Predictive Modeling of Interest Rates: Developed vs. Developing Nations

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INTRODUCTION:

In the domain of monetary policy, setting interest rates is a crucial decision-making process that has a substantial impact on a country's economic environment. In order to establish interest rates, central banks—which maintain monetary stability—carefully consider a range of economic variables with the goal of achieving macroeconomic goals including price stability, sustainable growth, and full employment. In this study, we attempt to answer how the determinants of a nation's short-term interest rate are affected by its development level. Specifically, we apply the machine learning techniques of Random Forest and Multi Layer Perceptron(MLP) regression for this question to measure their performance and see if they are able to model this system more effectively than a baseline Ordinary Least Squares Regression. Through the identification of the relative weights assigned to these variables in different development environments, this study seeks to shed light on the complex details that underlie the formulation of monetary policy in both emerging and developed countries.

DATA SOURCES AND STRUCTURE:

In order to answer this question, we took a sample of ten developed and nine developing nations as classified by the IMF.

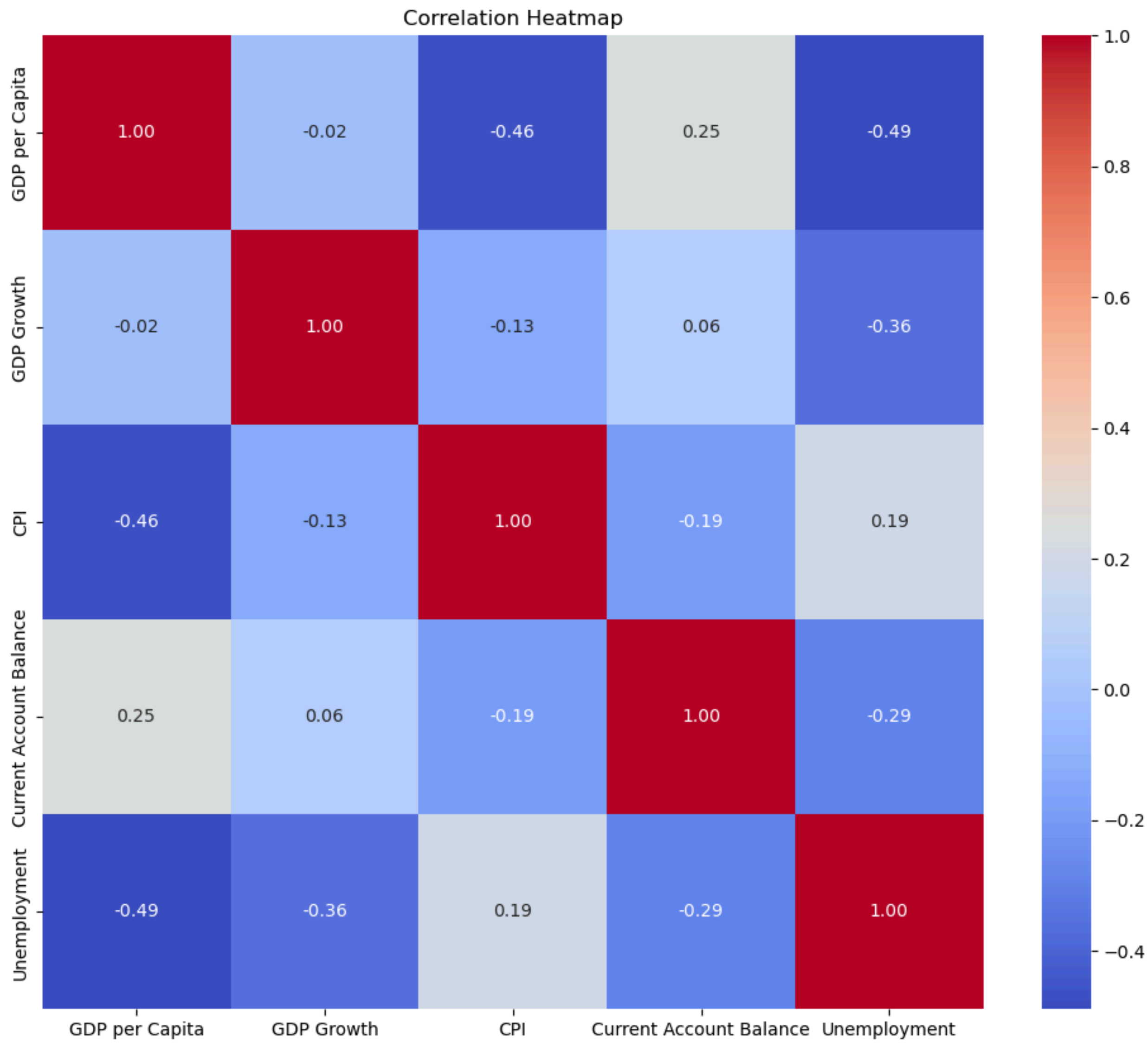
Developed Nations Sample	Developing Nations Sample
Canada	Senegal
Iceland	Vietnam
Korea	Brazil
Norway	Colombia
Russia	South Africa
UK	Turkey
US	Malaysia
Australia	Mexico
Hungary	Gambia
Switzerland	

Utilizing data from the IMF's Financial and Monetary Database, we collected data from 2006-2016 on these nations' short-run central bank interest rates at a quarterly frequency. We chose the rate listed by the IMF as the Central Bank Policy Rate because it best reflected the rate that a central bank was using to implement its inflation targets. However, the published name for this rate varies between central banks, which is why we chose data from a global source, rather than collecting data from individual central banks. After this, we identified five X variables — GDP per Capita (constant 2015 dollars), percentage GDP growth over the last year, CPI, Current Account Balance as a percentage of GDP, and unemployment rate. This data came from the World Bank, IMF, and the International Labor Organization(ILO).

