vs Actual values of Returns using VAR

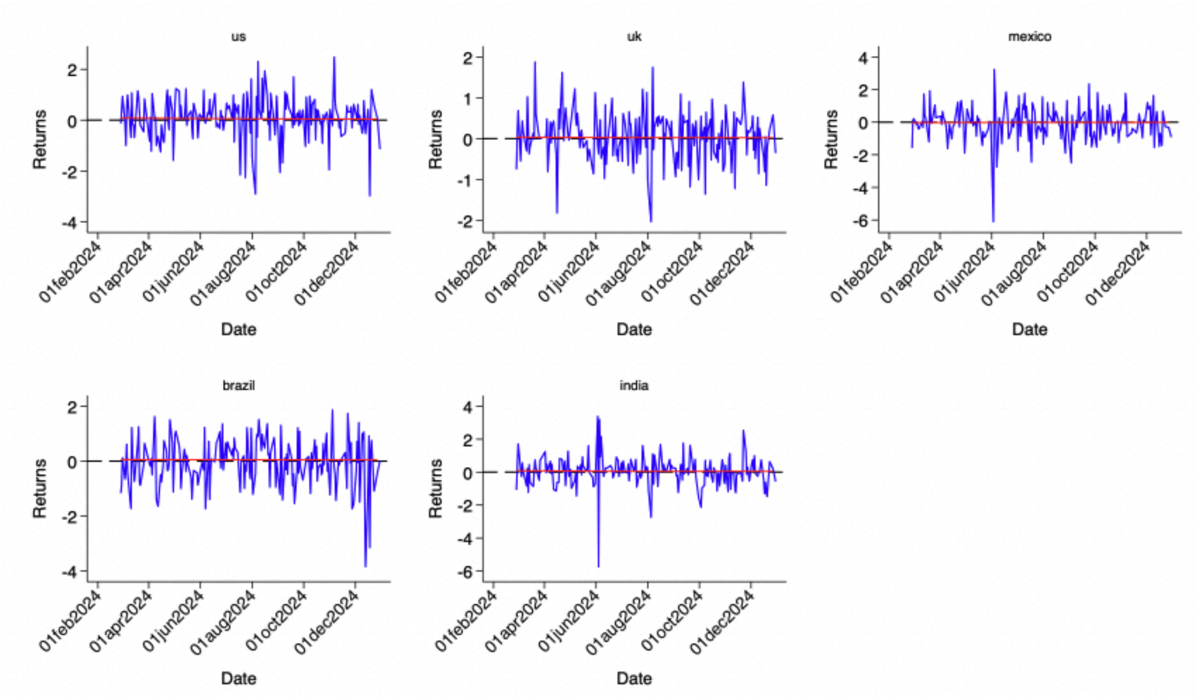


Figure 11. Forecasts vs Actual values for Bivariate ARIMA model

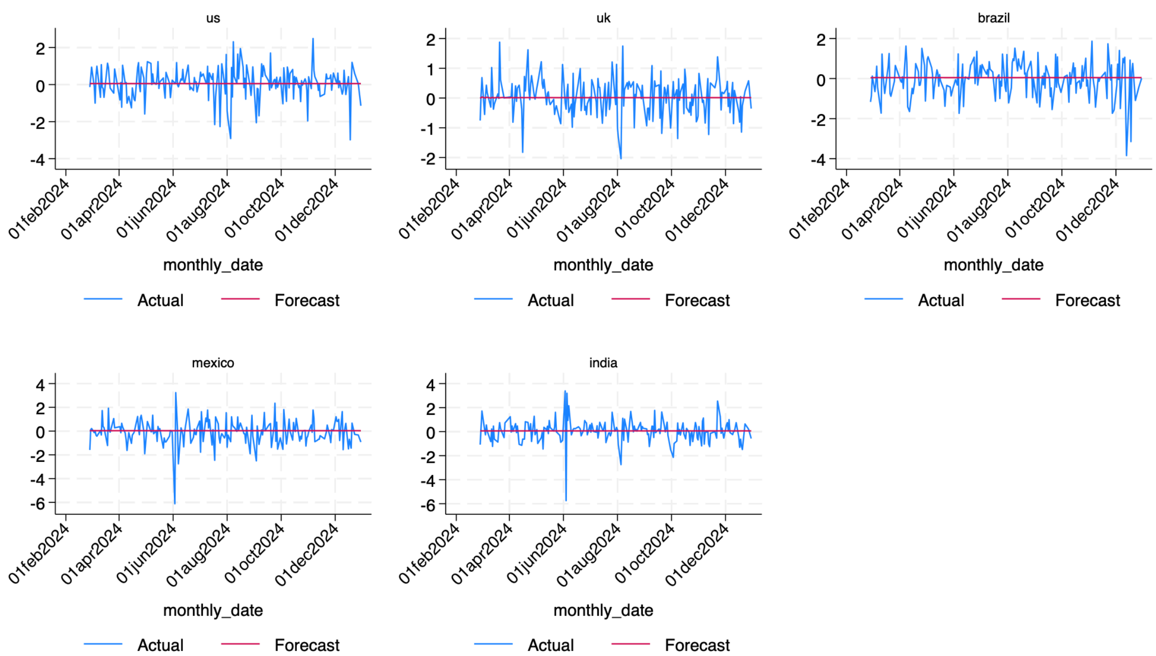


Figure 12. Forecasts vs Actual values for Multivariate ARIMA model

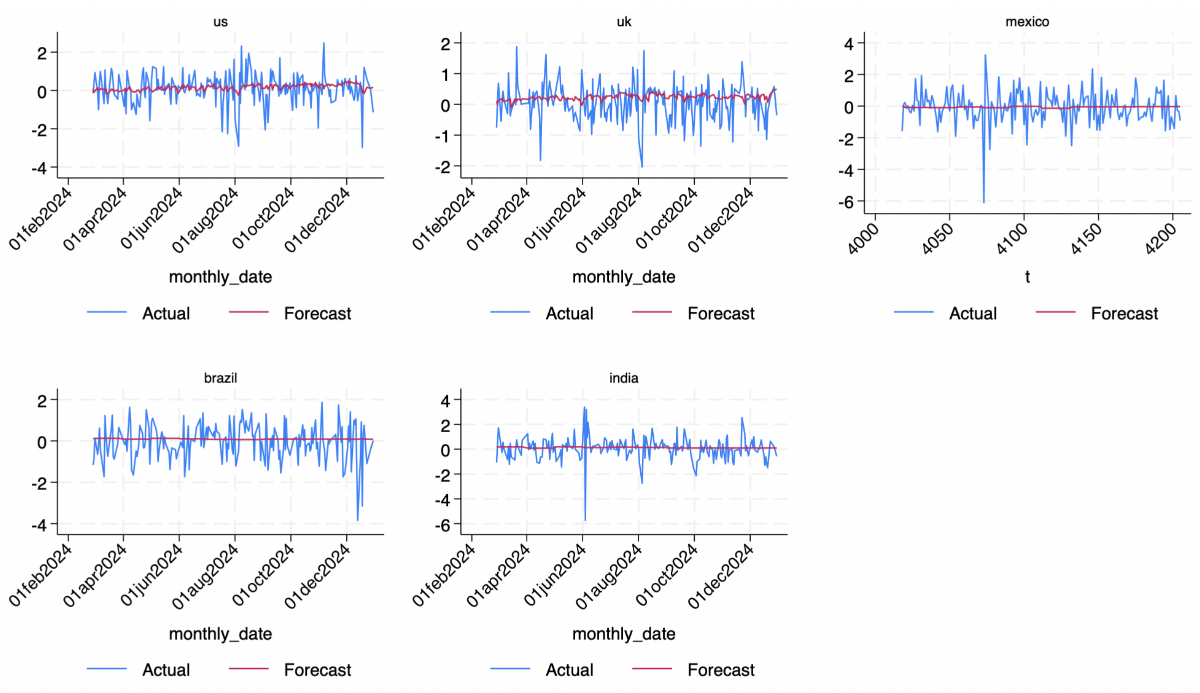


Figure 13. Forecast of Volatility using a GARCH model

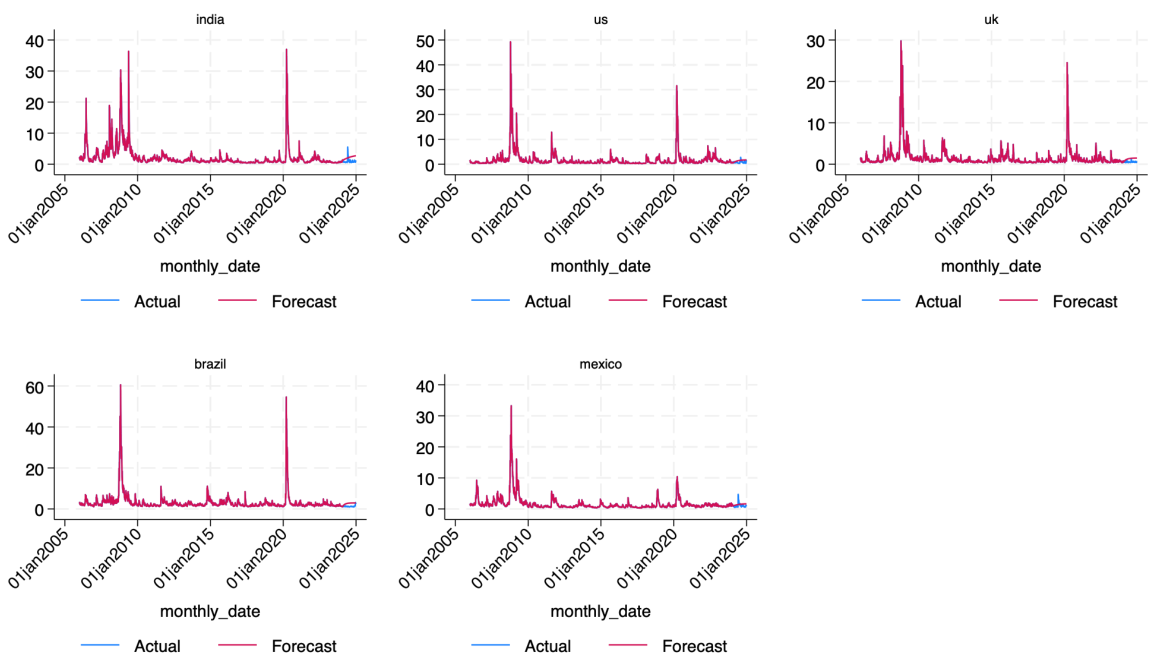


Figure 14. Forecasts vs Actual values for Multivariate ARIMA model with GARCH terms

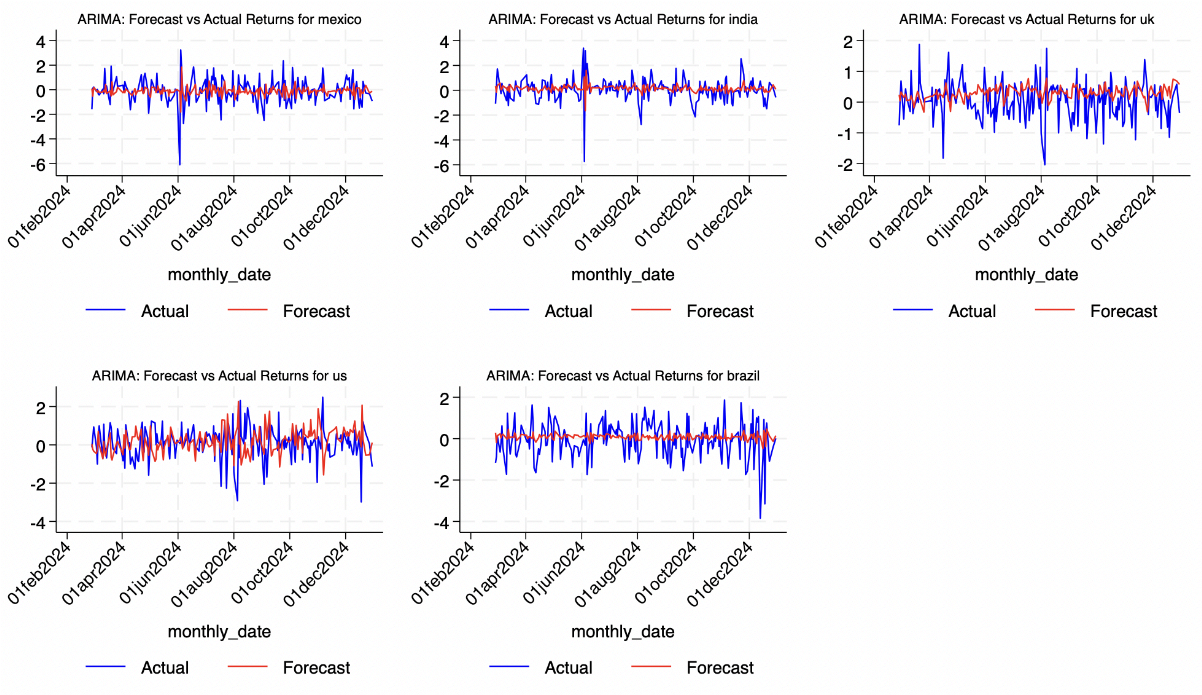


Figure 14. Forecasts vs Actual values for Random Forest Without Control Variables

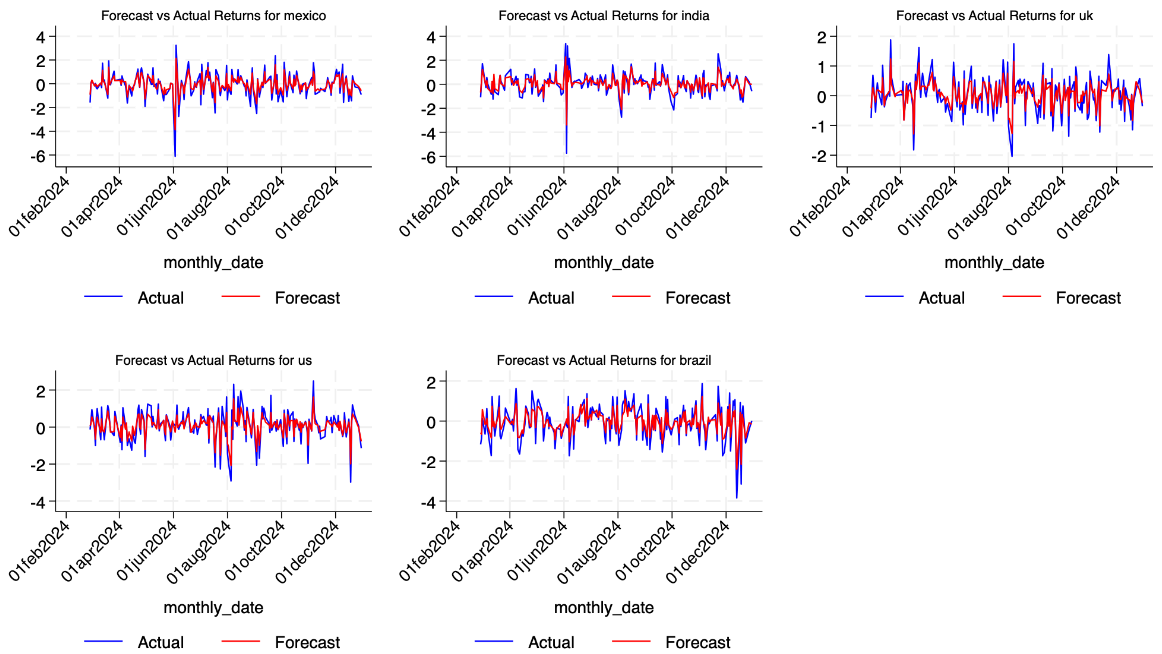


Figure 15. Forecasts vs Actual values for Random Forest With Control Variables

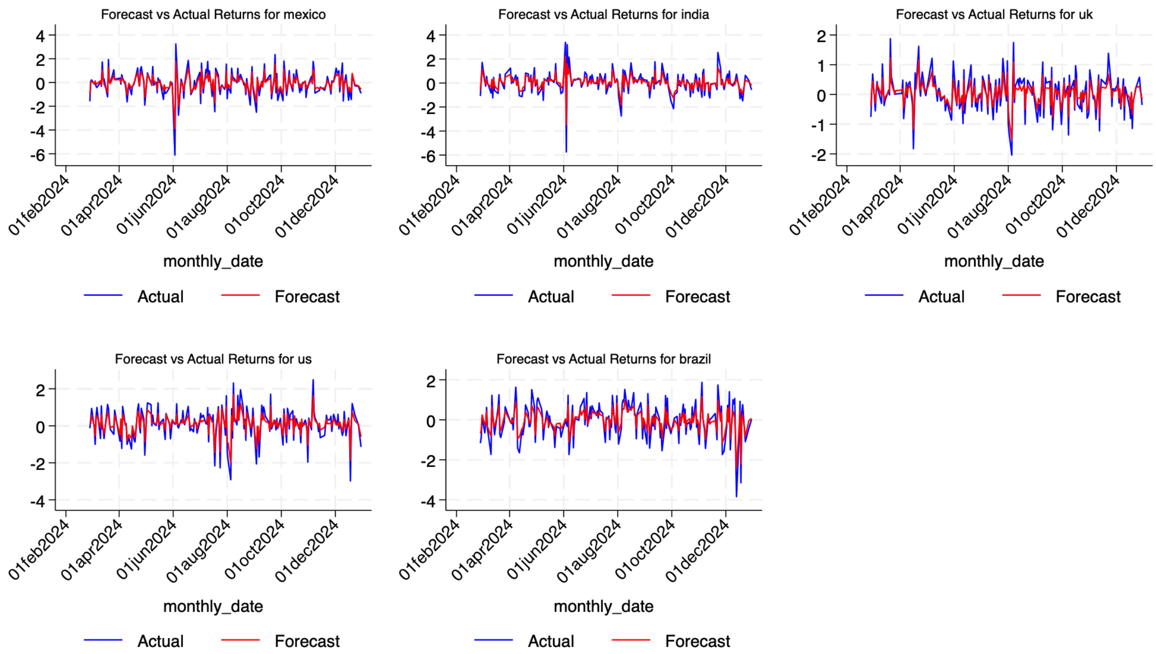


Table 5. Feature importance in Random Forest

	US	UK	Brazil	India	Mexico
L.return	0.61887058	0.59976178	0.72107475	0.67220948	0.59965353
L2.return	0.69420446	0.77896889	0.88119379	0.79139633	0.72461715
GARCH	0.77792697	0.79034029	0.8592992	0.84679763	0.87335131
Risk	0.67940328	0.61651552	0.68451014	0.65721237	0.69109809
Volume	1	0.91262742	0.90386325	1	0.90270571
Interest	0.61217485	0.70082507	0.65641674	0.78376538	0.65663491
VIX	0.77962071	1	1	0.99639353	1
NEXP_GDP	0.71203762	0.77241639	0.83267191	0.72608069	0.75370705

5.5 Diebold-Mariano Test

To gauge which model has the most predictive accuracy, it is necessary to provide a formal measure. The Diebold-Mariano Test (DMT) compares the forecast errors of two models and then tests whether there is a significant difference in the model accuracy; the null hypothesis is that the forecast errors from both models are the same. To implement this, I calculated the forecast error of each model and each country; these values are squared, and then I generated a loss difference between the two models. Finally, I perform a t-test on each of these values.

