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Yield Curves and Macro Variables Interactions and Predictions

Bahaa Ali, Tarek

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Yield Curves and Macro Variables Interactions and Predictions

by

Tarek Bahaa Ali

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Author's Declaration

At no time during the registration for the degree of Doctor of Philosophy has the author been registered for any other University award without prior agreement of the Doctoral College Quality Sub-Committee.

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Signature: Tarek Bahaa Ali

Tarek Bahaa Ali

Date: 31 Oct 2023

Dedication

This Thesis is dedicated to my mother and deceased father, thank you for everything you’ve done for me in life, I am very grateful, and whatever I do, I will not be able to repay you back.

Yield Curves and Macro Variables Interactions and Predictions

By

Tarek Bahaa Ali

Abstract

This research is based on the yield curves and five macro variables, namely equity indices, FX rates, central banks' policy rates, inflation rates and the GDP growth rates, for nine different markets, from different geographical regions. Our aim was to identify common trends in yield curves and macro variables behaviors, from two perspectives: the interaction and predictive power of the variables. Firstly, we studied the interaction between yield curves and macro variables based on: Granger Causality, Impulse Response Function and Variance Decomposition. Afterwards, we predicted yield curves based on ANN Regression Multitask learning, and lastly, we predicted our five macro variables based on three different ANN Classifiers, in order to generalize and present results that are not specific to a country, or region, or model. The most persistence trend, amongst the variables, was the association between the GDP, inflation, policy rate and the Level. Based on Multitask learning, we achieved a 1-mnth average yield curves prediction accuracy of 80.2% for all yield maturities and studied markets. Additionally, we found out that increasing the hidden nodes led to overfitting the data, hence, we recommend the use of a simple neural network architecture. Furthermore, we designed a model that computes the optimum number of hidden nodes based on: the number of input/output nodes and forecasted months ahead. The Independent Variable Contribution analysis increased the weight of Slope on average for all markets. Weighted KNN caused a deterioration in the prediction accuracy of macro variables, and K of KNN increased with the horizon forecasted. In terms of predictive power of the variables, the yield curve on its own had predictive powers over long term equity markets, and the policy rate seemed to be affected by macro variables in the short term. Furthermore, the inflation and GDP were dominated by their own past values.

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List of Abbreviations

ANN	Artificial Neural Networks
BRA	Brazil
MEX	Mexico
US	United Sates
EGP	Egypt
SAF	South Africa
UK	United Kingdom
EUR	Euro Area
CHI	China
IND	Indonesia
YC	Yield curve
EQUITY	Stock Market Index
FX	Foreign Exchange Rate
POLRATE	Central Bank Policy Rate
GDP	National Gross Domestic Product Growth rate
INF	Inflation Rate
PCA	Principal Component Analysis
VAR	Vector Autoregressive
IRF	Impulse Response Function
Level	Yield curve Parallel Shift
m	Month
Y	Year
TBills	Treasury Bills
TBonds	Treasury Bonds
Level	Yield curve PCA1
Slope	Yield curve PCA2
Curvature	Yield curve PCA3
W1	Eigenvector 1 from PCA
W2	Eigenvector 2 from PCA
W3	Eigenvector 3 from PCA
AllPCA	Yield curves and macro variables PCA
AllPCA1	Yield curves and macro variables first PCA
AllPCA2	Yield curves and macro variables second PCA
AllPCA3	Yield curves and macro variables third PCA
Term Spread	10Y yield-3m yield representing the Slope of the yield curve
PCASD	Yield curve standardized PCA
AR	Autoregressive Process
MA	Moving Average
MA3mYC	3-month moving average of yields
MA3m	3-month moving average

MAC	Macro variables
MAC PCA	Macro variables standardized PCA
R2	Coefficient of Determination
H	Number of hidden nodes
I	Number of input nodes
F	Forecasted months ahead
shortYC	Short term yield curve proxy, average of 3m, 6m, 1Y
mediumYC	Medium term yield curve proxy, average of 3Y, 5Y
longYC	Long term yield curve proxy, average of 7Y,10Y
HoldOut	Hold out period of 70% training and 30% out of sample
Kfold	K-fold cross validation
Outsample	Out of sample data
KfoldW	K-fold cross validation weights
HOW	Hold out period weights
KNN	K nearest neighbors
wKNN	Weighted K nearest neighbors