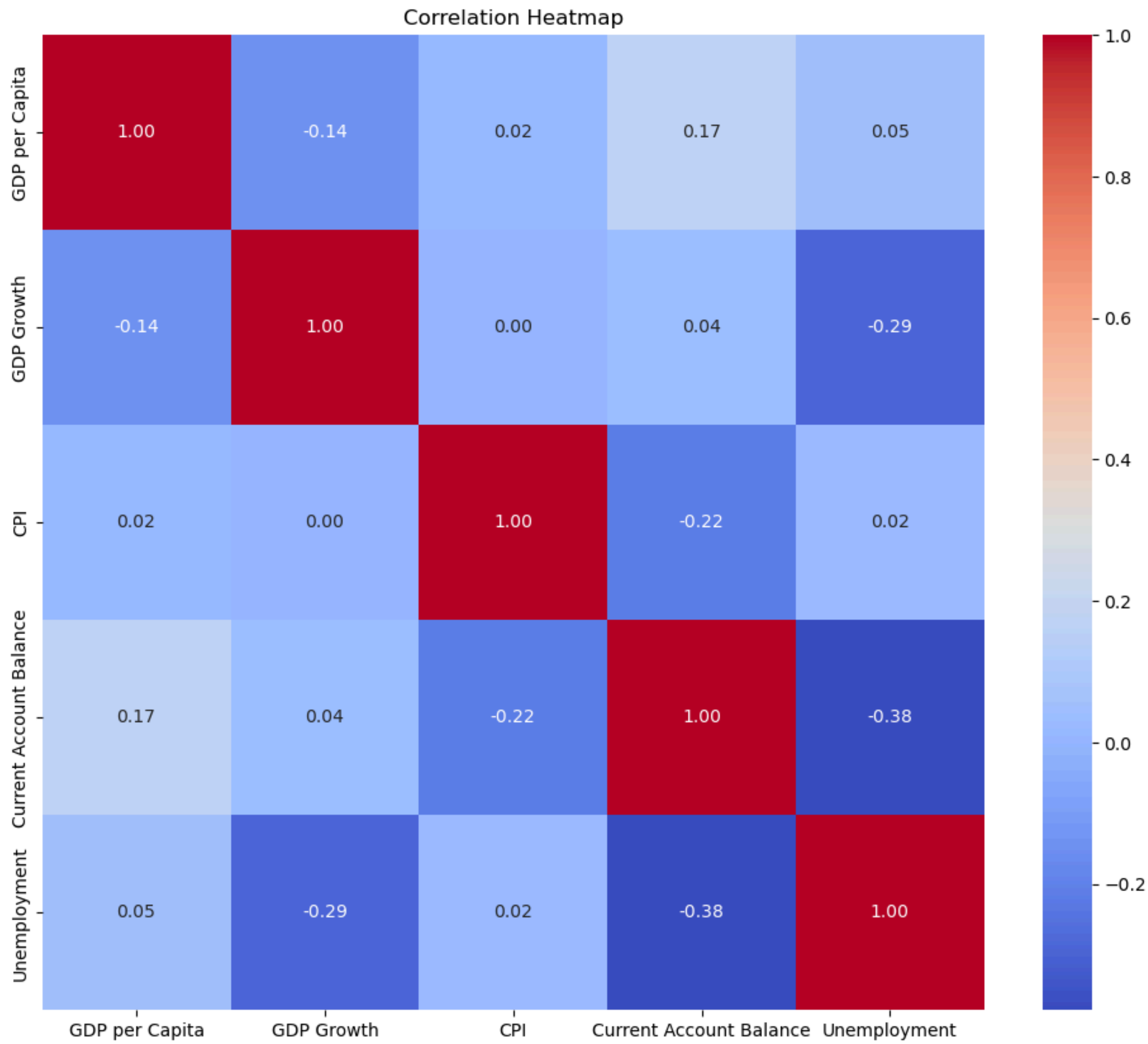
Frequency of publication for these statistics varied. Interest rate and CPI data was available on a quarterly basis from the IMF, but the World Bank and ILO only published data on an annual level, so to obtain regression results with quarterly frequency, we had to duplicate the annual data for unemployment, GDP, GDP Growth, and Current Account Balance to fill each quarter. Alternatively, we could have filled the annual data using more advanced methods, like Chow-Lin or Denton interpolation, which are able to estimate intermediate values with greater accuracy than linear interpolation (Marini, 2016). However, these methods also come with downsides. In some applications, for example, the Chow-Lin method tends to underestimate the target variable, which limits its effectiveness in explaining a greater portion of the variance in interest rates, so we decided not to use this method.