Table 6 presents the results of the DMT. For each country, there is no significant difference in the effectiveness of the forecast. The most effective actually changes between nations, so it cannot be said that one is even minutely better; thus, whilst these models are effective, controlling for GPR does not improve the predictive power of the model. Resultantly, the effectiveness of GPR for forecasting is insignificant.

Table 6. Diebold-Mariano Test

Country	Mean < 0	Mean != 0	Mean > 0	RMSE_bv	RMSE_mv
US	0.7420	0.5161	0.2580	0.3670	0.3593
UK	0.3475	0.6950	0.6525	0.2703	0.2736
Brazil	0.4262	0.8524	0.5738	0.3928	0.3947
India	0.4196	0.8392	0.5804	0.4023	0.4045
Mexico	0.2565	0.5130	0.7435	0.4147	0.4222

5.6 Ex-Ante Forecast

Assuming the use of the random forest is the strongest model- a safe assumption based on comparative testing against ARIMA models (with and without GARCH volatility adjustments), to produce values that are no better than the initial Random Forest- I proceeded to conduct ex-ante forecasting.

Ex-ante forecasting requires no data leakage. To maintain this, I train the model on all available data, then predict new unseen observations. So new blank observations are generated to be populated by the predictions. However, Table 7 shows that the model is inaccurate for all nations. This is potentially the fault of the random forest which is notoriously good for interpolation but poor at extrapolation. Additionally, the noisy nature of returns at the daily level has complicated the ability to make predictions as returns are often influenced by random shocks and irrational behaviour.

To address these challenges, rolling retraining can be used. This method retrains the model on updated parameters which become available periodically, consequently responding to regime changes faster. This is a laborious process in STATA, of which I would recommend using R. Moreover, future iterations should include interaction terms for the Random Forest to capture. My initial results suggest that this model can have some power, however it may be better suited to monthly returns, given that daily returns are dominated by noise.

Table 7. Ex-Ante Predictions

Returns	US	UK	India	Brazil	Mexico
Real	-0.2457%	1.0645%	0.4715%	-0.1314%	0.5088%
Predicted	0.5636%	0.0149%	0.0586%	0.0451%	0.0451%

6. Conclusion

This study examines the relationship of geopolitical risk (GPR) and stock returns, whilst controlling for key macroeconomic variables on time series data for the US, UK, India, Mexico, and Brazil. The analysis finds that GPR does not have a Granger-causal effect on stock returns, suggesting that past values of GPR do not contain predictive information for stock returns. Moreover, this study concludes that traditional models are sometimes limited in their ability to forecast stock returns.

To enhance model performance, I developed a layered modelling approach, first modelling an ARIMA as a baseline, before modelling a GARCH. The GARCH models volatility in the market, which I can then use to forecast the estimated volatility in the test data to incorporate into a random forest algorithm to capture nonlinear interactions. This leverages the strength of traditional time series modelling and modern machine learning, substantially improving forecast accuracy.

The framework in the study is an original contribution which can be extended by implementing more complex machine learning methods with higher-order VARs. Importantly, the framework provided in this paper doesn't have to be used to investigate the effect of GPR on stock returns, but can also be used to find how any variable affects stock returns. This research could prove useful in supplementing key financial research being conducted today and hopefully help markets to be understood.

The overarching conclusion of the paper is that, whilst GPR has no significant effect on predicting stock returns, it can still be a useful variable in the future, especially if a new index for GPR is produced. Baker, Bloom, and Davis's (2016) work was exceptionally rigorous, it still has limitations. Because it relies on measuring newspaper articles, there may be an inclination to avoid printing certain topics, or print more news on a topic, thus the effect of GPR could be understated or overstated according to the measure, depending on how the media wants people to perceive it. In a future iteration of Baker, Bloom, and Davis' index, there should be an events-based metric incorporated such as the Global Database of Events, Language, and Tone (GDELT). It should also include market-based signals, such as the VIX and public sentiment analysis, such as Google Trends, which can also intertwine with expert analysis from think tanks or intelligence agencies to collate an average of reports they share.

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Appendix A- Granger causality for each nation on every variable

Dependent	Excluded	p_value
log_us_volume	return_us_close	2.12232480539852E-14
log_us_volume	log_usrisk	0.0220566096347831
log_us_volume	log_volatility_close	2.19728943860812E-19
log_us_volume	us_NEXP_GDP	0.0567286862285891
log_us_volume	us_interest	0.000109164914174157
log_usrisk	return_us_close	0.237626918922751
log_usrisk	log_volatility_close	0.00533080914894386
log_usrisk	us_NEXP_GDP	0.996639334993672
log_usrisk	us_interest	0.761174004054143
log_usrisk	log_us_volume	0.126671501405169
log_volatility_close	return_us_close	1.55247565299879E-05
log_volatility_close	log_usrisk	0.760933974160643
log_volatility_close	us_NEXP_GDP	0.285540302115244
log_volatility_close	us_interest	0.981320949154242
log_volatility_close	log_us_volume	0.000161131100025187
return_us_close	log_usrisk	0.0979910672678623
return_us_close	log_volatility_close	4.61482146469985E-08
return_us_close	us_NEXP_GDP	0.0941212160577965
return_us_close	us_interest	0.840697817364379
return_us_close	log_us_volume	0.676581243467562
us_interest	return_us_close	0.00918094205240832
us_interest	log_usrisk	0.399320157528366
us_interest	log_volatility_close	0.205840536552314
us_interest	us_NEXP_GDP	0.951384982990646
us_interest	log_us_volume	0.00145089972429624
us_NEXP_GDP	return_us_close	0.0812078674488378
us_NEXP_GDP	log_usrisk	0.00442074309411231
us_NEXP_GDP	log_volatility_close	0.706160253414171
us_NEXP_GDP	us_interest	0.268782558143464
us_NEXP_GDP	log_us_volume	0.186450974055045

