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Forecasting Stock Prices: Do Taylor Rule Fundamentals Matter?

by

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Declaration

I, Thabo Molefe, declare that the research work reported is my own, except where otherwise indicated and acknowledged. It is submitted to fulfil the requirements for the Masters of Management in Finance and Investment Degree at the University of Witwatersrand. It has not, either in whole or in part, been submitted for any other degree or diploma to any other university or institution.



Thabo Molefe

29 August 2024

Date

Dedication

To those family, friends, and relatives who have provided unwavering support throughout my academic journey

Acknowledgment

Thank you to Professor Christopher Malikane for his guidance and patience in assisting me in completing this research report. A very special thank you to my wife, for her encouragement, understanding, proofreading, and just for being pure awesome.

Abstract

We build on studies by Ince et al. (2016), and Dladla and Malikane (2019) to explore the role of Taylor rule fundamentals in forecasting stock market returns in a small open economy. We investigate a mix of 11 countries from 1970 to 2022. We derive a stock return forecasting model using the dividend yield interest rate spread and introduce Taylor rule fundamentals into our model using Taylor's (1993) rule. We compare the performance of our model to the autoregressive with lag-2 benchmark model and the historical average using Theil's U, Diebold and Mariano's (1995) *MSE-T*, and Harvey et al.'s (1998) *ENC-T* statistics to test for relative forecast accuracy, equal forecast ability, and model encompassing. Since the models are linear and nested, we follow McCracken (2007) in using asymptotic critical values for MSE tests and proceed to also follow Clark and McCracken (2007) in using asymptotic critical values for ENC tests.

We split the data 50-50 and conduct an OLS regression on the in-sample portion of the data to obtain parameters. We obtain in-sample results that show the signs of the coefficients for most of our endogenous variables to be as per literature. The sign of the coefficient of inflation is negative in line with studies by Sousa, Vivian, and Wohar (2016), and Cooper and Priestley (2009) among others, and the output gap has ambiguous signs in line with Good News Case (GNC) and Bad News Case (BNC) by Blanchard (1981). However, the sign of the coefficient of the real effective exchange rate is positive for most countries in contrast to the reviewed literature by Wong (2017), and Hau and Rey (2006). We conduct out-of-sample forecasting using the recursive method due to its sensitivity to data structure changes and adaptability to data patterns. The results of the out-of-sample analysis show our model outperforming the autoregressive-lag 2 benchmark model for the 3-month horizon US and Brazil, and the 12-month horizon for most countries. It also outperforms the 3-month horizon Australia, and the 12-month horizon Poland historical average benchmarks.

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1. Introduction

1.1. Background of the Research

This paper investigates whether open economy Taylor rule fundamentals provide better information to forecast stock returns compared to existing stock forecasting models. The variables that form part of the Taylor rule as set out by Taylor (1993) and its variants, have been a subject of many studies in investigating their stock returns forecast potential. The predictive potential of the output gap as in Cooper and Priestley (2009), inflation, and the real effective exchange rate as in Dladla and Malikane (2019), are well documented in stock forecasting literature. Studies of a similar nature regarding other macroeconomic variables such as industrial production, GDP ratio, and interest rates have also been mentioned in works as in Ince et al. (2016), Peiró (2016), Sousa et al. (2016), and Zhang (2021).

Investigations on stock market forecasting using quantitative models have approached the topic from various angles. Examples include using approaches of interpreting predictors in the model such as constraining inferior predictors as in Pan et al. (2020) or using inferior multiple predictors to develop a superior model as in Zhang et al. (2019). Other approaches in stock market forecasting have focused on firm-specific output determinants as in Atilgan et al. (2021); while Tokic and Jackson (2023), and Davis and Taylor (2019) looked at the relationship of credit to stock market returns. Scheffer and Weiß (2020) investigated the relationship from a data analysis perspective by looking into how stock returns relate to search engine queries. The use of models with a Taylor rule component has also been successfully employed as in Ince et al. (2016), and Dladla and Malikane (2019).

1.2. Gap Identification

We contribute to the existing stock forecasting literature that investigates the relationship between Taylor rule fundamentals and stock returns. Of note is the study conducted by Ince et al. (2016), whose work is amongst the first to investigate the relationship between Taylor rule fundamentals and stock market returns. They focused only on the US market to conduct 1-

month ahead forecasts for the period 1970 to 2008 and used a model derived from the Fed model to establish the link between financial and economic factors. Their study concludes in favour of the hypothesis that the inclusion of Taylor rule fundamentals leads to the improved economic and statistical performance of various benchmark models. The Fed Model has however been shown to have limitations as outlined in Asness (2003) and Estrada (2006), thus creating some doubt about the methodology employed in their investigation.

Other related noteworthy studies on this topic are by Dladla and Malikane (2019), and Heimonen et al. (2017). Dladla and Malikane (2019) use the dividend discount theory to derive a stock forecasting model that has Taylor rule fundamentals as some of the exogenous variables. Their model incorporates both the short-term and long-term interest rates which are not Taylor rule fundamentals and hence not the subject of this study. Heimonen et al. (2017) also conducted an analysis of a forward-looking Taylor rule and its effect on the stock market and exchange rate in 14 OECD countries for the period 1999 to 2016. They found the relevance of stock market dividend information to the Taylor rule. We build on these works and develop a different approach that looks at an open economy.

1.3. Research Problem

This research investigates the effect that Taylor rule fundamentals in an open economy have on stock market returns on monthly, quarterly, and yearly horizons. The focus of the research is on 11 countries from both emerging and advanced economies for the period 1970 to 2022. The usual macroeconomic factors of inflation and the output gap are enhanced with the inclusion of the real effective exchange rate to determine their effect on stock market returns. This is a version of the open economy Taylor rule that we call the expanded Taylor rule. It takes the foreign effective exchange rate into account. This study aims to investigate the forecast capability of the expanded Taylor rule variables namely inflation, output gap, and real effective exchange rate, on stock market returns. Put differently, what role do Taylor rule fundamentals play in stock market forecasting?

1.4. Research Objectives and Questions

The research aims to determine the forecast ability of the expanded version of the Taylor rule on stock market returns in three different time horizons for 11 countries. The research will investigate this by formulating a stock forecasting model with all the Taylor rule fundamentals stated above being exogenous variables in the model, and stock returns being the endogenous variable. The forecast results will then be compared against stock benchmark models, and an evaluation of the forecast will be conducted to determine the forecast potential of the model. The questions that the research seeks to answer are: firstly, does the Taylor rule have any stock forecasting potential? And secondly, how does the model perform in comparison to existing forecasting models?

1.5. Significance of the Research

Macroeconomic activities and monetary policy decisions have a direct effect on the financial markets in general, particularly the stock market. Bernanke and Kuttner (2005), as quoted by Ince et al. (2016), allude to “the direct and immediate impact that monetary policy decisions have on financial markets”. If stock market participants were to be able to forecast the effect and extent of monetary policy decisions in advance, it would provide a valuable tool for their management of stock market assets. Thus, the investigation that this study will embark on will provide a meaningful contribution to the existing literature. Should such a relationship be found to be significant, this would enable practitioners to gauge the likely direction and extent that equity markets will take in response to Taylor rule fundamentals changes.

1.6. Contribution of the Research

This research extends the investigation of the stock market forecast potential of the expanded Taylor rule fundamentals by first expanding the period from 1970 to 2022. Secondly, the research looks at 11 countries with a mix of emerging and advanced countries that are spread across different regions of the world to ensure a balanced representation of various economic types. Thirdly, the research focuses on three different time horizons which are monthly, quarterly, and yearly. Fourthly, the research will use an expanded version of the Taylor rule

which includes the real effective exchange rate, to contribute to the existing literature on the topic. The rest of the research will be structured in the following way: Section 2 discusses the literature review; Section 3 presents the model and the theoretical framework; Section 4 is the methodology; Section 5 is the empirical analysis; and finally, Section 6 is the conclusion.

2. Literature Review

2.1. Determinants of Stock Returns

We investigate literature that deals with stock return forecasting, a financial market topic that is important to finance and economics practitioners, researchers, and policymakers. The review first investigates determinants of stock returns in this subsection, and stock return forecasting in the next subsection. The studies by Rapach and Wohar (2006), and Welch and Goyal (2008) provide comprehensive summaries of variables that had been studied and found to be stock return predictors. We use some of the findings from these studies to broadly outline some of the critical aspects of stock forecasting literature and then zone in on those drivers of stock returns that are also Taylor rule fundamentals, specifically inflation and the output gap.