We measured the performance of our models by using the Mean Absolute Error(MAE), Mean Squared Error(MSE), and Root Mean Squared Error(RMSE). As r^2 is a measure of variance explained by a linear relationship, we opted not to use it as a metric because of the application of machine learning models that may pick up on non-linear relationships in the data.

Variable multicollinearity in developed nations:



Variable multicollinearity in developing nations:



Multicollinearity among the variables is limited, but there are still some relationships to take note of. First, unemployment levels are negatively correlated with GDP per capita, and less so with growth, in developed countries, but this relationship is weaker in developing nations. This also holds true for the relationship between GDP per capita and CPI in developing nations. The comparison of three models allows us to see how multicollinearity is handled differently using machine learning techniques.

LITERATURE REVIEW:

In order to choose relevant factors and interpret them in the context of real-world policies, we first had to understand the frameworks used by central banks to set short-run interest rates. Since the 1990s, inflation targeting(IT) has become a prominent central bank policy across developed and developing countries. In simple terms, central banks in an inflation targeting regime openly declare the inflation rate they want – normally around 2% – and adjust short term interest rates to push the economy towards the middle-run target. Among developed nations, IT regimes have become standard. 35 of the 36 OECD nations fall under a central bank that utilizes IT, either by setting a hard target or a range of values, like the US Federal Reserve. After its use surged in developed nations during the early 1990s, IT spread to emerging economies throughout the 90s, including major economies like Mexico, Thailand, Indonesia, Brazil, Turkey, and India. IT regimes have been found to be successful in developed nations overall(Mishkin & Posen, 1998), and more conservatively in developing countries(Rose, 2020). Nations adhering to similar policies have faced far fewer currency shocks, leading to its widespread adoption.

In lower-income countries, results are less impressive. This is qualified by the fact that far fewer LICs have defined central bank policy, as many are reliant on currency pegs to larger nations that they are otherwise dependent on. Additionally, lower access to credit economy-wide in LICs mean that central banks have little control over prices via interest rates. In a study comparing the effect of the addition of an IT regime, the effect of the dummy variable was not statistically significant in LICs, indicating no change in inflation before or after the implementation of the policy(Morozumi et. al, 2020). Generally, IT regimes follow the *Taylor Rule*, expressed below:

$$i_t = \pi_t + r_t^* + a_\pi(\pi_t - \pi_t^*) + a_y(y_t - \bar{y}_t).$$

Where i_t is the target short-term interest rate, π_t the current inflation rate, π^*_t the target inflation rate, y_t the output (in real-world applications, y_t is sometimes taken to be the log of GDP), and $\bar{y}_t$ the potential full-employment output. a_π and a_y are positive constants, sometimes taken to be .5. Overall, this regime places currency valuation and economic output as the main drivers of change in interest rates. Thus, CPI, GDP growth, and GDP per capita were included in our model as X variables.

Current Account Balance measures non-financial flows of money between nations, mostly through trade. Thus, its impacts on currency valuation could also explain some of the variation in interest rates. A deficit in the current account indicates that the nation is on net borrowing from international markets to finance its spending on imports, which leads to depreciation with respect to other currencies because the nation is demanding more foreign currency than other nations are demanding its currency(Dornbusch and Fischer, 1980) Thus, the correlation between current account deficits and increased relative prices of foreign goods could capture some of the change in central bank interest rate targets.

Random Forest and MLP regressions were chosen to answer these questions because of their strengths in nonlinear modeling(van der Wel & Overes, 2022). Random Forest models do this by creating a large number of decision trees on different subsets and features of the data, and combine them to create a model that is better than an individual tree could. Because there are five X variables at a low frequency, an individual tree would struggle to divide data points in five-dimensional space in a manner that allowed useful conclusions to be drawn, as many divisions of the data would have very sparse data. The Random Forest approach has been shown to be successful in predicting instruments with similar determinants, like sovereign bonds(Martin et. al, 2023).

Artificial Neural Networks(ANNs), and MLPs more generally, are designed to broadly mimic the structure of a brain's neurons. By adding multiple levels of operations in a hidden layer and adjusting the weights of the connections between the values that are passed onto the next layer of neurons, neural networks can be scaled to classify and predict highly complex systems – provided that they are given enough data to train on(Zheng et. al, 2023). Its strengths in predicting inflation (Nakamura, 2005) better than linear models was encouraging, given the relationship between interest rates and inflation discussed above. However, interpretation of these models is highly difficult. Due to the 'hidden layer' neurons performing computations on multiple inputs from previous neurons and weighting them, observing the relationships between the input neurons and the output quickly becomes extremely complicated in even the simplest architectures. Thus, this model is not used to understand the determinants of inflation and how they differ across development levels, but rather to observe their performance and critique based on time-series analysis. To limit overfitting, each model was trained on a 75/25 training/test split.