1 Introduction

1.1 Background Information

The yield curve is not only a way to measure risk reward relationships on risk free investments, but it influences the economy as a whole, hence, an understanding of the information contained in the yield curve will help make better informed investment decisions. Financial markets participants often refer to the yield curve as the proxy for investor sentiment on the direction of the economy and future inflation, which in return affects the consumer business, the stock market, the real estate market and the unemployment rate. Therefore, comprehending and forecasting the behavior of the term structure of interest rates and macro variables is essential for banks, portfolio managers, and the central bank's monetary policy, in terms of hedging, investment decisions, and managing the target inflation rate and debt issuance for regulators. We have identified, in this research, general/common trends in yield curves and macro variables behaviors from two perspectives: firstly, the perspective of co-movement or the interaction between the variables, and secondly from the perspective of prediction. From this stand point, we have conducted our analysis on nine different studied markets, from different geographical regions: the United States (US), the United Kingdom (UK), the Euro Area (EUR), Mexico (MEX), Brazil (BRA), Egypt (EGP), South Africa (SAF), Indonesia (IND) and China (CHI). This research was based on the yield curves and five macro variables, namely equity indices (EQUITY), FX rates (FX), central banks' policy rates (POLRATE), GDP growth rates (GDP), and finally the inflation rate (INF). Studying the yield curves and macro variables from different geographical regions, ensures that results are not specific to a particular country or region. Initially, we have analyzed the interaction between the yield curves and macro variables by use of the three VAR structural analysis reports: Granger Causality, Impulse Response Function and Variance Decomposition. Afterwards, we have predicted yield curves based on ANN Regression Multitask learning, and lastly, we have predicted our five macro variables based on three different ANN Classifiers: KNN, Sigmoid and Softmax, in order to generalize and present results that are not country, nor region, nor model specific.

The association between yield curves and macro variables has been extensively studied by scholars, whether it is to measure the interaction or co-movement between the yield curves and macro variables, or whether it is for prediction purposes. Although, Rudebusch & Wu (2003) suggested that the relationship between interest rates and macroeconomic variables may have changed during the past 40 years, Ang and Piazzesi (2003) showed that macro variables explained up to 85% of the forecast variance of yields long-term forecast horizons. Diebold et al. (2006) found out strong evidence of the effects of macro variables on the future movements of yields and the reverse influence as well, in fact at longer-term horizons, macro variables quickly became more influential, for the 60-month horizon they accounted for 40% of the variation in yields. Pooter et al. (2010) stated that models with macro variables are the more accurate in recession periods, while models without, do well in low-volatility subperiods. However, Yan & Guo (2015) stated that there is incoherence between the real economy and financial markets in China, due to the incomplete liberalization of financial markets. In academic literature, the use of Vector Autoregressive (VAR), and dimensionality reduction techniques, was the founding base for yield curves and macro variables studies on the interactions of variables (Ang and Piazzesi, 2003; Diebold et al., 2005; Pooter et al., 2010; Djuranovik, 2014; Sowmya & Prasanna, 2018; Rubin, 2020). Although, the majority of academic work on that topic covers the US market, other academic scholars have covered different specific countries such as: Turkey, Indonesia, China, Germany, India, and Pakistan. On the other hand, other scholars opted to study a specific region, rather than presenting a study on a specific country, such as Sowmya & Prasanna (2018) who studied Asian markets. From that perspective, we have generalized and identified common trends in yield curves and macro variables co-movements based on the analysis of nine studied markets, from different geographical regions. Studying yield curves and macro variables interaction from different geographical regions ensures that our results are not specific to a country or region. Castello and Resta (2022) stated that studying the yield curves of the BRICS countries (Brazil, Russia, India, China, South Africa) ensures that the results are not specific to a particular country or region, since they are from different regions.

The prediction of yield curves is vital for market participants and policy makers, as insights on the yield curve behavior is an indicator of future economic activity, inflation levels, or even the performance of the country's equity market, as depicted by academic literature. Researchers have all attempted at predicting the yield curve using traditional statistical techniques such as VAR or ARIMA models Box and Jenkins (1968). However, these models suffered from the linearity constraint, meaning that they were not able to capture the non-linear behavior of variables. Recently, machine learning in financial markets has become a part of key financial services and applications, including asset management, risk management, credit scoring, and loans approvals. Machine learning focuses on analyzing data, recognizing patterns, and making predictions. Nowadays, many fintech and financial services companies are incorporating machine learning into their operations, resulting in better processes, lower risks, and better optimized portfolios. Forecasting economic time series is a difficult task, especially for developing economies where the idiosyncratic risk of each economy has a major impact on the behavior of variables, therefore, neural networks have become very popular in that domain due to their architecture design flexibility, and capabilities to capture the non-linear behavior of variables. Although, the prediction of the US yield curve has drawn the attention of academic scholars based on different neural network methodologies, others have moved away from studying developed markets, and focused on markets less covered by academic literature, such as Brazil, or a specific region, such as Latin American countries (Vela, 2013). From another perspective, Castello & Resta (2022) did not focus on a specific country, nor a specific region, but rather they used neural networks to study the yield curves of the BRICS (Brazil, Russia, India, China, South Africa) countries. The authors confirmed that their sample of countries is less bias to a country or region since it generalizes.