Rapach and Wohar (2006) investigated a comprehensive list of some of the key studies on stock market forecasting that have been conducted over the years. They categorized these according to the financial variables used as predictors for stock returns. These range from the dividend-price ratio by Rozeff (1984), Campbell and Shiller (1998a), Fama and French (1988), and Hodrick (1992). Another category was short-term interest rates with studies such as that of Campbell (1987), Hodrick (1992), and Ang and Bekaert (2007). The key finding from the Rapach and Wohar (2006) study was that most of the financial variables included in the literature have stock return forecasting ability. The study looked at the yearly time horizon for the study.

Welch and Goyal (2008) investigated a broad range of variables that at the time, previous studies had suggested to be good stock market predictors. The study investigated how these predictors would have performed for a period prior and found the predictors to be inadequate and unstable over 30 years. The investigated predictors included the dividend payout ratio, inflation, dividend yield, earning price ratio, and term spread. Out of these, the variable that is of interest for our study is inflation, and Welch and Goyal (2008) found that it has “marginally good out-of-sample performance, but poor in-sample performance”. They found their study to also be consistent with similar studies such as Rapach and Wohar (2006) whose data ended in 1999 as opposed to 2005.

Monetary policy decisions have been showed to have a lackluster direct impact on financial markets. According to Fuhrer and Tootell (2008), monetary policy decisions made by central banks do not intend to have a direct influence on financial markets. They investigated the relationship between changes in equity values and the US monetary policy, as reflected through the Federal Open Market Committee (FOMC) decisions. They found little evidence that the FOMC responds to stock prices directly. Furthermore, regarding the impact that the financial market has on the European Central Bank (ECB) policy decisions, Papadamou et al. (2018) found a small but significant reaction, which is weak but positive, of the ECB to stock prices. They used the augmented Taylor rule with financial sector variables to illustrate the behavior of the ECB and to be able to make direct comparisons between interest rates proposed by the Taylor rule and those observed from 11 Eurozone member states.

In contrast to the arguments above, Filardo et al. (2022) investigated the relationship between systematic monetary policy responses and financial imbalances. They measured the Fed's policy responsiveness to various markets including the equity market and found that the Taylor rule is important in assisting to anchor inflation expectations as it indicates practitioners of the possible reactions by policymakers to future shocks. Furthermore, Clarida et al. (1998) investigated the monetary policy regimes of three G3 and three E3 countries and found that the G3 countries have implicitly targeted inflation and have been forward-looking. Their findings were, as quoted by Dladla and Malikane (2019), that interest rates of countries that implicitly target inflation can still be explained using Taylor rule principles. Heimonen et al. (2017) also investigated the effect of a forward-looking Taylor rule in their study, focusing on the stock market and exchange rate in 14 Organization for Economic Co-operation and Development (OECD) countries for the period 1999 to 2016. They found the relevance of stock market dividend information to the Taylor rule.

The link between macroeconomics and the financial market is shown in studies such as Bekaert and Engstrom's (2010) investigation into the co-movement between inflation and the yields of bonds and equity. They found that there was empirical evidence of the high correlation between equity yields and bond yields that is consistent with asset pricing theory. In contrast, Tokic and Jackson (2023) made use of the discretionary macro approach to explain the cause of excessive stock market drawdowns. They determined that an increase in credit risk at the onset of the drawdown contributes to the depth of the drawdown. They also found that expected monetary

policy tightening (or reduction in liquidity) can serve as a correction especially if there is a probable recession on the horizon, and an expected monetary policy easing can exacerbate the drawdown if there is a probable recession on the horizon.

The studies mentioned above are amongst many that show the existence of a relationship between macroeconomics and the financial markets whether it is direct and intentional, or not. The intentional nature of these relationships is shown by those macroeconomic or financial sector variables that drive asset prices. Understanding the drivers of stock returns plays an important role in developing accurate forecast models. Of greater importance are those business-related factors that indicate the well-being of companies, such as dividend yields, and macroeconomic factors that indicate the well-being of an economy, such as inflation, gross domestic product (GDP), industrial production, and exchange rate.

Dividend yields have been shown to be drivers of stock returns in various studies. In their study, Ang and Bekaert (2007) achieved robust results regarding dividend yields and stock returns. However, this relationship only existed on the short horizon. Heimonen et al. (2017) also found the relevance of stock market dividend information to the Taylor rule. Furthermore, as stated in Dladla and Malikane (2019), dividend yield is used as the basic predictor of asset returns by many asset return models. Thus, making it an important driver of stock returns. Dividend yields also serve as a signal for investor intentions as investors incorporate the information provided by dividend yields when making asset allocation decisions.

The output gap has been found to be a strong driver of stock returns as shown by Cooper and Priestley (2009) who found a strong IS and OOS relationship, as well as by Sousa et al. (2016) who found the output gap to GDP ratio to be a strong stock return predictor in some emerging countries. They study the output gap with findings of its strong forecast ability on stock market returns both in-sample and out-of-sample showing the output gap to be a strong driver of stock returns. Vivian and Wohar (2013) also showed how the output gap can beat historical benchmarks when used in simple regression forecasts. Peiró (2016) showed how industrial production, which has been used as a proxy for output in many studies, and long-term interest rates, account for more than the annual stock price movements. The findings illustrate a negative relationship between the output gap, a key Taylor rule fundamental, and expected stock market returns.

Inflation and interest rates have also been found to be drivers of stock returns, but the nature of the relationship between inflation and stock returns has had mixed results. Sousa et al. (2016) found inflation to have little predictive power for all BRICS countries. On the other hand, Zhang (2021) illustrates the negative relationship between inflation and stock returns under various monetary regimes and conditions from 71 countries. Inflation has also been found to be a driver of stock returns by Ince et al. (2016) using a model that makes use of Taylor rule fundamentals. Jiang (2014) found inflation together with the output gap, to be one of the main drivers of monetary policy.

The real exchange rate has been found to have a negative and significant relationship to stock returns by Wong (2017) for the countries of Malaysia, Singapore, Korea, and the UK. The study also finds the exchange rate markets and the stock market to have a strong influence on Asian economies. On the other hand, Hau and Rey (2006) found that there is a negative correlation between domestic currency foreign equity excess returns and their corresponding exchange rate. This means that when there is an increase in foreign equity denominated in domestic currency, there is a depreciation of the domestic currency. Hau and Rey (2006) do note that this “contradicts the conventional belief that strong equity markets are accompanied by currency appreciation.” However, it further points to a negative relationship between stock returns and the real exchange rate.

Interest rates are the tool through which monetary policy is carried by central banks’ direct manipulation to achieve economic objectives. In terms of emerging markets, interest rates have been found to have little stock return predictive power for all BRICS countries by Sousa et al. (2016). Peiró’s (2016) analysis of long-term interest rates and industrial production to stock price movements which was explained above, found long-term interest rates, together with industrial production, to account for more than the annual stock price movements. On the other hand, Ang and Bekaert (2007) show that short-term rates are strong short-horizon forecasters of stock returns, with the relationship between the two being negative.

The country choice and time horizon at which forecasting of stock returns is possible is also of importance. Ang and Bekaert (2007) argue that the phenomenon of time horizon is mainly present in the short horizon. This is consistent with the findings by Ince et al. (2016), and Cooper and Priestley (2009) who used 1-month horizons. However, other studies such as Dladla and Malikane (2019) have found the relationship to exist on both short 1-month

horizons and long 12-month horizons. Also, positive stock forecasting results were reported in studies were multiple countries from different economy types such as Dladla and Malikane (2019) who used a mixed bag of emerging and developed countries, and Zhang (2021) who included 71 countries in their study.

2.2. Stock Return Forecasting

Ince et al. (2016) provide valuable insight into stock forecasting using Taylor rule fundamentals by combining the Fed model with two of the Taylor rule fundamentals of inflation and the output gap. The result is a model that performs better in-sample and out-of-sample when benchmarked with the Fed model and the constant return model. The model also derives greater utility gains when used as part of a trading strategy and compared with the constant return model and the original Fed Model-based strategies. There is also evidence supportive of the hypothesis of a boost to benchmark model statistical and economic performance by Taylor rule fundamentals. Their study added to the simplified Fed Model formula to derive an expanded formula that illustrates the positive stock returns due to stock price increases in the next period because of investor incentives to hold more stocks. They cite the demonstration by Lander et al. (1997) in explaining that the reason is due to undervalued stock prices. The result is the “Original Fed Model”.