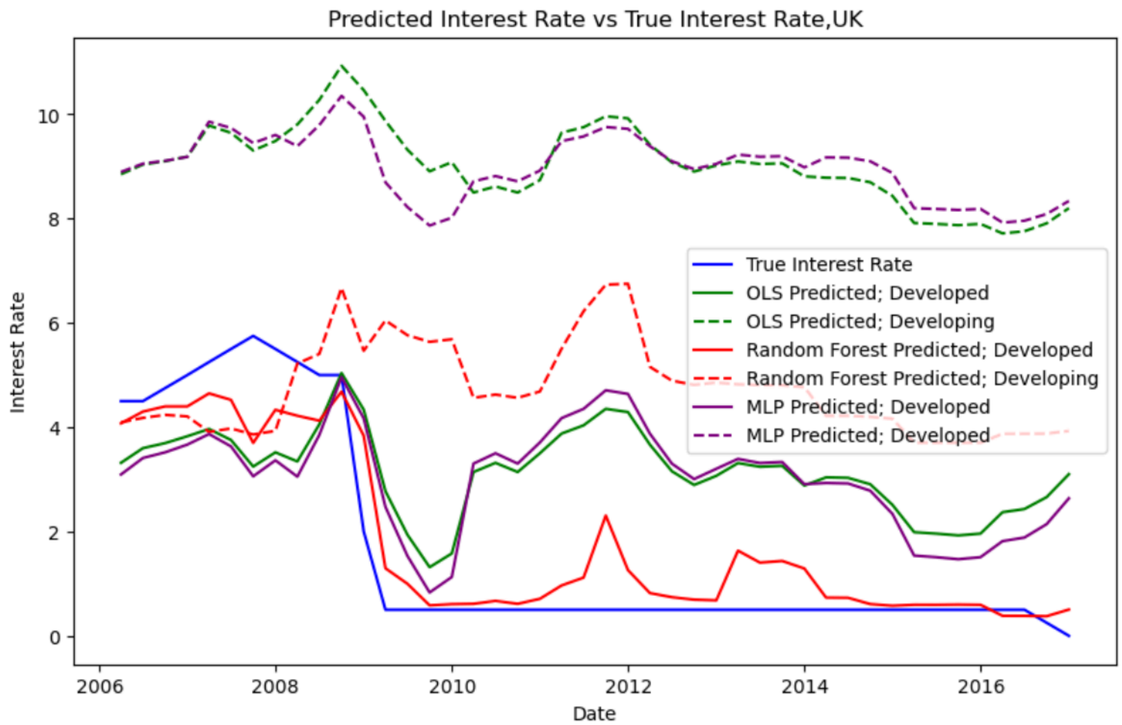
RESULTS AND PERFORMANCE METRICS

Metric	OLS Developed	OLS Developing	RF Developed	RF Developing	MLP Developed	MLP Developing
MAE	1.55	2.31	0.67	.78	1.54	2.27

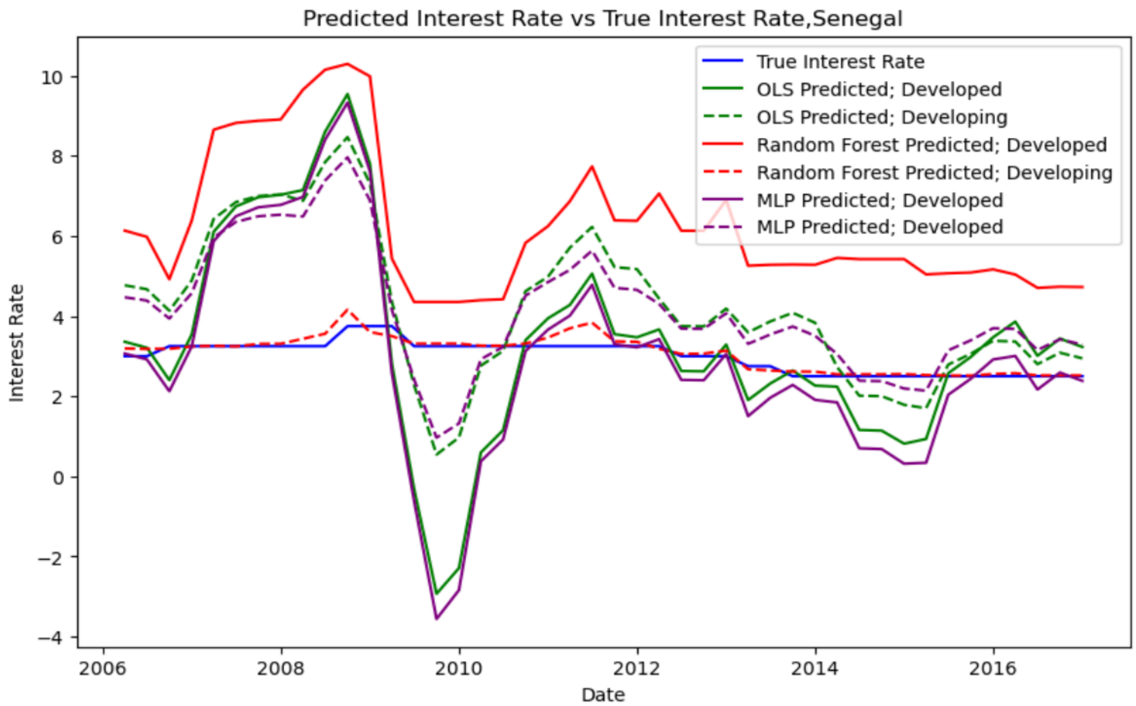
RMSE	2.02	2.89	1.29	1.24	2.04	2.86
MSE	4.08	8.37	1.67	1.52	4.15	8.20

Upon reviewing metrics across the three models, the Random Forest performs the best for our dataset for both developing and developed nations. However, the degree of improvement from OLS and MLP models to Random Forest is much larger than for developing nations. This improvement suggests that developing nation central banks interest rate policies do not respond as linearly as in developing countries. This can be attributed to multiple reasons. Possibly, IMF and World Bank data is less reliably collected in developing nations, leading to noise that was more effectively filtered out in a Random Forest model. On the flip side, there could simply not be as strong of a relationship observable in this sample set, leading to the Random Forest model overfitting on the training data. Another possibility is that central banks in developing nations are less independent from political considerations, leading to some adopting procyclical and some adopting counter-cyclical policies depending on short-term government needs (this is discussed further in the OLS section).