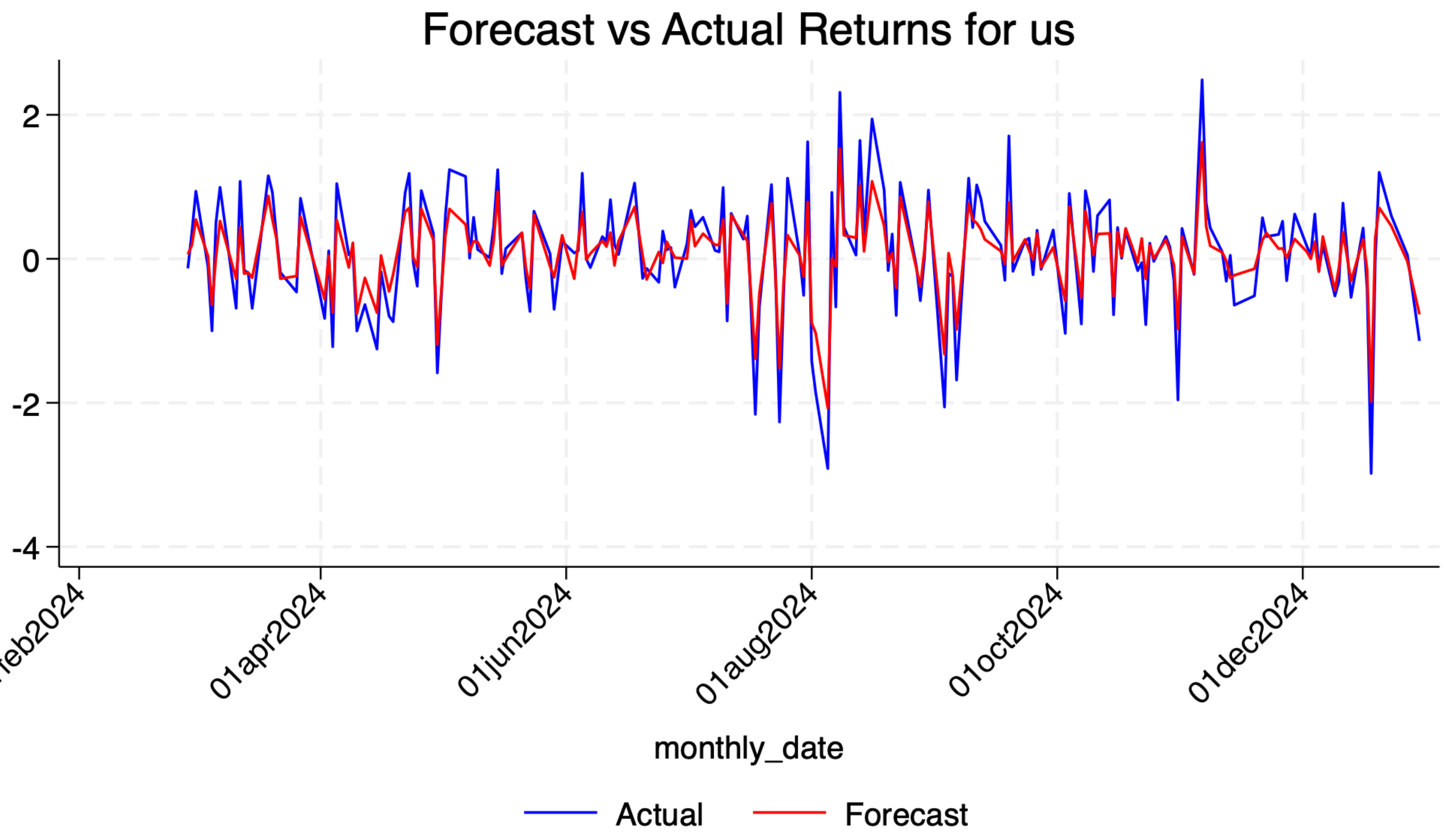
Dependent	Excluded	p_value
brazil_interest	return_brazil_close	0.479654785861066
brazil_interest	log_brazilrisk	0.10818550201691
brazil_interest	log_volatility_close	0.95444673222906
brazil_interest	brazil_NEXP_GDP	0.0625780544629318
brazil_interest	log_brazil_volume	0.887090178841719
brazil_NEXP_GDP	return_brazil_close	0.541385629993956
brazil_NEXP_GDP	log_brazilrisk	0.770779942744997
brazil_NEXP_GDP	log_volatility_close	0.955706326026225
brazil_NEXP_GDP	brazil_interest	0.957513671173492
brazil_NEXP_GDP	log_brazil_volume	0.00390040290116211
log_brazil_volume	return_brazil_close	0.00370284231414195
log_brazil_volume	log_brazilrisk	0.563193058626129
log_brazil_volume	log_volatility_close	0.00192300441163508
log_brazil_volume	brazil_NEXP_GDP	0.00187227103481836
log_brazil_volume	brazil_interest	0.466294861239308
log_brazilrisk	return_brazil_close	0.201205617898672
log_brazilrisk	log_volatility_close	0.998669866873998
log_brazilrisk	brazil_NEXP_GDP	0.866337110530679
log_brazilrisk	brazil_interest	0.981434212731736
log_brazilrisk	log_brazil_volume	0.687921242608848
log_volatility_close	return_brazil_close	0.00408688992577036
log_volatility_close	log_brazilrisk	0.532357907777621
log_volatility_close	brazil_NEXP_GDP	0.450777419919113
log_volatility_close	brazil_interest	0.934787519709751
log_volatility_close	log_brazil_volume	0.677663659583454
return_brazil_close	log_brazilrisk	0.12411844062848
return_brazil_close	log_volatility_close	0.00395913263079616
return_brazil_close	brazil_NEXP_GDP	0.657159685939593
return_brazil_close	brazil_interest	0.589541819575974
return_brazil_close	log_brazil_volume	0.343797608337053

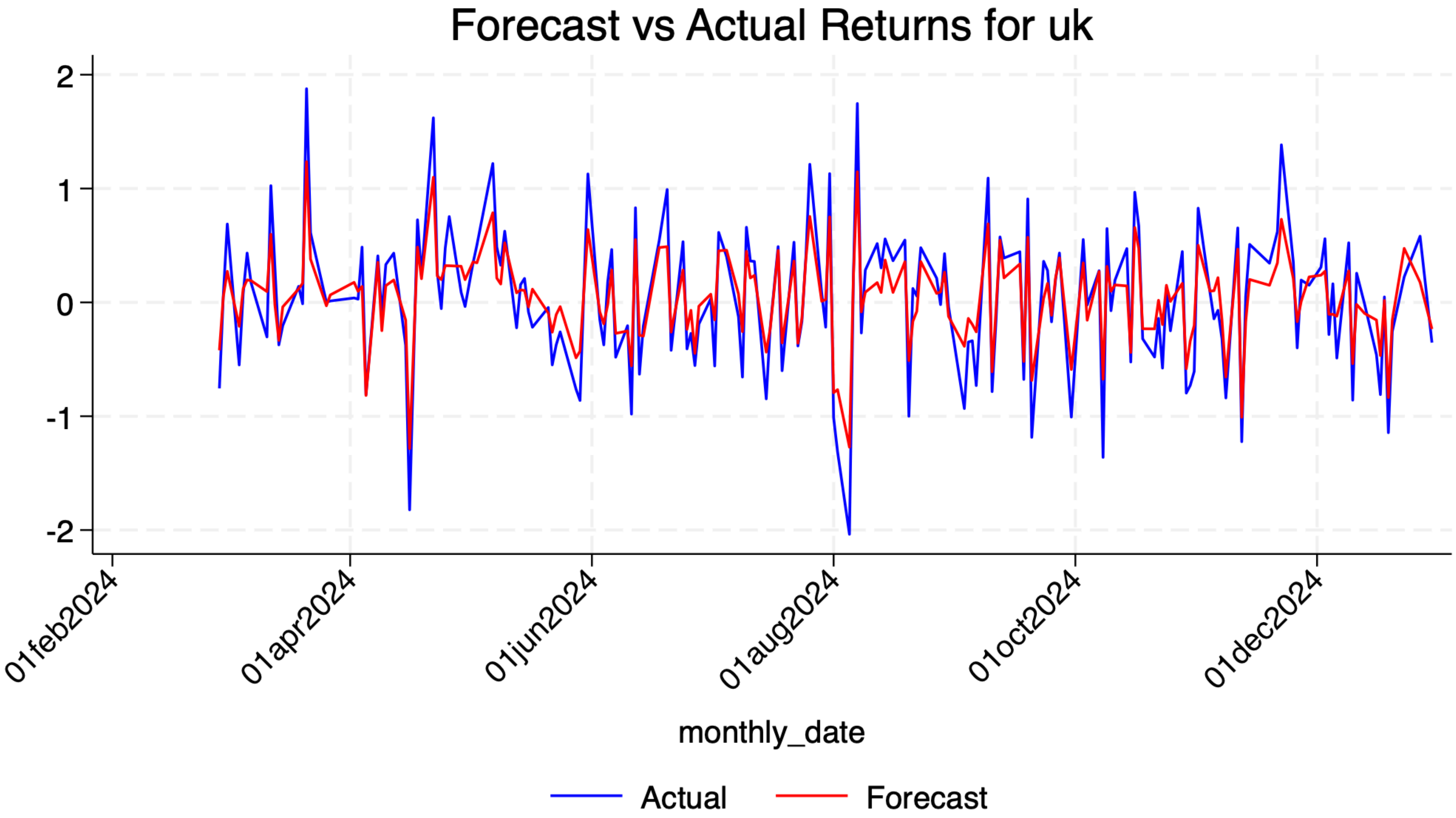
Dependent	Excluded	p_value
india_interest	return_india_close	0.333417012962659
india_interest	log_indiarisk	0.904320875950302
india_interest	log_volatility_close	0.00848690058268682
india_interest	india_NEXP_GDP	0.612784689963609
india_interest	log_india_volume	0.000370578772101282
india_NEXP_GDP	return_india_close	0.740033863907887
india_NEXP_GDP	log_indiarisk	0.153058400245628
india_NEXP_GDP	log_volatility_close	0.947681687285825
india_NEXP_GDP	india_interest	0.129644809327842
india_NEXP_GDP	log_india_volume	0.158788727899266
log_india_volume	return_india_close	0.746772909528594
log_india_volume	log_indiarisk	0.622555076145719
log_india_volume	log_volatility_close	1.98100880240443E-09
log_india_volume	india_NEXP_GDP	0.269682049150767
log_india_volume	india_interest	0.231321337047472
log_indiarisk	return_india_close	0.859704252548446
log_indiarisk	log_volatility_close	0.00541109500361916
log_indiarisk	india_NEXP_GDP	0.118000004700722
log_indiarisk	india_interest	0.277935906106462
log_indiarisk	log_india_volume	0.86447728567097
log_volatility_close	return_india_close	0.0261680160312353
log_volatility_close	log_indiarisk	0.880627844106949
log_volatility_close	india_NEXP_GDP	0.0245625699841241
log_volatility_close	india_interest	0.979339748861847
log_volatility_close	log_india_volume	0.4363386459024
return_india_close	log_indiarisk	0.467149504070135
return_india_close	log_volatility_close	0.0088559439317502
return_india_close	india_NEXP_GDP	0.0199789245497245
return_india_close	india_interest	0.129252994487455
return_india_close	log_india_volume	0.323750800222049