The study further amended the “Original Fed Model” using the results from the works of Taylor (1993), Campbell (1987), and Fama and French (1989) to derive a short-term nominal interest rate equation with only inflation and output as its variables. The study finally allows for the interest rate to adjust to target levels as set out in Clarida et al. (1998) to obtain an equation that forecasts the net period short-term rate using inflation, and the output gap as exogenous variables. Ince et al. (2016) evaluate the OOS performance of their model using the statistics by Diebold and Mariano (1995) and West (1996), and Clark and West (2006). The two statistics that are based on the mean square prediction error (MSPE) comparison.

There have been opposing views on the validity of the Fed Model that Ince et al. (2016) so eloquently used in the derivation of their model. Asness (2003) and Estrada (2006) outline some of the shortfalls of the model, while Bekaert and Engstrom (2010), as quoted by Dladla and Malikane (2019) state some advantageous use cases in favour of the Fed Model. Estrada

(2006) further discusses the Fed Model and sights findings from his investigation of 20 countries. Only 2 countries out of these had earnings yield (E/P) and government bond yield (Y) being cointegrated. He further found that in 17 of these, the usual Price/Earnings (P/E) ratio, as opposed to the E/P ratio of the Fed Model, performed as a superior forecasting tool for stock returns. Thus, further proving how inadequate and flawed the Fed Model is.

Asness (2003) argues against the widely used Fed Model that has garnered widespread application by market practitioners. He notes that the simplicity of the model together with its descriptive ability could be the reason behind the model's popularity. He however cautions against confusing this prescriptive potential as a tool that can be used to make investment decisions. He states three widely accepted yet erroneous arguments that Fed Model pundits follow which involve the E/P and the Y, and investment choices between bonds and stocks based on comparisons of these factors; as well as empirical evidence involving historical highly positive correlations between the earnings yield. He also outlines the failures of the fed model in forecasting long-term stock returns.

Another stock forecasting model of interest is one developed by Dladla and Malikane (2019) who make use of the dividend discount model to derive a model relating stock market returns to macroeconomic variables with the inclusion of Taylor rule fundamentals. Theirs is a linear model with inflation, the output gap, the real effective exchange rate, bond yield, and the short-term interest rate as exogenous variables. Their objective being to systematically derive a model from proven theoretical concepts whose parameters can be easily explained in terms of economic implications, which they built from the work of Ince et al. (2016) to use the short-term interest rate to introduce Taylor rule fundamentals into their formulation. They used three statistics for model performance evaluation in the same fashion as Rapach et al. (2005). The statistics used are Thiel's U which is the ratio of the root-mean-square error (RMSE) of the model and that of the benchmark, the MSE-T statistic by Diebold and Mariano (1995), and the ENC-T statistic by Harvey et al. (1998).

Dladla and Malikane (2019) used the asset return two-lag autoregressive (AR) model and the historical average as benchmarks for forecast evaluation. The performance of their model had superior stock return forecasting capabilities and provided a clear link between stock returns and monetary policy as expressed through Taylor rule fundamentals. With regards to annual returns, it outperformed the historical average on the 1-month horizon and the 12-month

horizon. Their model also outperformed the AR (2) benchmark on the 1-month horizon but failed to outperform it on the 12-month horizon. The countries investigated in their study are the same 11 countries that have been chosen in this study.

3. Theoretical Derivation of the Model

3.1. Formulation of Linear Stock Forecasting Equation

The model derived in this section will be a simple linear asset pricing equation that forecasts stock market returns in the next period, given the output gap, inflation, and real effective exchange rate as the dependent variables. The model will make use of the linear Taylor rule format in creating a linear equation that describes the relationship between the stock price in the next period and the three Taylor rule fundamentals. The starting point is based on rational decisions that a potential financial market participant undertakes when looking to purchase dividend-paying stock instead of making an investment at the prevailing interest.

A decision to invest in the stock market can be made based on the expected returns that can be obtained based on owning shares. This can be in the form of the appreciation of the stock, capital gains, or the annual income derived from owning the stock, also known as dividend yield. For a stock priced at Q_t , and dividend payment Div_t , the dividend yield is $\frac{Div_t}{Q_t}$, and the capital gains is $\frac{Q_{t+1} - Q_t}{Q_t}$.

The dividend yield can be compared with the prevailing interest rate of the time, i_t . A decision to purchase this stock in the next period will be made based on whether the dividend yield is greater than the interest rate, which can be expressed as $\frac{Div_t}{Q_t} > i_t$. Alternatively, this can be restated as $\frac{Div_t}{Q_t} - i_t > 0$, termed the dividend-yield interest rate spread. This means that an increase in the dividend yield interest rate spread leads to an increase in capital gains, $\frac{Q_{t+1} - Q_t}{Q_t}$. According to Blanchard (1981), this can be interpreted in terms of current or anticipated monetary policy change, which in turn leads to stock market responses from market participants acting in anticipation of profits and interest rates. This linear relationship can be expressed as follows:

$$\frac{Q_{t+1} - Q_t}{Q_t} = \alpha + \beta \left(\frac{Div_t}{Q_t} - i_t \right). \quad (1)$$

Now, an increase in the output of an economy, which is an increase in the output gap y_t , leads to an increase in profits for firms, which leads to an increase in household income in the form of dividend payments. We follow Dladla and Malikane (2019) and Ince et al. (2016) in defining the output gap as the percent deviation of actual output from its potential level. Therefore, there is a positive relationship between dividend yield $\frac{Div_t}{Q_t}$, and the output gap y_t . This relationship can be expressed as follows:

$$\frac{Div_t}{Q_t} = \gamma + \delta y_t. \quad (2)$$

We then substitute eq. (2) into eq. (1) to obtain:

$$\frac{Q_{t+1} - Q_t}{Q_t} = \alpha + \beta(\gamma + \delta y_t - i_t). \quad (3)$$

Eq. (3) illustrates the relationship between capital gains and the output gap. An increase in the output of an economy, which is an increase in the output gap y_t , leads to an increase in firm profits, which leads to an increase in demand for shares, which in turn leads to an increase in capital gains. Therefore, there is a positive relationship between capital gains, $\frac{Q_{t+1} - Q_t}{Q_t}$, and the output gap, y_t , as expressed in eq. (3).

Now if we let $\hat{q}_{t+1}$ denote the expected stock market return rate, then eq. (3) becomes:

$$\hat{q}_{t+1} = \alpha + \beta(\gamma + \delta y_t - i_t) + \varepsilon_t. \quad (4)$$

Eq. (4) can be simplified further by grouping common terms to obtain:

$$\hat{q}_{t+1} = \tau + \zeta y_t - \beta i_t + \varepsilon_t. \quad (5)$$

where $\tau = \alpha + \beta\gamma$, and $\zeta = \beta\delta$. Eq. (5) is a next period forecast of stock returns using the output gap and interest rate as independent variables.

3.2. Introducing the Taylor Rule into the Forecasting Equation

We now introduce the Taylor rule by Taylor (1993) into our model. If we assume that the economy is open and allows for trade, and we further loosen restrictions by considering a country that does not produce anything with an economy that relies on imports (e.g., total reliance on tourism), then the output gap will be foreign. Thus, the exchange rate becomes relevant. This means that an augmented Taylor rule is introduced into eq. (5) above instead. It makes allowance for the real effective exchange rate and is expressed as follows:

$$i_{t+1} = \pi_t + \phi(\pi_t - \pi^*) + \sigma y_t + \gamma e_t + r^* \quad (6)$$

where i_t is the interest rate, π_t is the inflation, π^* is the target inflation, y_t is the output gap, e_t is the real effective exchange rate, and r^* is the equilibrium real interest rate. The term i_{t+1} is the short-term nominal interest rate. To further interpret the significance of the coefficients of the various variables of eq. (6), we note that each coefficient measures the degree to which a central bank would react to its associated variable. We follow Dladla and Malikane (2019) in assuming that the coefficients are constant.