To see the different model predictions in a single-country case, we plotted the real and predicted interest rates of a developed and developing nation (the UK and Senegal, respectively).



Consistently, the true values are more static than the predicted values. Additionally, the developed nations' predictions respond more rapidly to changes; rate cuts after the 2008 financial crisis in both nations have a sharper rate of change across the three developed nations models. An important qualifier for the time-series analysis is that the results are based on the true feature values, which would likely be different when examining the counterfactual, as interest rates have reverse causal effects on the chosen X variables.



Ordinary Least Squares

The weighting of important economic factors—unemployment, GDP growth rate, GDP per capita, current account deficit, and Consumer Price Index (CPI)—in determining interest rates was predicted by our analysis using Ordinary Least Squares (OLS) regression analysis. In order to shed light on the direction and strength of these variables' influences on monetary policy decisions, we used OLS regression to find the linear correlations between these variables and interest rate changes. We were able to estimate the economic components' coefficients by OLS regression, which gave us a clear understanding of how they affected interest rates. We were able to evaluate the impact of each economic element and quantify their importance in influencing changes in interest rates by using the OLS methodology.

	Developed				Developing		
Variable	Coefficient	t-stat	P > |t|		Coefficient	t-stat	P > |t|
GDP per Capita	-8.484x10^-6	3.179	0.141		0.0001	2.058	0.041
GDP Growth	.1427	-1.475	.002		-.1591	-2.562	0.011
CPI	0.8782	3.139	.000		.5826	12.659	.000
Current Acct. Balance	-0.0771	-4.180	.000		-.0282	-.751	.453
Unemployment	-0.1708	-2.327	.021		.0248	.737	.462

A negative current account deficit coefficient (-0.0771) in developed countries indicates that a decrease in the current account balance is linked to higher interest rates. Higher interest rates attract foreign investors by making domestic assets more attractive, leading to increased capital inflows and financing the current account deficit. This leads to currency appreciation, which can make exports more expensive and less competitive in global markets for foreign buyers and cheaper for domestic consumers, reducing the current account deficit over time. Additionally, higher interest rates can dampen domestic consumption and investment, resulting in a decrease in import demand, which narrows the gap between imports and exports, reducing the current account deficit. The smaller and statistically negligible current account deficit coefficient (-0.0282) in developing nations, on the other hand, points to a weaker or non-linear relationship between the deficit and interest rates. This could be because developing nations may be more vulnerable to capital flow volatility and external shocks, which can have an impact on the current account balance (Pagliari & Hannan, 2017).

The coefficients of the developing nation model imply procyclical interest rate policies at odds with the Taylor Rule. For example, the negative relationship between GDP growth and interest rate indicates that in times of high growth, developing nation central banks cut rates further to spur growth, rather than raising them to avoid inflation and overheating. This is consistent with prior findings of higher natural rates of full-employment inflation due to higher average growth(Domaç & Yücel, 2005) . Another example of counter-cyclical policy is the weak positive relationship between unemployment and inflation, indicating that in times of higher unemployment, rates increase. Pro-cyclical policies are more common in developing nations(Ilzetzki & Vegh, 2005) in fiscal policy, and these results may imply a lack of central bank independence.

Another takeaway could be the possibility of reverse causality. As discussed above, these variables have significant impacts on interest rate policy. However, interest rate policy also has impacts in the other direction — on GDP and GDP growth and unemployment via changes in access to investment, on CPI through changes in the money supply, and on Current Account balance through changes in capital account flow. This is complicated by the fact that short-run changes in all variables except for CPI and Interest rate are not captured in annual data, a limitation on the interpretability of these results.