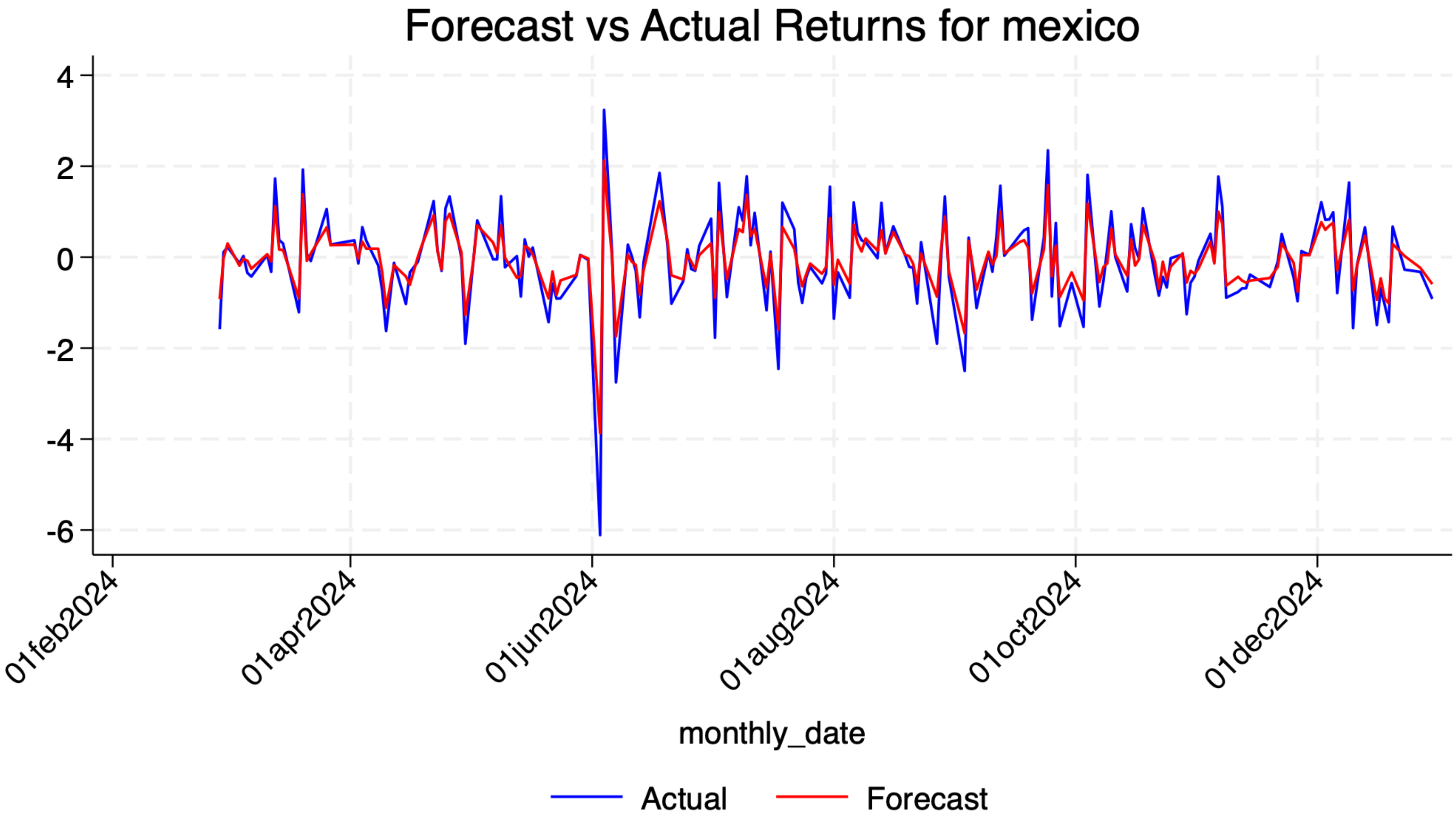
Dependent	Excluded	p_value
log_mexico_volume	return_mexico_close	0.006413053044869
log_mexico_volume	log_mexicorisk	0.0058469522762823
log_mexico_volume	log_volatility_close	0.0901482593364036
log_mexico_volume	mexico_NEXP_GDP	0.758012791209509
log_mexico_volume	mexico_interest	0.00158606698781507
log_mexicorisk	return_mexico_close	0.0165566127611569
log_mexicorisk	log_volatility_close	0.00080440095637843
log_mexicorisk	mexico_NEXP_GDP	0.431661877252888
log_mexicorisk	mexico_interest	0.0370762499246436
log_mexicorisk	log_mexico_volume	0.372823757409165
log_volatility_close	return_mexico_close	0.00737588594521762
log_volatility_close	log_mexicorisk	0.56972705083144
log_volatility_close	mexico_NEXP_GDP	0.504174125537502
log_volatility_close	mexico_interest	0.928369028060356
log_volatility_close	log_mexico_volume	0.223034979122901
mexico_interest	return_mexico_close	0.187211082801572
mexico_interest	log_mexicorisk	0.0581042188392801
mexico_interest	log_volatility_close	0.0534367921988605
mexico_interest	mexico_NEXP_GDP	4.86218709874524E-06
mexico_interest	log_mexico_volume	0.0387831152074459
mexico_NEXP_GDP	return_mexico_close	0.157548394510877
mexico_NEXP_GDP	log_mexicorisk	0.6331503640314
mexico_NEXP_GDP	log_volatility_close	0.968428561970285
mexico_NEXP_GDP	mexico_interest	0.847602633344986
mexico_NEXP_GDP	log_mexico_volume	3.96638241022134E-07
return_mexico_close	log_mexicorisk	0.803013880633803
return_mexico_close	log_volatility_close	0.00127479278719435
return_mexico_close	mexico_NEXP_GDP	0.170429421349166
return_mexico_close	mexico_interest	0.054644757588902
return_mexico_close	log_mexico_volume	0.804835997239216

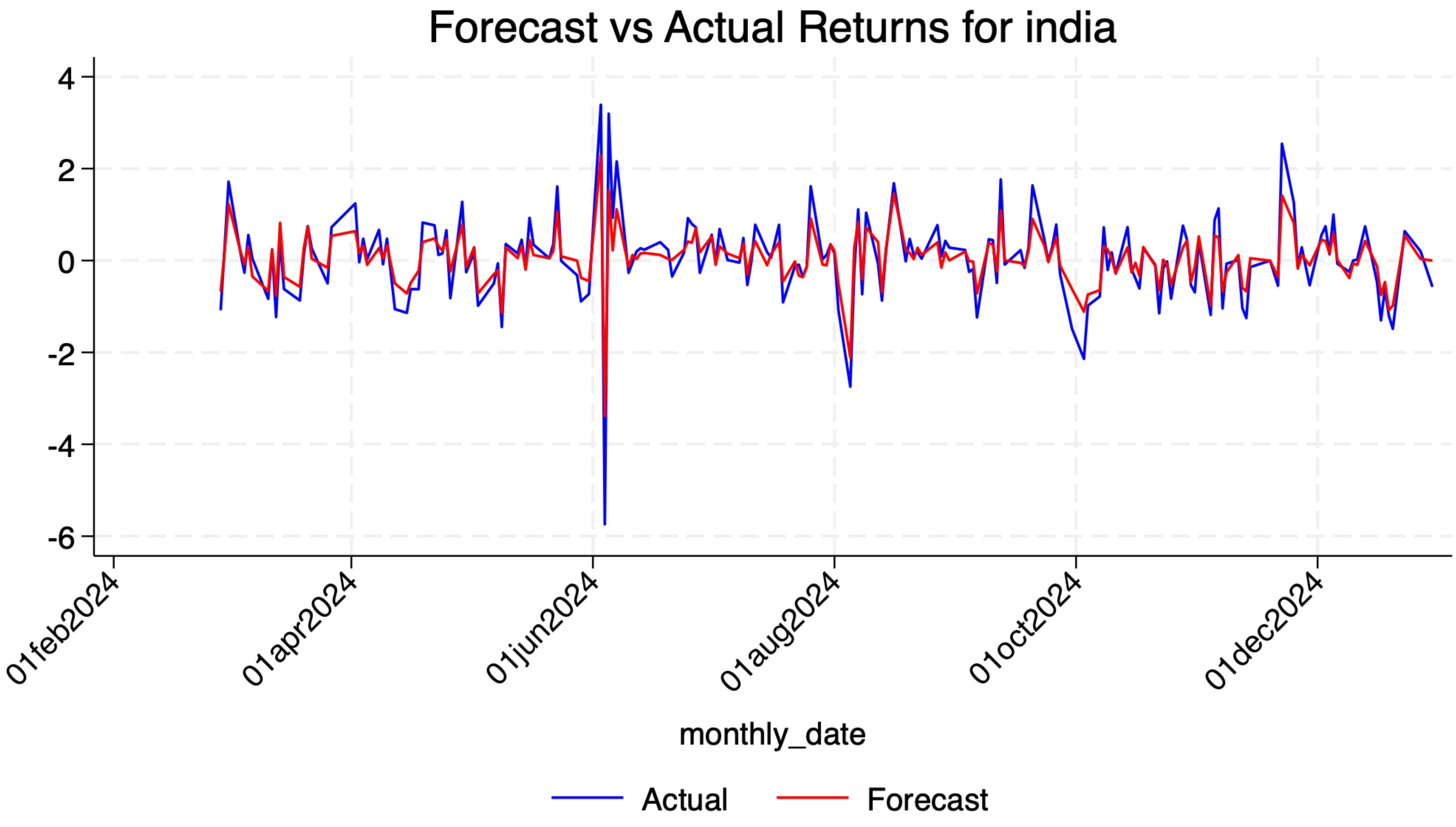
Dependent	Excluded	p_value
log_uk_volume	return_uk_close	0.00180095706505538
log_uk_volume	log_ukrisk	4.87455573143502E-11
log_uk_volume	log_volatility_close	6.01575853033358E-05
log_uk_volume	uk_NEXP_GDP	0.837667785390445
log_uk_volume	uk_interest	7.04544480215258E-10
log_ukrisk	return_uk_close	0.125953808118881
log_ukrisk	log_volatility_close	0.097750212882129
log_ukrisk	uk_NEXP_GDP	0.174153961314894
log_ukrisk	uk_interest	0.169983004113223
log_ukrisk	log_uk_volume	0.877696979069232
log_volatility_close	return_uk_close	0.000112024369584274
log_volatility_close	log_ukrisk	0.982566111765468
log_volatility_close	uk_NEXP_GDP	0.160880958158885
log_volatility_close	uk_interest	0.945038457982899
log_volatility_close	log_uk_volume	0.331385694866306
return_uk_close	log_ukrisk	0.715770064303611
return_uk_close	log_volatility_close	0.00555610701144653
return_uk_close	uk_NEXP_GDP	0.863797888285581
return_uk_close	uk_interest	0.48589745543086
return_uk_close	log_uk_volume	0.381844816724299
uk_interest	return_uk_close	0.821932281216542
uk_interest	log_ukrisk	0.827690330996232
uk_interest	log_volatility_close	0.992131971756395
uk_interest	uk_NEXP_GDP	0.941258572642956
uk_interest	log_uk_volume	0.254549764992608
uk_NEXP_GDP	return_uk_close	0.364382656196528
uk_NEXP_GDP	log_ukrisk	0.950204848255985
uk_NEXP_GDP	log_volatility_close	0.898800772925549
uk_NEXP_GDP	uk_interest	0.285244658003879
uk_NEXP_GDP	log_uk_volume	0.225230349239953