We can now introduce eq. (6) above by substituting it into eq. (5). This effectively replaces the i_t term in eq. (5) to obtain the following new stock forecasting equation:

$$\hat{q}_{t+1} = \tau + \zeta y_t - \beta[\pi_t + \phi(\pi_t - \pi^*) + \sigma y_t + \gamma e_t + r^*] + \varepsilon_t. \quad (7)$$

We expand the term in the bracket, group common terms, and further simplify some coefficients to obtain the following:

$$\hat{q}_{t+1} = \alpha_0 \pm \alpha_y y_t - \alpha_\pi \pi_t - \alpha_e e_t + \varepsilon_t, \quad (8)$$

where $\alpha_y = \zeta - \beta\sigma$, $\alpha_\pi = -\beta(1 + \phi)$, $\alpha_e = -\beta\gamma$, and $\alpha_0 = \tau + \beta\phi\pi^* - \beta r^*$ captures all constant terms. This is the stock forecasting model for an open economy where inflation, the output gap, and the real effective exchange rate are the exogenous variables. The signs of the different coefficients are consistent with existing literature. The sign of the coefficient of y_t is ambiguous and follows the Good News Case (GNC) and Bad News Case (BNC) by Blanchard (1981) in a closed economy. The sign of the coefficient of π_t is supported by Zhang (2021), Ince et al. (2016), and Cooper and Priestley (2009). The sign of e_t is negative as in the Dladla and Malikane (2019) model. This is further supported by the studies of Wong (2017), and Hau and Rey (2006).

3.3. Comparison Benchmark Models

We now select comparison models to answer the central question of this research of whether the Taylor rule fundamentals offer better forecasting potential compared to existing stock forecasting models. To determine prediction accuracy, the results of the model will be compared against two benchmark models in the same fashion as Dladla and Malikane (2019). The first benchmark model is the historical average:

$$\hat{q}_t = \lambda_0 + \varepsilon_t, \quad (9)$$

where j is the forecast horizon.

The second benchmark is the autoregressive model with two lags AR(2):

$$\hat{q}_t = \lambda_0 + \lambda_1 q_{t-1} + \lambda_2 q_{t-2} + \varepsilon_t, \quad (10)$$

for forecast horizon j .

4. Empirical Methodology

4.1. Data Collection and Econometric Method

Monthly country data was used in this study and was obtained from the Federal Reserve Economic Data (FRED), Bank of International Settlements (BIS), Bloomberg, the Organization for Economic Co-operation and Development (OECD) databases, and the national statistical and central bank authorities of the respective countries. The period was from January 1970 to December 2022. Country selection was a mix of emerging and advanced economies as listed in Table 1 below. There were variations in the size of the data and as a result, the periods were shortened for countries where the data was not available as outlined in the next paragraph. As such, the choice of dates was informed by the earliest date on which the data for all required variables was available. The country choices reflect economy size and type, as well as regional and continental representation. The data from these sources was revised.

Table 1: Description of data to be used in the regressions.

#	Country	Stock Market Index	Output Gap	Inflation	Real Effective Exchange Rate
1	South Africa	JSE All Share Index	IPI	CPI	RNEER Index
2	South Korea	Korea Composite Stock Price Index	IPI	CPI	RNEER Index
3	Brazil	BOVESPA Index	IPI	CPI	RNEER Index
4	Turkey	Borsa Istanbul 100 Index	IPI	CPI	RNEER Index
5	Poland	Warszawski Indeks	IPI	CPI	RNEER Index
6	Mexico	Indice de Precios y Cotizaciones	IPI	CPI	RNEER Index
7	US	S&P 500	IPI	CPI	RNEER Index
8	France	CAC 40	IPI	CPI	RNEER Index
9	Canada	S&P/TSX Composite Index	IPI	CPI	RNEER Index
10	Germany	DAX	IPI	CPI	RNEER Index
11	Australia	S&P/ASX 200	Manufacturing	CPI	RNEER Index

The US had data for all variables from 1970. Data for the Canada S&P/TSX Composite Index was only available from February 1972. For France and Germany data for CAC 40 and DAX stock market indices was available from January 1999. For Australia IPI data was available from 1975, CPI data from 1985, and S&P/ASX 200 index data from May 1992. For South Africa, IPI data was available from 1990, and JSE All Share Index was available from June 1995. For South Korea, IPI data was available from 1975, and Korea Composite Stock Price Index data was available from 1980. For Mexico Indice de Precios y Cotizaciones data was available from November 1991 and IPI data was available from 1993. For Brazil, data for all measurements was not available from 1970, with the latest being REER available from 1994. For Turkey IP data was available from 1986, Borsa Istanbul 100 Index was available from 1988, and REER data was available from 1994. All data for Poland was only available from 1985 with the earliest being Warszawski Indeks which was available from May 1994.

For the model variables measurement, the industrial production index (IPI) was used as the measure for the output gap, and manufacturing data was used in instances where IPI data was not available. As stated by Cooper and Priestley (2009), and Ince et al. (2016), there is no definitive way in which the output gap is measured, and they thus considered four ways of measuring the output gap. They both considered the linear trend and quadratic trend, while Cooper and Priestley (2009) further considered the linear trend with breakpoints method, as well as the deviation of actual GDP from potential GDP. The additional two measures considered by Ince et al. (2016) were the Hodrick-Prescott (1997) (HP) trend filter and the Baxter and King (1999) (BK) trend filter. For our study, we use the HP trend filter with the smoothing parameter, λ , set to 1600 as recommended by Hodrick and Prescott (1997).

The consumer price index (CPI) was used to capture inflation by calculating the log of the CPI and differencing it. The real effective exchange rate (REER) was calculated in the same way as the inflation. It was measured using the real narrow effective exchange rate (RNEER) index of each currency obtained from the BIS and the central bank authorities of the various countries. The narrow REER was chosen over the broad REER due to the availability of data for all periods necessary for this study. It uses a basket of 26 economies to measure the relative strength of a particular currency, using the year 2010 as the benchmark. The benchmark stock market returns was derived by taking the log of the stock market index and differencing it. This was done for all the major stock market indices of each country listed in Table 1. The choice of indices reflects the performance of the stock market of each respective country in its entirety.

Table 2: Country Correlation Matrices

US					Canada				
	CPI	REER	St. Index	IPI		CPI	REER	St. Index	IPI
CPI	-	-0.06	-0.15	0.13	CPI	-	0.04	-0.05	0.07
REER	-0.06	-	-0.14	-0.12	REER	0.04	-	0.52	0.06
St. Index	-0.15	-0.14	-	0.00	St. Index	-0.05	0.52	-	0.13
IPI	0.13	-0.12	0.00	-	IPI	0.07	0.06	0.13	-
France					Germany				
	CPI	REER	St. Index	IPI		CPI	REER	St. Index	IPI
CPI	-	-0.11	-0.05	0.15	CPI	-	-0.11	-0.09	0.18
REER	-0.11	-	0.25	0.03	REER	-0.11	-	0.27	0.05
St. Index	-0.05	0.25	-	0.21	St. Index	-0.09	0.27	-	0.19
IPI	0.15	0.03	0.21	-	IPI	0.18	0.05	0.19	-
Australia					S. Africa				
	CPI	REER	St. Index	IPI		CPI	REER	St. Index	IPI
CPI	-	0.04	0.39	0.14	CPI	-	-0.20	-0.50	0.06
REER	0.04	-	0.77	0.24	REER	-0.20	-	0.53	0.05
St. Index	0.39	0.77	-	0.30	St. Index	-0.50	0.53	-	0.15
IPI	0.14	0.24	0.30	-	IPI	0.06	0.05	0.15	-
S. Korea					Brazil				
	CPI	REER	St. Index	IPI		CPI	REER	St. Index	IPI
CPI	-	-0.20	-0.37	-0.07	CPI	-	0.07	0.02	0.06
REER	-0.20	-	0.30	0.14	REER	0.07	-	0.74	-0.03
St. Index	-0.37	0.30	-	0.19	St. Index	0.02	0.74	-	0.01
IPI	-0.07	0.14	0.19	-	IPI	0.06	-0.03	0.01	-
Mexico					Turkey				
	CPI	REER	St. Index	IPI		CPI	REER	St. Index	IPI
CPI	-	-0.04	-0.15	-0.11	CPI	-	0.10	-0.03	-0.02
REER	-0.04	-	0.67	0.20	REER	0.10	-	0.59	0.12
St. Index	-0.15	0.67	-	0.11	St. Index	-0.03	0.59	-	0.16
IPI	-0.11	0.20	0.11	-	IPI	-0.02	0.12	0.16	-
Poland									
	CPI	REER	St. Index	IPI					
CPI	-	0.30	0.07	-0.02					
REER	0.30	-	0.44	-0.11					
St. Index	0.07	0.44	-	0.04					
IPI	-0.02	-0.11	0.04	-					

St. Index = Stock Index. Each country has a stock index as indicated in Table 1.