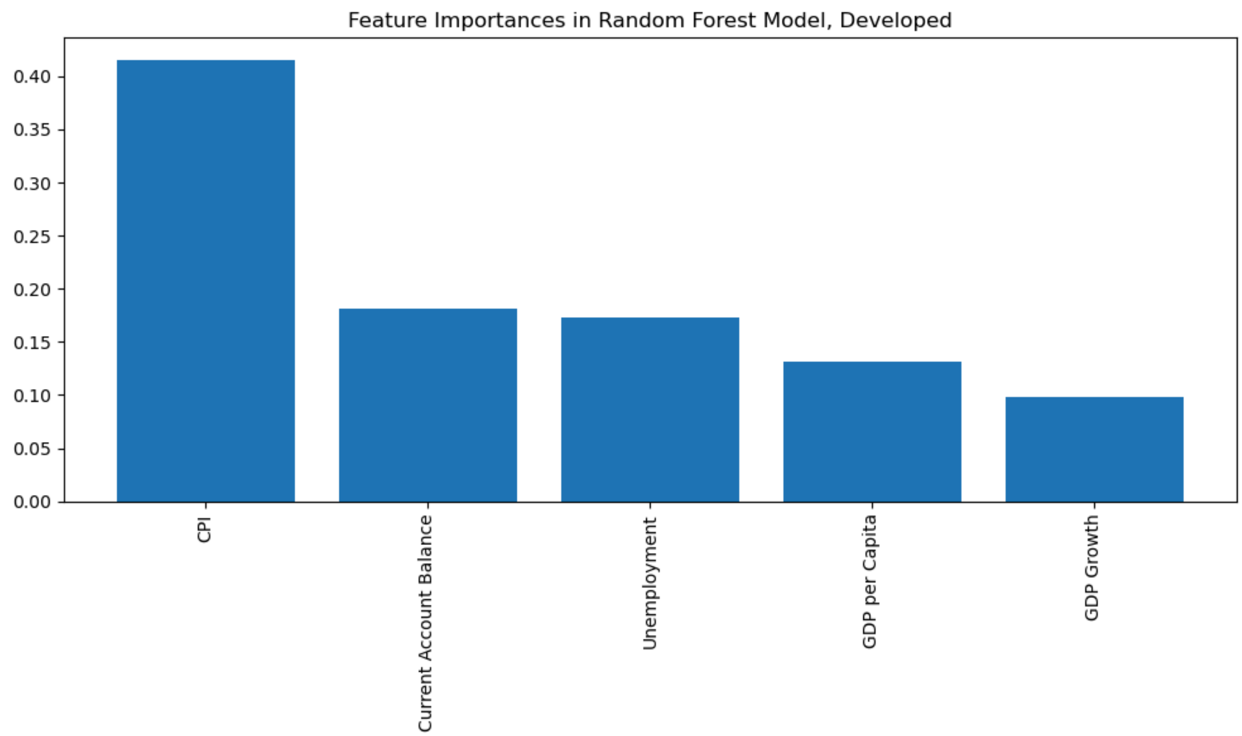
Random Forest

We sought to determine the relative significance of these variables in influencing monetary policy decisions by utilizing Random Forest's predictive power to analyze the complex relationship between these variables and interest rate modifications. Since economic datasets often contain nonlinear correlations, Random Forest made processing high-dimensional data easier. By combining predictions from several decision trees, we were able to increase the stability and resilience of our regression results thanks to its ensemble learning technique. This is especially useful considering the nonlinearity in the results of our OLS model for developing nations – despite the same frequency of data and variables, the model was significantly less reliable than the OLS model for developing countries.

To set up the model, we used the Optuna package in Python to perform a grid search across the hyperparameters of the regression: number of estimators (decision trees) produced, the maximum depth of each individual tree from node to leaf, the minimum number of samples needed to split a node into new branches, the minimum samples required per leaf (chosen to prevent previous hyperparameter from creating arbitrarily small leaves), and maximum features of X. The last hyperparameter exists for variable selection, which is not relevant in 5 dimensional space. Optuna was chosen because it intelligently chooses hyperparameters to test along the search space to minimize time while minimizing MSE. A traditional exhaustive grid search was not possible due to computational restraints.The Random Forest model was the best performing of the three we produced.

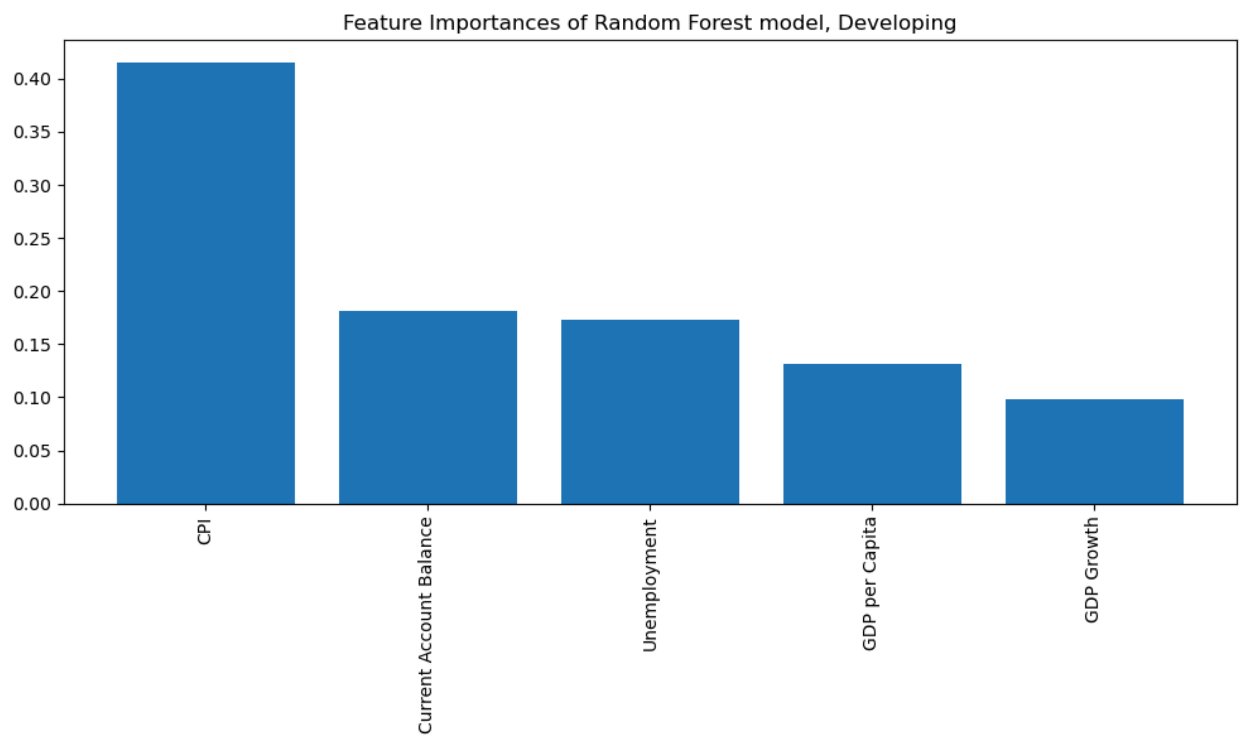
HYPERPARAMETERS	Estimators	Max Depth	Min Samples/Split	Min Samples/leaf	Max Features
Developed	414	17	6	1	sqrt
Developing	764	28	3	1	sqrt