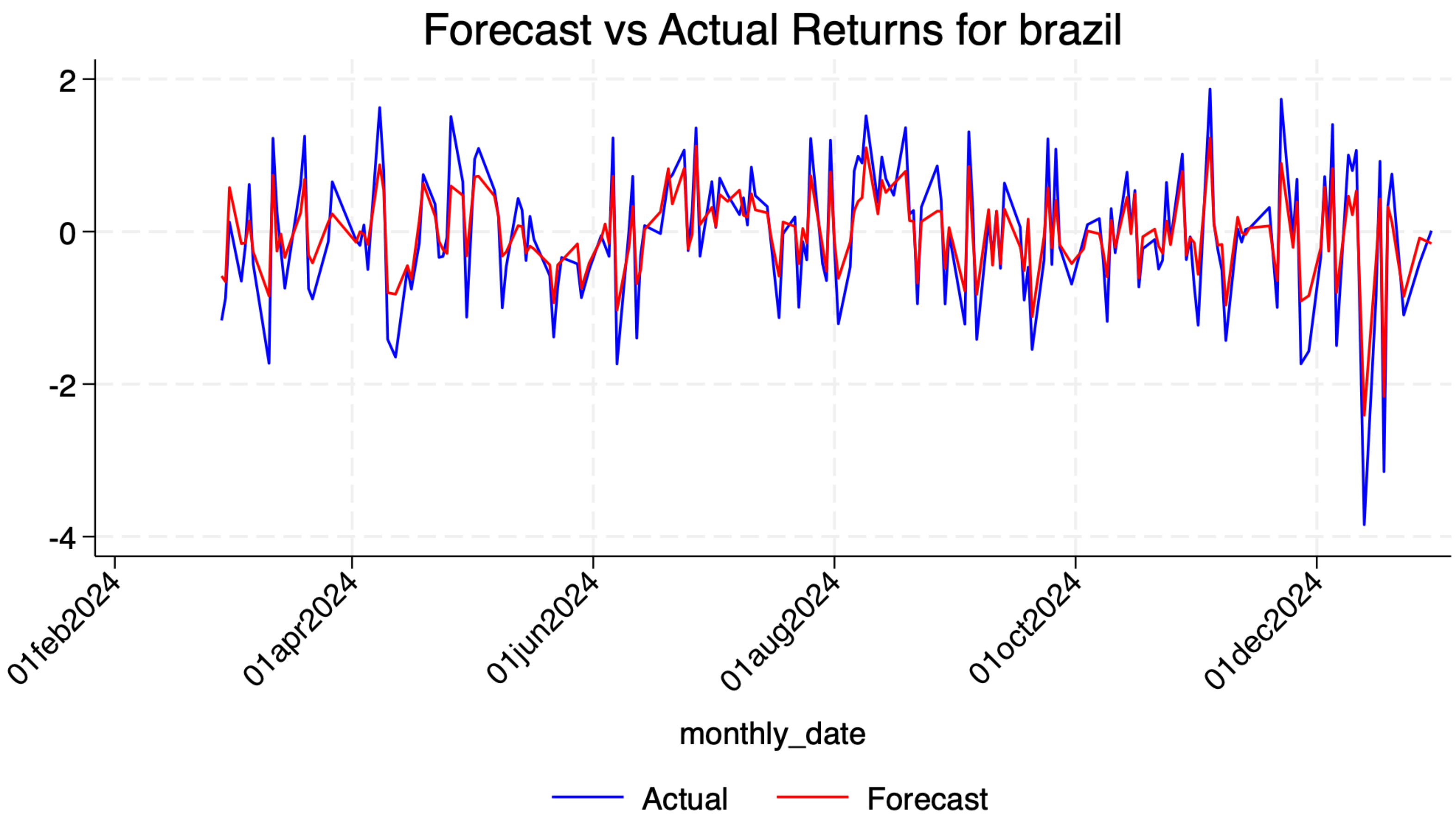
Appendix B- "Bivariate" Random Forest forecast