To rule out any multicollinearity in the data, the correlation matrices of the data of all the countries used in the study is included in Table 2 above. The correlation coefficient of the

variables for US, France, Germany, South Korea, and Germany is low with a magnitude less than 0.5. This signifies no sign of multicollinearity between the variables. For Canada, South Africa, Mexico, and Turkey, there are variables with moderate correlations of between 0.5 and 0.7. For Australia and Brazil the stock market indices and REER have a correlation of between 0.7 and 0.8 . This is a significant margin and points to the possibility of these variables providing redundant to the model.

The study used three forecast horizons which are monthly, quarterly, and yearly. For the quarterly and yearly horizons, overlapping monthly stock returns observations were used to determine the quarterly return $\Delta q_t = q_t - q_{t-3}$, and the yearly return $\Delta q_t = q_t - q_{t-12}$, where q_t is the share price natural log. Interest rate smoothing was assumed for quarterly and yearly inflation and was calculated as $\pi_t = p_t - p_{t-3}$, and $\pi_t = p_t - p_{t-12}$ respectively, where p_t is the natural log of the CPI. The quarterly and yearly output gap and real effective exchange rate were calculated similarly, $y_t = g_t - g_{t-3}$, $y_t = g_t - g_{t-12}$, $e_t = r_t - r_{t-3}$, and $e_t = r_t - r_{t-12}$ where g_t and e_t are the natural log of the IPI and REER index respectively.

Since the equation derived for the model is linear, an ordinary least squares (OLS) regression was used for analysis. The necessary data transformations were conducted to ensure reliability. A 60-40 data split was adopted for in-sample and out-of-sample analysis to make allowance for enough data to estimate the regression parameters and perform forecasting. The dates for the in-sample and out-of-sample periods will be as shown in Table 3 below. Performance evaluation will be conducted relative to selected benchmark models using Thiel's U, *MSE-T*, and *ENC-T* statistics. Forecasting will be conducted using recursive forecasting as it is more sensitive to changes in the data structure over time and allows for dynamic assessment model adaptation to changes in data patterns.

Table 3: Country in-sample and out-of-sample periods.

#	Country	Available data	Total obs.	IS Period	IS obs.	OOS Period	OOS obs.
1	US	1970 – 2022	612	1970 – 1997	306	1997 - 2022	306
2	Canada	1971 – 2022	599	1971 – 1997	299	1998 - 2022	300
3	France	1999 – 2022	264	1999 – 2011	132	2012 - 2022	132
4	Germany	1999 – 2022	264	1999 – 2011	132	2012 - 2022	132
5	Australia	1992 – 2022	344	1992 – 2008	172	2008 - 2022	172
6	South Africa	1995 – 2022	307	1995 – 2010	153	2010 - 2022	154
7	South Korea	1980 – 2022	492	1980 – 2002	246	2002 - 2022	246
9	Brazil	1994 – 2022	324	1994 – 2009	162	2009 - 2022	162
8	Mexico	1993 – 2022	348	1993 – 2007	174	2008 - 2022	174
10	Turkey	1994 – 2022	324	1994 – 2009	162	2009 - 2022	162
11	Poland	1994 – 2022	308	1994 – 2009	154	2009 - 2022	154

obs. = observation.

4.2. Forecast Evaluation

In evaluating the out-of-sample performance of the model, we followed Dladla and Malikane (2019) in using three statistics against the two benchmarks which are AR (2) and the historical average. Since the models under consideration are linear and nested, with the derived model nesting the benchmarks, we followed McCracken (2007) in using asymptotic critical values for MSE tests and proceeded to also follow Clark and McCracken (2001, 2005) in using asymptotic critical values for ENC tests. Similar to Clark and West (2007), we conducted forecast evaluation by comparing the Mean Squared Prediction Error (MSPE) of the parsimonious null model, the benchmarks in this regard, which is nested in a larger less parsimonious but noisier model, the derived model. We then estimated the parameters with zero population sizes with the expectation that the MSPE of the benchmark should be less than the derived model.

The first statistic is Thiel's U which measures relative forecast accuracy. We defined it in the same manner as Dladla and Malikane (2019), as the ratio of the RMSE of the model and that of the benchmark model. A lower Thiel's U value indicates forecast accuracy, whilst a value of zero indicates a perfect forecast. A value of 1 on the other hand implies that the forecast is no

better than a naïve forecast. While a value greater than 1 indicates that the forecast model performs worse than a naïve forecast model. The formula for calculating Thiel's U is as follows:

$$U = \sqrt{\frac{\sum \left(\frac{Y_{t+1} - \hat{Y}_t}{Y_{t+1}} \right)^2}{\sum \left(\frac{Y_{t+1} - Y_{b,t}}{Y_{t+1}} \right)^2}} \quad (11)$$

where Y_t is the actual value, $\hat{Y}_t$ is the forecasted value, $Y_{b,t}$ is the value of the benchmark, and n is the number of observations.

The second statistic is Diebold and Mariano's (1995) *MSE-T* statistic to test for equal forecast ability. The statistic is first constructed by calculating the difference of the squares of the errors of the derived model, $(\hat{\varepsilon}_{0,t+1}^k)^2$ with that of the benchmark model, $(\hat{\varepsilon}_{1,t+1}^k)^2$. This is expressed as:

$$d_{t+1}^k = (\hat{\varepsilon}_{0,t+1}^k)^2 - (\hat{\varepsilon}_{1,t+1}^k)^2. \quad (12)$$

If we let the number of forecast errors be given by $P = T - R - k + 1$, where T is the population size, R is in-sample observations, and k is the forecast period. And if we further let $\hat{f}_d(0)$ be the loss differential consistent spectral density at frequency 0, then the *MSE-T* statistic is stated as follows:

$$MSE - T = \frac{\bar{d}}{\sqrt{P^{-1} 2\pi \hat{f}_d(0)}}. \quad (13)$$

As stated in Diebold and Mariano (1995) it is common practice to estimate $2\pi \hat{f}_d(0)$ using the weighted autocovariance sample sum as follows:

$$2\pi \hat{f}_d(0) = \sum_{\tau=-(T-1)}^{(T-1)} l\left(\frac{\tau}{S(T)}\right) \hat{\gamma}_d(\tau), \quad (14)$$

where $\hat{\gamma}_d(\tau)$ is defined as,

$$\hat{\gamma}_d(\tau) = \frac{1}{T} \sum_{t=|\tau|+1}^T (d_t - \bar{d})(d_{t-|\tau|} - \bar{d}). \quad (15)$$

$S(T)$ is truncation lag, $l(\tau/S(T))$ is the window lag, and can be expressed using the rectangular lag window as,

$$l\left(\frac{\tau}{S(T)}\right) = 1 \quad \text{for } \left|\frac{\tau}{S(T)}\right| \leq 1 \quad (16)$$

$$= 0 \quad \text{otherwise.}$$

As expressed in Diebold and Mariano (1995) the null hypothesis is that the derived and benchmark models are of equal accuracy. This means that the $MSE-T$ statistic signifies a superior derived model relative to the benchmark if it is significant and positive as restated by Dladla and Malikane (2019).

The third statistic is Harvey et al.'s (1998) $ENC-T$ statistic. It tests for model encompassing as also described in Clark and McCracken (2001). The null hypothesis is that the derived model encompasses the benchmark model, whilst the alternative hypothesis is that the benchmark model contains additional information in explaining the forecast results compared to the derived model. Clark and McCracken (2001) formulate the $ENC-T$ statistic as follows:

$$ENC - T = (P - 1)^{1/2} \frac{\bar{c}}{\sqrt{P^{-1} \sum (c_{t+1}^k - \bar{c})^2}}, \quad (17)$$

where c_{t+1}^k is defined as:

$$c_{t+1}^k = \hat{\varepsilon}_{0,t+1}^k (\hat{\varepsilon}_{0,t+1}^k - \hat{\varepsilon}_{1,t+1}^k). \quad (18)$$

The average of the term c_{t+1}^k is $\bar{c}$, and is defined as follows:

$$\bar{c} = P^{-1} \sum_{t=R}^{T-k} c_{t+1}^k. \quad (19)$$

When the ENC-T statistic is greater than zero, then the null hypothesis is true which means that the derived model encompasses the benchmark model.