Developed:



The feature importances of the model seems to confirm the OLS significance derived via t-test. CPI remains the most predictive factor of a developed nation's interest rates, followed by current account balance, unemployment, GDP per capita and GDP growth. Current Account balance's high importance may be attributed to the short-run currency depreciation(and thus, changes in the price level of foreign goods that central banks respond to,) that comes with capital flight. Because data on current account balance as percentage of GDP was only available annually, some of this impact may be captured by the model. The only variation between OLS and Random Forest comes from the relative feature importances of GDP growth and GDP per capita. GDP growth contributes the least predictive power to the Random Forest model, despite being second to last(and statistically significant) in the OLS regression. This could be attributed to many factors. As GDP growth can be represented by the derivative of GDP, it is possible that some of the change in GDP may have been attributed to GDP per capita rather than GDP growth in the Random Forest. Alternatively, differences in scale between GDP per capita and GDP growth may mean that the OLS underestimated the impact of variance in GDP per capita. However, the overall similarity of feature importances and t-test values between the two models is an encouraging sign that the true impact of these variables is reasonably close to the modeled values.

The hyperparameters chosen for developing nations indicate a less linear relationship, as fewer samples are chosen for each leaf, and a greater number of trees were needed in the optimal model.



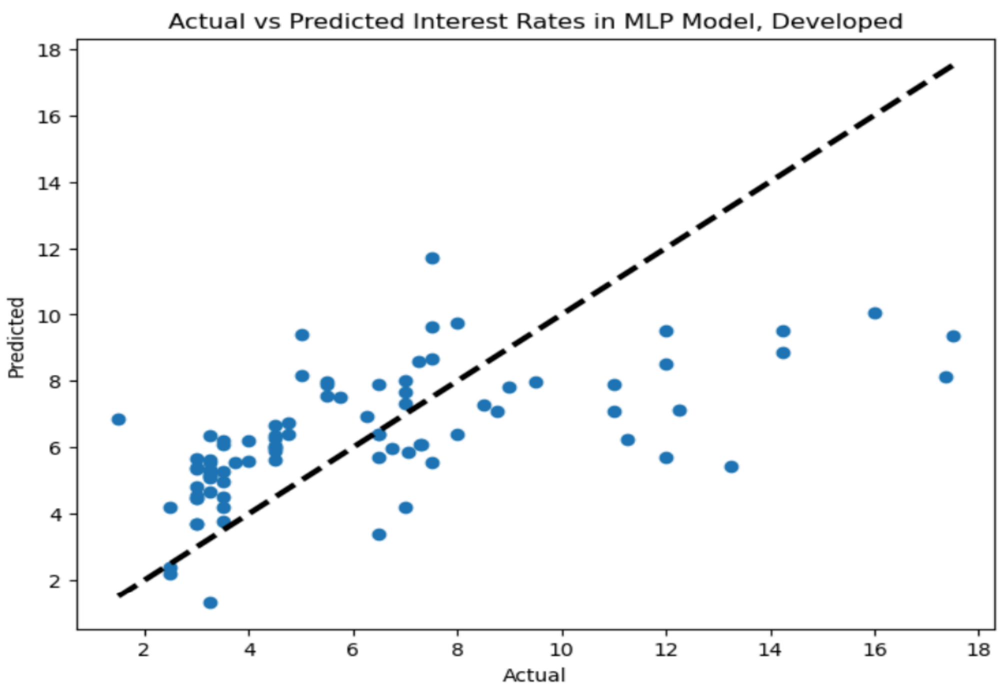
The feature importances of both Random Forest models are in the same order and of roughly the same weights. However, the Random Forest model predicting developing country interest rates differs drastically from OLS. The OLS model only had three variables that were statistically significant: CPI, GDP per capita, and GDP growth. The high feature importance of current account balance conflicts with its lack of significance in OLS; this is another example of the non-linearity in the Random Forest model capturing more variation in developing nation central bank policy than OLS. The discrepancy between unemployment's effect in the two models also requires examination. In the linear model, unemployment is weakly positively correlated with interest rate for developing nations, but the percentage of variation explained in the random forest model is higher. Here, the lack of information on positive and negative relationships in Random Forest is a limiting factor; we are unable to understand if the pro-cyclical policies implied by the coefficients of the developing linear model are true reflections of the nations' policies.