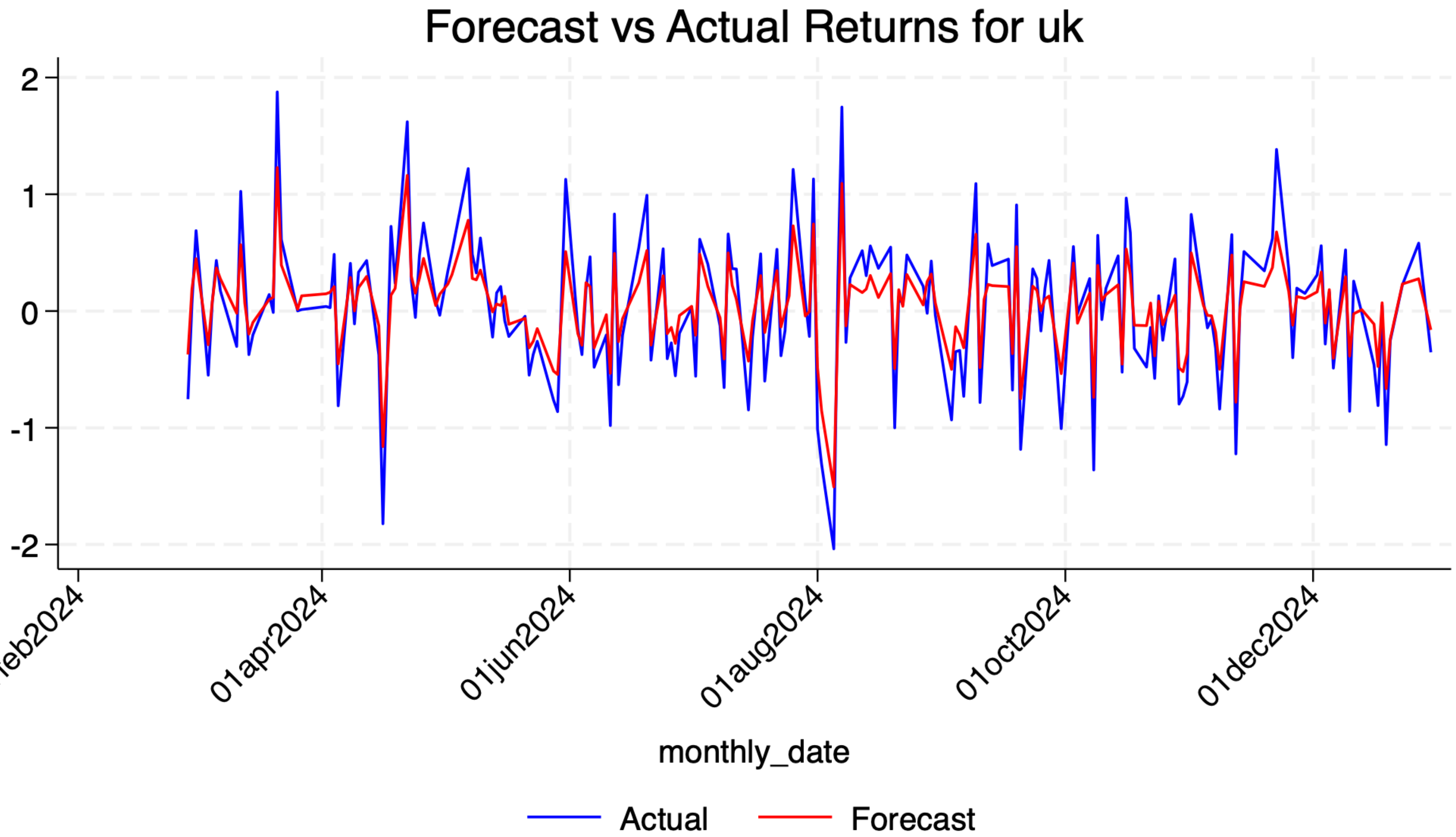

Forecast vs Actual Returns for uk
2
1
0
-1
-2
01feb2024
01apr2024
01jun2024
01aug2024
01oct2024
01dec2024
monthly_date
Actual
Forecast

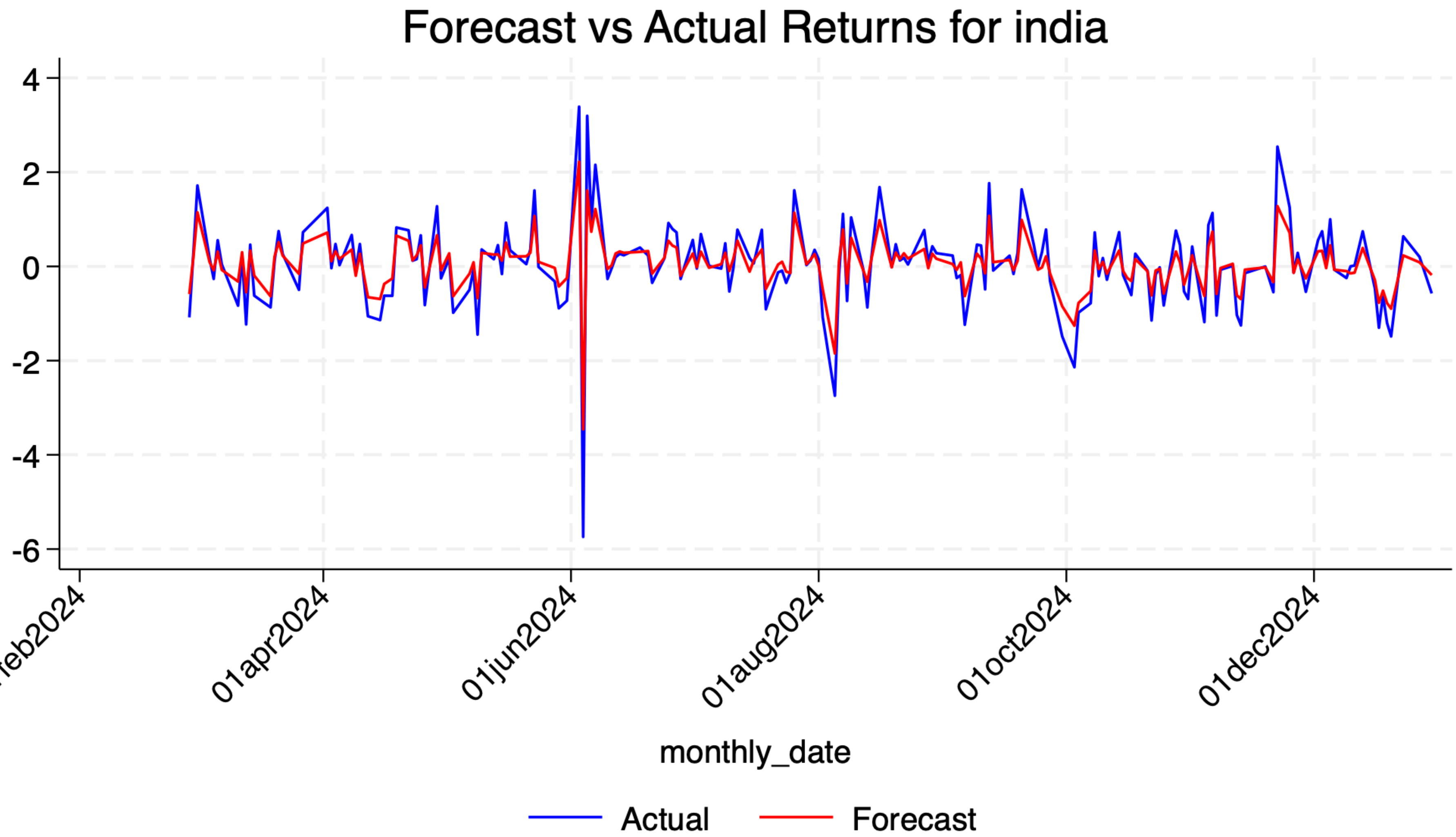

Forecast vs Actual Returns for mexico
4
2
0
-2
-4
-6
01feb2024
01apr2024
01jun2024
01aug2024
01oct2024
01dec2024
monthly_date
Actual
Forecast


Forecast vs Actual Returns for india
4
2
0
-2
-4
-6
01feb2024
01apr2024
01jun2024
01aug2024
01oct2024
01dec2024
monthly_date
Actual
Forecast

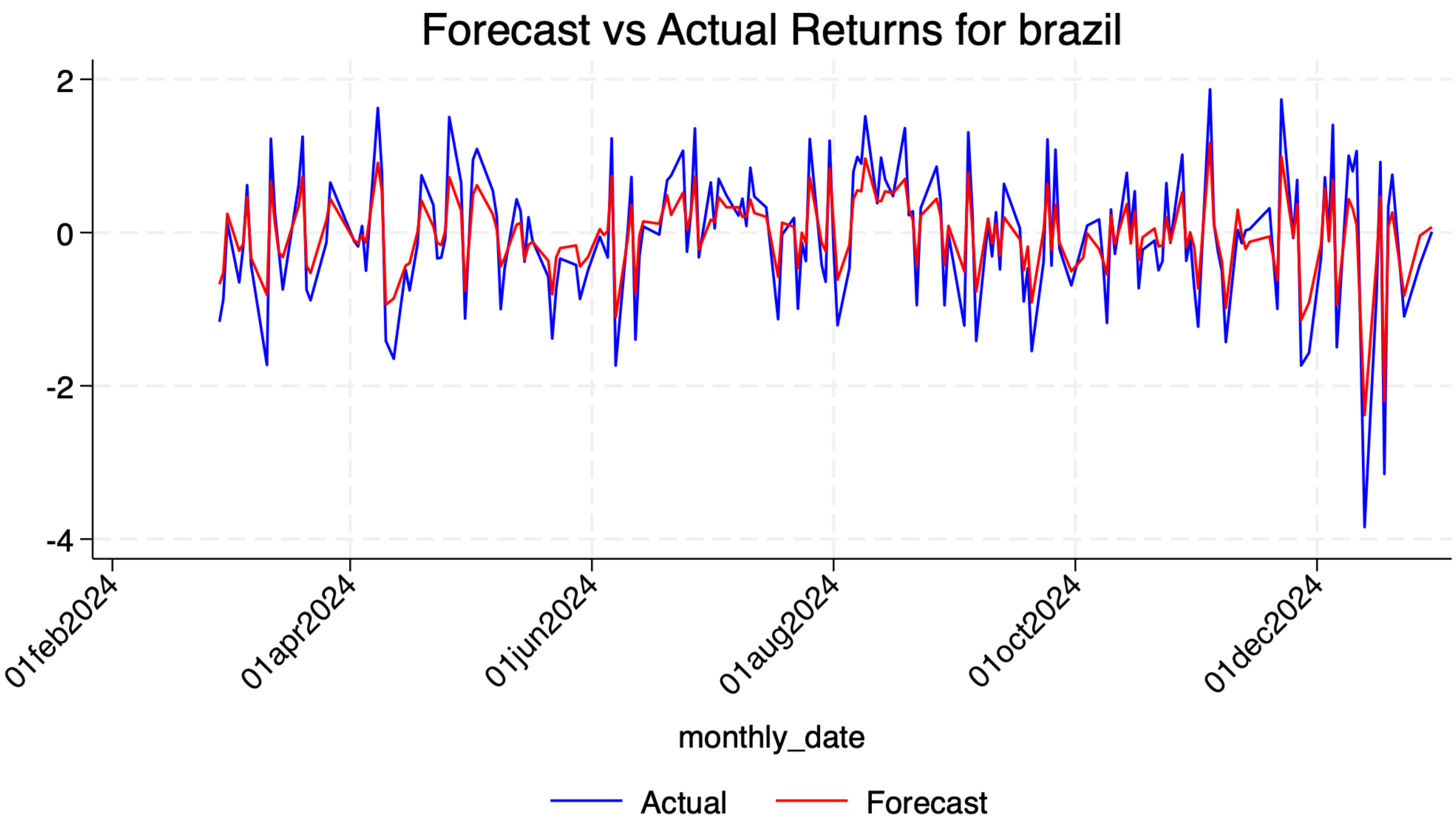

Forecast vs Actual Returns for brazil
2
0
-2
-4
01feb2024
01apr2024
01jun2024
01aug2024
01oct2024
01dec2024
monthly_date
Actual
Forecast