5. Empirical Analysis

5.1. In-sample Results

5.1.1. Parameter Estimation for the Equation with Taylor Rule

Fundamentals

The in-sample regression results for eq. (8), which is the derived equation with the 3 Taylor rule, is presented in Table 4. The results of the monthly, quarterly, and annual parameter estimates are given in Table 4. The standard error is given in brackets and the asterisk indicates the significance of the parameter, where one asterisk indicates significance at 1%, 2 asterisks indicate significance at 5%, and 3 asterisks indicate significance at 10%. The R-squared measure is also presented for all 3 periods to show the proportion of the variance in the endogenous variable that can be explained by the exogenous variables presented in our model. The R-squared measure ranges from 6% to 61% for the monthly horizon, 9% to 42% for the quarterly horizon, and 4% to 55% for the annual horizon. The parameters used in Table 4 are the coefficients of the variables of the model in eq. (8); where α_y is the coefficient for the output gap, α_π is the coefficient for inflation, α_e is the coefficient for REER, and α_0 is the constant term.

For inflation, we observe that in the monthly and annual horizons, the coefficients are mostly negative and mixed in the quarterly horizon. This is in line with eq. (8). Thus, a decrease in inflation leads to an increase in stock returns, pointing to this variable being a driver of stock return as observed in Zhang (2021), Ince et al. (2016), and Cooper and Priestley (2009) among others. The coefficients are also statistically significant for most of the countries, across all three horizons, with the US, Canada, Mexico, South Korea, and South Africa being statistically significant at 1% in all time horizons. Germany is statistically insignificant in all three horizons. We note that the results for the US inflation are negative and significant at 1% in line with the results of Ince et al. (2016).

Table 4: Parameter estimates of the Taylor rule forecasting equation.

Sample	US	Canada	France	Germany	Australia	S. Africa	S. Korea	Brazil	Mexico	Turkey	Poland
	70-97	70-97	99-11	99-11	92-08	95-10	80-02	94-09	93-07	94-09	94-09
Monthly Regressions											
α_0	0.19*	0.13*	0.08	0.04	0.06*	0.34*	0.66*	0.08	0.11*	0.04	0.08***
	(0.02)	(0.02)	(0.07)	(0.08)	(0.01)	(0.03)	(0.10)	(0.05)	(0.04)	(0.06)	(0.04)
α_y	-1.96*	-1.19*	-5.91	-0.88	2.98*	-4.93*	-14.21*	0.81	-0.71*	-0.17	-0.78
	(0.25)	(0.31)	(4.01)	(4.57)	(0.56)	(0.48)	(2.00)	(0.69)	(0.27)	(0.15)	(0.57)
α_π	-2.78*	-0.54	5.60*	2.91**	-0.50	4.35*	2.50**	0.02	-0.04	1.27	2.20***
	(0.53)	(0.65)	(1.53)	(1.18)	(0.60)	(0.67)	(0.98)	(0.03)	(0.03)	(1.32)	(1.14)
α_e	0.31*	0.59*	2.52**	1.00	1.55*	1.07*	0.86**	1.92*	1.98*	2.37*	1.07*
	(0.12)	(0.20)	(1.20)	(1.09)	(0.11)	(0.13)	(0.41)	(0.15)	(0.19)	(0.32)	(0.33)
$\bar{R}^2$	0.25	0.06	0.13	0.07	0.55	0.61	0.24	0.52	0.44	0.35	0.07
Quarterly Regressions											
α_0	0.00	-0.00	-0.01	-0.00	-0.01	0.01	0.06	0.00	0.00	0.01	-0.02
	(0.00)	(0.01)	(0.01)	(0.04)	(0.01)	(0.01)	(0.05)	(0.02)	(0.02)	(0.03)	(0.02)
α_y	-3.78*	-3.67*	0.75	-5.32	1.80***	-3.05*	-15.60*	1.72	1.60*	1.80*	1.22
	(0.71)	(0.89)	(2.67)	(4.48)	(1.04)	(0.84)	(3.50)	(1.18)	(0.61)	(0.68)	(1.56)
α_π	-1.25*	-1.17**	2.02**	3.39*	0.94***	2.35*	1.46**	0.02	-0.00	-0.06	-0.05
	(0.43)	(0.48)	(0.81)	(1.09)	(0.52)	(0.58)	(0.60)	(0.02)	(0.02)	(0.66)	(0.57)
α_e	0.06	2.13*	4.06*	0.76	0.95*	1.20*	-0.40	1.52*	1.43*	1.35*	1.60*
	(0.15)	(0.23)	(0.94)	(1.01)	(0.14)	(0.15)	(0.50)	(0.14)	(0.17)	(0.23)	(0.27)
$\bar{R}^2$	0.12	0.24	0.18	0.09	0.25	0.38	0.10	0.42	0.32	0.21	0.25
Annual Regressions											
α_0	-0.00	-0.00	-0.02	-0.00	-0.01	-0.00	0.06	-0.02	0.04	0.02	-0.02
	(0.01)	(0.02)	(0.03)	(0.04)	(0.01)	(0.02)	(0.09)	(0.04)	(0.03)	(0.03)	(0.04)
α_y	-3.71*	-4.33*	-11.17*	-5.32	0.79	-4.02*	-22.63*	-0.33**	1.94*	1.80*	2.30***
	(0.52)	(0.76)	(3.57)	(4.48)	(0.59)	(0.52)	(2.50)	(0.19)	(0.35)	(0.68)	(1.36)
α_π	-2.71*	-1.31**	7.73*	3.39*	-0.36	4.20*	0.42	0.02	-0.07*	-0.06	0.41
	(0.50)	(0.57)	(1.47)	(1.09)	(0.65)	(0.64)	(1.83)	(0.04)	(0.03)	(0.66)	(0.96)
α_e	0.28***	1.64*	0.82	0.76	1.21*	1.78*	-0.56	1.63*	1.96*	1.35*	0.27
	(0.15)	(0.24)	(1.10)	(1.01)	(0.12)	(0.12)	(0.57)	(0.16)	(0.15)	(0.23)	(0.33)
$\bar{R}^2$	0.23	0.19	0.19	0.08	0.40	0.55	0.26	0.41	0.54	0.33	0.04

Note: * significant at 1%, ** significant at 5%, *** significant at 10%

For the output gap, we observe mixed results with regard to the sign of the coefficient. The monthly horizon has four countries with negative signs, and the quarterly and yearly horizons have five each. This is also in line with eq. (8) where the sign of the coefficient of the output gap is ambiguous. This is also in line with the GNC and BNC as alluded to by Blanchard (1981), in that the nature of the relationship between the output and stock returns will depend on whether the prescribed monetary policy changes are anticipated or not. There are also mixed

results with regard to the significance of the coefficients, with the US and South Africa being significant at 1%, and France and Germany being significant at 5% across all horizons. Thus, for these four countries, a decrease in the output gap leads to an increase in stock returns, pointing to the output gap being a strong driver of stock return as observed by Ince et al. (2016) among others. This is consistent with Sousa et al. (2016), and Cooper and Priestley (2009) who showed the output gap to have a strong in-sample relationship with stock returns. The coefficients are also statistically significant in most countries.

For the real effective exchange rate, the sign of the coefficient is significant and positive in most of the countries across all three horizons. The positive sign is not consistent with eq. (8) and what is suggested by the literature reviewed for this study. The sign is positive in all three horizons for France, Germany, and South Africa. The parameters are statistically significant in most of the countries across the three horizons. Canada, Australia, South Africa, Brazil, Mexico, and Turkey are all significant at 1% across all three horizons, while Germany is the only statistically insignificant country across all three horizons. The studies by Wong (2017), and Hau and Rey (2006) show that the coefficient of the real effective exchange rate should be negative. We further observe that the model seems to be well-suited for South Africa since all coefficients, except for the real effective exchange rate, carry the right signs and are significant at 1% across all three horizons. The R-squared for South Africa ranges from 38% to 55%.