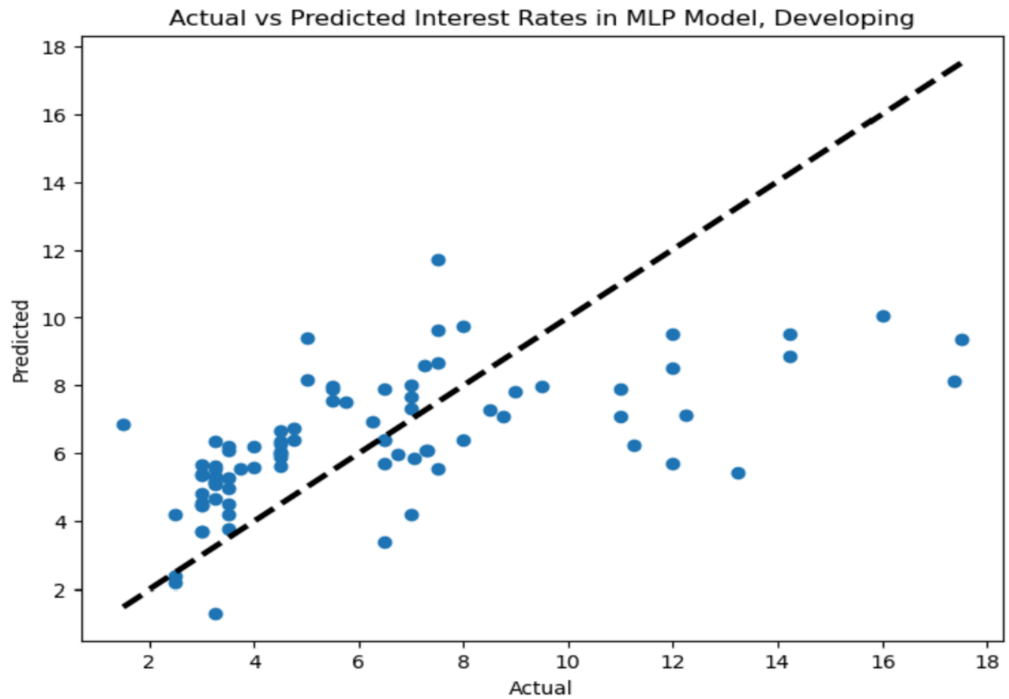
Multilayer Perceptron

We used Multilayer Perceptrons (MLPs) to examine how economic data affected the choice of interest rates factor. MLPs efficiently describe the nonlinear correlations in high-dimensional data. This ANN model aggregates predictions from several neural layers, and provides a strong foundation for comprehending and forecasting the intricate dynamics of changes in monetary policy. The MLP, also used the Optuna package in Python to perform a grid search across the hyperparameters of the regression. We used the following hyperparameters: hidden layers size (number of hidden layers and neurons), activation(introduces the non-linearity to the neural network), solver(specifies the optimization algorithm to train the neural network), alpha(regularization strength to the neural network to prevent overfitting), learning rate(the step-size to update the weights and biases during optimization of the model). The MLP model is used here to compare the outcomes with the other models because measuring factor importance is difficult.

Hyperparameters Table:

HYPERPARAMETERS	Hidden Layer size	Activation	Solver	Alpha	Learning rate
Developed	97	relu	lbfgs	5.68e-5	invscaling
Developing	78	relu	lbfgs	2.22e-3	adaptive





	MAE	RMSE	MSE
Developed	1.54	2.04	4.15
Developing	2.27	2.86	8.20

The results of MLP cannot be interpreted due to its black box nature. However, there may be reasons for its weaker performance. First, we did not scale or z-score normalize our data. Because we wanted the dataset to stay constant for each model, and such transformations make interpreting linear models more difficult, we used the raw statistics for the input layer. However, because the scale of some variables, especially GDP, was multiple orders of magnitude larger than the others, which were mostly percentages, this choice may have led to decreased model performance.

Another possibility could be the lack of data. We were only able to find 10 nations for each model that had accessible data for each X variable. Additionally, with only 10 years of training data, it is possible that the MLP models were unable to pick out a relationship between the variables. This could be exacerbated by the duplication of annual data, which could lead to changes in the true quarterly values of X variables failing to be captured in the y variable. With access to more comprehensive databases like Trading Economics, it is possible that this could be remedied.

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LINKS TO DATA:

- Interest Rate:

  https://data.imf.org/regular.aspx?key=61545855

- Unemployment:

  https://data.worldbank.org/indicator/SL.UEM.TOTL.ZS

- Annual GDP growth(percentage):

  https://data.worldbank.org/indicator/NY.GDP.MKTP.KD.ZG

- GDP per capita(constant 2015 dollars):

  https://data.worldbank.org/indicator/NY.GDP.PCAP.KD

- Current Account Balance(percentage of GDP):

  https://data.worldbank.org/indicator/BN.CAB.XOKA.GD.ZS

- CPI:

  https://data.imf.org/?sk=4ffb52b2-3653-409a-b471-d47b46d904b5&sid=1485878855236