Appendix C- “Multivariate” Random Forest Forecast

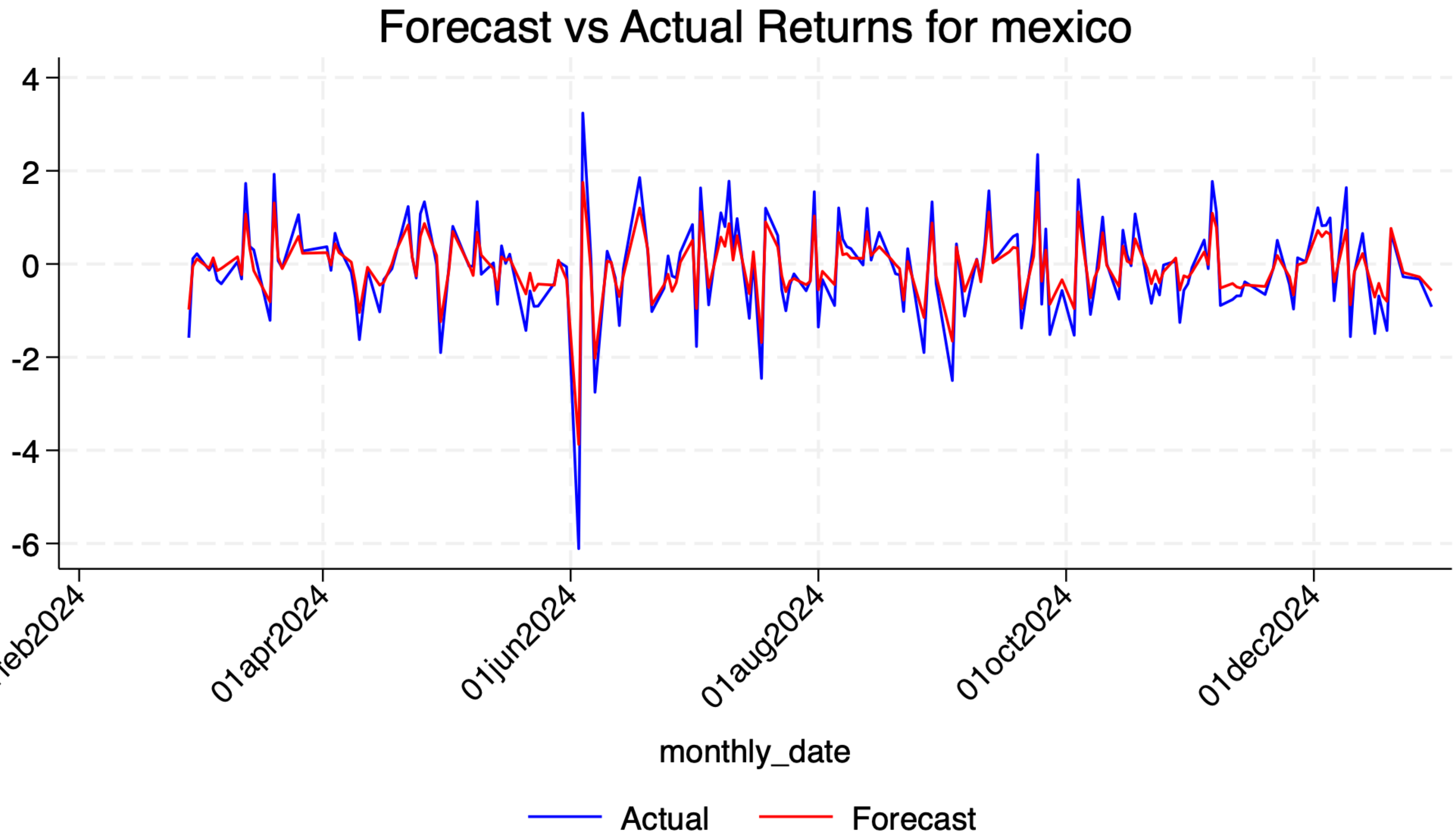


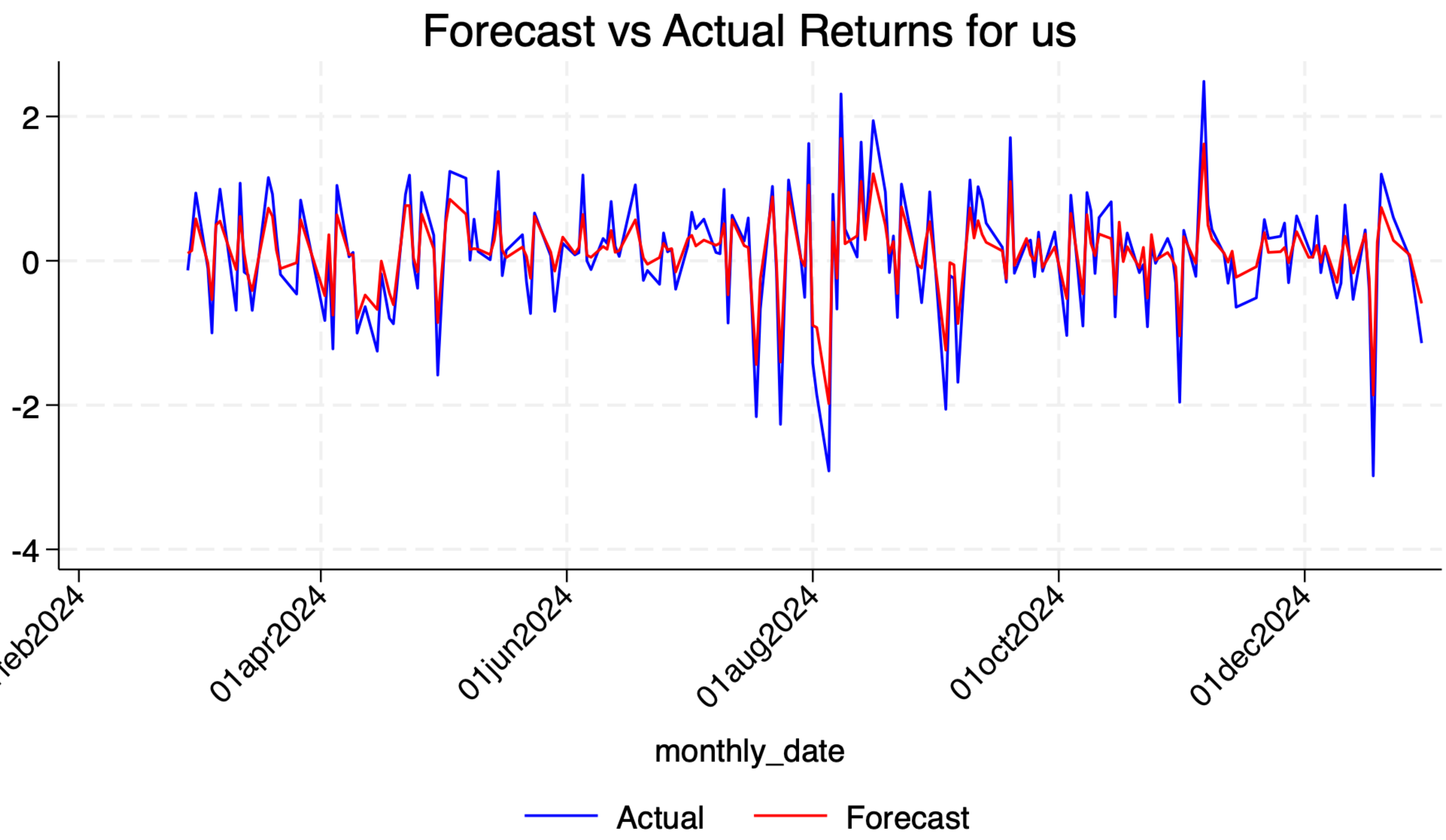


Forecast vs Actual Returns for india
4
2
0
-2
-4
-6
01feb2024
01apr2024
01jun2024
01aug2024
01oct2024
01dec2024
monthly_date
Actual
Forecast



Forecast vs Actual Returns for brazil
2
0
-2
-4
01feb2024
01apr2024
01jun2024
01aug2024
01oct2024
01dec2024
monthly_date
Actual
Forecast


Forecast vs Actual Returns for mexico
4
2
0
-2
-4
-6
01feb2024
01apr2024
01jun2024
01aug2024
01oct2024
01dec2024
monthly_date
Actual
Forecast


Forecast vs Actual Returns for us
2
0
-2
-4
01feb2024
01apr2024
01jun2024
01aug2024
01oct2024
01dec2024
monthly_date
Actual
Forecast