5.1.2. Robustness Check

To determine the robustness of the in-sample parameter estimates of our OLS model, we perform a Newey-West test and compare the results to those obtained in the regression. The Newey-West test does not alter the original coefficients from our OLS regression model but rather adjusts the standard error to account for serial correlation and heteroskedasticity. The results are shown in Table 5 below. In each row, the original OLS standard errors are shown in brackets the Newey-West standard errors are shown above the OLS errors. Significantly high values of the Newey-West standard error will point out the possible presence of serial correlation in the data, and a possible heteroskedasticity.

The results are obtained from the Newey-West test are mixed. The standard error for the constant term, α_0 , for all countries does not differ much from that of the OLS standard error.

For the standard error to the output gap parameter, α_y , the Newey-West standard error is significantly larger for South Korea across all time horizons, Germany for the monthly and yearly horizon; France, and Australia for the quarterly and yearly horizons; Mexico for the quarterly horizon only; Canada, Poland and for the yearly horizon only. For the inflation parameter, α_π , only Germany and South Korea's monthly horizons have a Newey-West standard error that is significantly higher than the OLS standard error. For the REER parameter, α_e , the Poland monthly horizon; and the France and South Korea quarterly horizon, are the only ones that exhibit significantly higher Newey-West standard errors when compared to those of the OLS.

Table 5: Newey-West Parameter Estimates Results

Sample	US	Canada	France	Germany	Australia	S. Africa	S. Korea	Brazil	Mexico	Turkey	Poland
	70-97	70-97	99-11	99-11	92-08	95-10	80-02	94-09	93-07	94-09	94-09
Monthly Regressions											
α_0	0.02 (0.02)	0.02 (0.02)	0.08 (0.07)	0.10 (0.08)	0.01 (0.01)	0.04 (0.03)	0.22 (0.10)	0.06 (0.05)	0.05 (0.04)	0.07 (0.06)	0.06 (0.04)
α_y	0.43 (0.25)	0.47 (0.31)	4.59 (4.01)	5.77 (4.57)	0.96 (0.56)	0.63 (0.48)	5.69 (2.00)	0.55 (0.69)	0.29 (0.27)	0.19 (0.15)	0.66 (0.57)
α_π	0.90 (0.53)	0.91 (0.65)	2.09 (1.53)	1.79 (1.18)	0.61 (0.60)	0.94 (0.67)	1.53 (0.98)	0.04 (0.03)	1.68 (1.18)	1.37 (1.32)	1.09 (1.14)
α_e	0.15 (0.12)	0.27 (0.20)	1.32 (1.20)	1.36 (1.09)	0.14 (0.11)	0.16 (0.13)	0.63 (0.41)	0.22 (0.15)	0.17 (0.18)	0.38 (0.32)	0.65 (0.33)
Quarterly Regressions											
α_0	0.01 (0.00)	0.01 (0.01)	0.02 (0.01)	0.02 (0.04)	0.01 (0.01)	0.02 (0.01)	0.04 (0.05)	0.02 (0.02)	0.02 (0.02)	0.03 (0.03)	0.02 (0.02)
α_y	0.88 (0.71)	1.19 (0.89)	3.50 (2.67)	4.49 (4.48)	1.54 (1.04)	0.87 (0.84)	10.36 (3.50)	1.26 (1.18)	1.12 (0.63)	0.77 (0.68)	1.99 (1.56)
α_π	0.58 (0.43)	0.53 (0.48)	0.90 (0.81)	0.74 (1.09)	0.70 (0.52)	0.72 (0.58)	0.98 (0.60)	0.02 (0.02)	0.82 (0.76)	0.69 (0.66)	0.61 (0.57)
α_e	0.20 (0.15)	0.25 (0.23)	1.52 (0.94)	1.34 (1.01)	0.17 (0.14)	0.20 (0.15)	0.96 (0.50)	0.22 (0.14)	0.34 (0.17)	0.19 (0.23)	0.36 (0.27)
Annual Regressions											
α_0	0.02 (0.01)	0.02 (0.02)	0.04 (0.03)	0.05 (0.04)	0.01 (0.01)	0.03 (0.02)	0.07 (0.09)	0.06 (0.04)	0.04 (0.03)	0.07 (0.03)	0.06 (0.04)
α_y	0.84 (0.52)	1.33 (0.76)	4.50 (3.57)	6.06 (4.48)	1.07 (0.59)	0.58 (0.52)	7.95 (2.50)	0.13 (0.19)	0.50 (0.41)	0.79 (0.68)	2.22 (1.36)
α_π	0.68 (0.50)	0.80 (0.57)	1.98 (1.47)	1.58 (1.09)	0.96 (0.65)	0.95 (0.64)	1.51 (1.83)	0.05 (0.04)	1.38 (1.01)	1.29 (0.66)	1.04 (0.96)
α_e	0.19 (0.15)	0.31 (0.24)	1.49 (1.10)	1.29 (1.01)	0.15 (0.12)	0.18 (0.12)	0.58 (0.57)	0.23 (0.16)	0.23 (0.15)	0.35 (0.23)	0.61 (0.33)

5.2. Out-of-sample Forecast Evaluation

Table 6 presents out-of-sample performance evaluation results of the derived model against the two benchmark models. The relative accuracy of our derived model against the historical average benchmark model fares poorly in terms of Theil's U in the 1-month and 3-month horizons. The U statistic is greater than 1 for all the 11 countries in the 1-month horizon, and 9 out of 11 countries in the 3-month horizon. However, in the 12-month horizon, the relative accuracy is significantly good, with the U statistic closer to zero in all countries. On the other hand, our derived model's relative accuracy against the AR(2) benchmark model is balanced in the 1-month and 3-month horizons. We note that the AR(2) model benefits from overlapping in these two horizons as alluded to by Dladla and Malikane (2019). In the 12-month horizon, the U statistic is less than 1 for both benchmark models in all countries. Thus, the derived model provides more accurate forecasts than the benchmarks on a longer horizon, and no better or worse forecasts than a naïve model on shorter horizons.

With regards to the results of the MSE-T statistic and its measure for equal forecast ability, we observe that it is insignificant for both benchmark models in all horizons. It is also negative in the 1-month and 3-month horizons in all but 2 observations for the AR(2) model, and mostly positive in the 12-month horizon. The historical average has balanced results in the 1-month and 3-month horizons, whilst being mainly negative in the 12-month horizon. This means that the derived model is superior in forecast ability only against the 12-month horizon AR(2) model. In terms of model encompassing, the ENC-T statistic is positive for both benchmark models across all horizons except for the 12-month horizon historical average benchmark, which is negative for most countries. This means that the derived model encompasses the benchmark models. It thus contains additional information in explaining the forecasts compared to the benchmark models, except for the historical benchmark in the 12-month horizon.

Table 6: Out-of-sample Performance Evaluation.

Models	US		Canada		France		Germany		Australia			
	97-22		98-22		12-22		12-22		08-22			
	AR	HA	AR	HA	AR	HA	AR	HA	AR	HA		
1 Month Ahead												
<i>Theil's U</i>	1.88	1.64	1.00	2.05	0.96	4.31	1.00	2.27	0.89	1.43		
<i>MSE-T</i>	-0.29	-0.20	-0.34	0.13	-0.33	-0.19	-0.39	-0.03	-0.25	0.27		
	(0.05)	(0.06)	(0.05)	(0.06)	(0.08)	(0.09)	(0.08)	(0.09)	(0.07)	(0.07)		
<i>ENC-T</i>	0.51	-1.83***	0.25	6.32*	0.75	4.36*	0.71	4.14*	1.76***	5.93*		
	(0.05)	(0.12)	(0.06)	(0.37)	(0.06)	(0.39)	(0.06)	(0.37)	(0.15)	(0.46)		
3 Months Ahead												
<i>Theil's U</i>	0.01	0.01	0.80	1.64	0.71	3.20	1.39	3.15	0.67	1.08		
<i>MSE-T</i>	-0.84	0.47	-0.35	0.14	-0.39	-0.16	-0.03	0.14	0.09	0.34		
	(0.03)	(0.05)	(0.05)	(0.06)	(0.08)	(0.09)	(0.08)	(0.09)	(0.08)	(0.07)		
<i>ENC-T</i>	5.80*	2.50**	5.88*	11.45*	-2.30**	8.35*	5.87*	9.75*	3.41*	8.92*		
	(0.34)	(0.15)	(0.35)	(0.66)	(0.22)	(0.73)	(0.52)	(0.86)	(0.27)	(0.69)		
12 Months Ahead												
<i>Theil's U</i>	0.01	0.01	0.11	0.23	0.16	0.72	0.34	0.78	0.54	0.88		
<i>MSE-T</i>	-0.24	-0.68	0.65	-0.09	0.15	-0.92	0.35	-0.81	1.06	-0.54		
	(0.06)	(0.04)	(0.04)	(0.03)	(0.09)	(0.03)	(0.09)	(0.05)	(0.12)	(0.07)		
<i>ENC-T</i>	7.18*	16.95*	4.17*	-9.02*	5.72*	-1.43	16.77*	-17.07*	11.53*	-1.88***		
	(0.41)	(0.97)	(0.25)	(0.52)	(0.51)	(0.15)	(1.47)	(1.49)	(0.89)	(0.16)		
Models	South Africa		South Korea		Brazil		Mexico		Turkey		Poland	
	10-22		02-22		09-22		08-22		09-22		09-22	
	AR	HA	AR	HA	AR	HA	AR	HA	AR	HA	AR	HA
1 Month Ahead												
<i>Theil's U</i>	1.57	3.39	2.43	18.50	1.75	3.84	2.17	12.93	0.69	3.38	0.68	6.82
<i>MSE-T</i>	-0.29	-0.20	-0.40	-0.16	-0.33	0.17	-0.31	0.02	-0.32	0.06	-0.35	0.10
	(0.08)	(0.08)	(0.06)	(0.87)	(0.07)	(0.08)	(0.07)	(0.08)	(0.07)	(0.08)	(0.08)	(0.08)
<i>ENC-T</i>	0.04	2.57**	-1.97**	6.86*	0.58	6.81*	-1.23	5.25*	-1.01	6.47*	0.84	4.24*
	(0.08)	(0.22)	(0.14)	(0.44)	(0.06)	(0.54)	(0.12)	(0.41)	(0.11)	(0.52)	(0.04)	(0.35)
3 Months Ahead												
<i>Theil's U</i>	0.93	2.00	0.17	1.31	0.04	0.10	1.10	6.53	1.27	6.20	0.17	1.75
<i>MSE-T</i>	-0.40	-0.26	-0.62	-0.52	-0.31	0.20	-0.39	-0.03	-0.45	-0.35	-0.21	0.16
	(0.07)	(0.08)	(0.05)	(0.05)	(0.08)	(0.08)	(0.07)	(0.08)	(0.07)	(0.07)	(0.08)	(0.08)
<i>ENC-T</i>	1.92***	10.61*	-4.23*	-1.02	7.63*	9.81*	-2.60*	6.99*	-0.18	2.56**	0.19	6.94*
	(0.17)	(0.86)	(0.28)	(0.09)	(0.61)	(0.78)	(0.21)	(0.54)	(0.08)	(0.22)	(0.08)	(0.57)
12 Months Ahead												
<i>Theil's U</i>	0.46	0.99	0.15	1.14	0.02	0.04	0.12	0.71	0.05	0.27	0.05	0.52
<i>MSE-T</i>	0.33	-0.82	-1.03	-1.26	0.48	-0.93	-0.60	-1.58	0.73	-0.36	1.24	0.34
	(0.08)	(0.05)	(0.09)	(0.11)	(0.07)	(0.03)	(0.06)	(0.15)	(0.06)	(0.08)	(0.13)	(0.08)
<i>ENC-T</i>	2.97*	11.58*	-5.97*	-2.48**	7.34*	-8.60*	9.20*	-26.94*	-25.64*	5.92*	4.61*	9.65*
	(0.25)	(0.94)	(0.39)	(0.17)	(0.58)	(0.68)	(0.70)	(2.05)	(2.02)	(0.47)	(0.38)	(0.78)

AR = Autoregressive, HA = Historical Average, * significant at 1%, ** significant at 5%, *** significant at 10%.

Significant errors in parentheses.

Overall, there are some instances where all three statistics simultaneously point to the derived model outperforming the benchmark models. Three of these are against the 3-month horizon for the US and Brazil historical average model and the Australia AR(2) model. Six of these instances are against the 12-month horizon AR(2) model for Canada, France, Brazil, South Africa, and Poland, and the historical average model for Poland. The performance of the derived model is uneven across countries, but it seems to perform relatively better in the 12-

month horizon as compared to the shorter horizon. In all these cases, ENC-T is significant at 1% except in the case of the 3-month horizon US historical average case which is significant at 5%. Since the periods for various countries are different due to the availability of data, the out-of-sample period may fall on either side of the 2008 subprime mortgage crisis. The AR(2) model results for countries in the post-crisis period are generally better, with a relatively lower U statistic, and a positive and lower ENC-T statistic.

6. Conclusion, Summary, and Implications

6.1. Concluding Remarks

The study derived a forecast model using open economy Taylor rule fundamentals of inflation, the output gap, and the real effective exchange rate to forecast stock returns for one-month, one-quarter, and one-year horizons. The study set out to determine whether the Taylor rule has any stock forecasting potential, and how such a model would perform compared to other stock forecasting benchmarks. The study focused on a mix of emerging and advanced economies spanning different regions of the world for balanced representation. The study used the dividend yield interest spread to derive the model and followed up with the methods set out by Ince et al. (2016), and Dladla and Malikane (2019) to introduce the necessary Taylor rule fundamentals by Taylor (1993), into our equation. In doing so, this study adds to the existing literature on the use of macroeconomic variables in stock return forecasting by using an expanded period of 1970 to 2022, studying 11 countries as outlined above.

The derived linear model yielded in-sample OLS regression estimates with coefficients that were consistent with existing asset return forecasting literature such as Sousa et al. (2016), and Cooper and Priestley (2009) among others. The coefficients were mainly significant across all forecast horizons. The signs of the coefficients of the model were also, in the main, as per the model in eq. (8), with inflation being negative, the output gap having ambiguous signs, and the real effective interest rate having a positive sign as per literature. The coefficients were also significant in most of the countries across all three horizons. The US, Canada, Mexico, South Korea, and South Africa show superior results for inflation by being significant at 1% across all three horizons, South Africa and the US again have superior results for inflation, whilst Canada, Australia, South Africa, Brazil, Mexico, and Turkey show superior results for the real effective exchange rate.

The out-of-sample performance of the model shows more favorable results on the longer 1-year forecast horizon relative to the shorter 1-month and 3-month horizons. The model has consistently accurate forecasts across most of the countries at the 12-month horizon as Theil's $U < 1$ for both benchmark models. The derived model also encompasses both benchmarks in most of the countries in the 12-month horizon since the ENC-T statistic is positive for most

countries and significant for all. The MSE-T statistic was found to be insignificant across all horizons for both benchmarks and positive for most countries for the 12-month horizon AR (2) model. Thus the derived model exhibits superior results when compared with the 12-month AR(2) benchmark model. There were also indications of superior results for the US, Brazil compared to the AR (2) model, and Australia compared to the historical average model in the 3-month horizon. This is also true in the 12-month horizon for Poland against both benchmark models and for Canada, France South Africa, and Brazil against the AR(2).

6.2. Recommendations

The 3 main stakeholders that might have an interest in the results of this study are practitioners, policymakers, and members of the academic community. For practitioners, the findings of the study can be used to refine investment strategies by incorporating the 3 macroeconomic indicators used in the study in their stock return forecasting models. For policymakers, the study can assist in better understanding of the effect of monetary policy actions have an impact on stock markets. For members of the academic community, the study extends on the existing knowledge base on the subject matter and provides a foundation for further research. This can be in the form of detailed studies of particular countries or exploring the relationship between the 3 Taylor rule variables and other asset classes.

6.3. Areas of Future Research

Future research areas on this topic could be on the use of a non-linear model which may offer better predictions than the OLS model. Techniques such as artificial intelligence and machine learning may provide better insights into the relationship between stock returns and the 3 Taylor rule fundamentals that were used in this study. Other areas can be an exploration of the forecast ability of these Taylor rule variables to different asset classes, or a detailed focus on particular countries as stated in the section above.

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