On the topic of ANN techniques for yield curve prediction, academic sholars mainly focussed on Singletask rather than Multitask learning. Multitask learning is based on a neural network with several outputs or targets, compared to only one output being predicted in a Singletask learning environment. A detailed description of Multitask learning vs Singletask learning was provided by Caruana (1997). More precisely, in a Multitask learning network the hidden layer is shared by all output targets, hence, the learning occurs at the same time, which could be an advantageous property for modelling variables such as yield curves, since several hidden nodes could focus on specific targets, such as the short or long end of the yield curve. As a matter of fact, academic literature on the use of ANN Multitask learning for yield curve prediction is very scare. Nunes et al. (2019) used a Multitask learning ANN to forecast European yield curves, and the researchers highlighted the lack of academic literature on the topic of Multitask learning ANN yield curve forecasting.

For macro variables predictions, ANN Classifier techniques have proven to be reliable and more stable than Regression ones, since it makes more sense to forecast the direction/cycle of the economy rather than a continuous variable (Estralla et al., 2003). Binary (Classifier) models are still being used to predict macro variables due to their superior prediction accuracy over linear statistical techniques (Priambodo et al., 2019; Maccarrone et al., 2021; Ogundunmade & Adepoju, 2022). Furthermore, academic scholars developed and used hybrid advanced techniques based on Classifiers to predict macro variables, such as Ballings et al. (2015) for stock market predictions, and Puglia and Tucker (2020) for the prediction of the US recession. Additionally, due to the non-linear effect of monetary variables that are more relevant in the longer run, as policy actions take about a year to be fully absorbed by macro variables, longer forecast horizons are preferred to shorter term for macro variables (Tkacz, 2001; Chirinos-Leañez & Pagliacci, 2015; Boeck & Feldkircher, 2021). Mostly, on the topic of macro variables predictions, academic scholars focused on the selection of the model that produces the best prediction results, and to a lesser extent on the predictive power of the variables. Therefore, the benefit of predicting five macro variables was to study the predictive power of the variables and identify general trends, i.e., how certain variables affected the future outcome of other variables. Additionally, the benefit of predicting macro variables based on three Classifiers was to generalize and present results that are not model specific.

In a closed economic environment, there are no interaction with other economies in the world, meaning that there are no exports, imports, nor capital flows. The closed economic system follows the guidelines set by the government, compared to the open economic system affected mainly by market forces, i.e., supply and demand (Mankiw, 2004). On the other hand, open economies interact with other economies freely by buying/selling goods and services, and capital flows freely (Mankiw, 2004). Although, there are no entirely closed economic systems in the world since most economies could be qualified as being a mixture of several systems, there are some countries that could be identified as having a relatively closed economy based on the trade to GDP ratio (import plus export divided by the GDP), called trade penetration (Bleaney & Tian, 2023). The UK, Germany, and French economies, are good examples of open economics, with a trade to GDP ratios equivalent to: 57%, 89%, 61%, respectively, according to the World Bank. On the other hand, Brazil has one of least open economies among the G20 countries, with a trade to GDP ratio equivalent to 39%, given the size of the Brazilian economy this ratio should be, theoretically, higher than that, compared for example to Mexico who has an open economy with a trade to GDP ratio equivalent to 84%, according to the World Bank (Canuto et al., 2015; Spilimbergo, 2019; Mexico Country Commercial Guide, 2022; Mexico Overview, 2023). Other open economies include as well a country like South Africa with a trade to GDP ratio equivalent to approximately 56%, compared to a closed Egyptian economy with a trade penetration equivalent to approximately 31% of GDP, according to the World Bank (South African Reserve Bank, 2018; Abed, 2020; South Africa's Trade Data Page, 2020). On the same train of thought, China and Indonesia are also considered closed economies, since their trade to GDP ratios are approximately 37% and 40% respectively, according to the World Bank. This debate of a closed versus open economy is a very ambiguous topic associated with many factors, not just the trade to GDP ratio, adding to the fact that economists might disagree on whether or not a certain economy is closed or open. For example, the US has a trade to GDP ratio of 25%, according to the World Bank, hence, one might think that China has a more open economy than the US.

We have conducted in this study a behavioral analysis on yield curves and macro variables, from different geographical regions, and we have identified general trends in yield curves and macro variables interaction and predictive power. We have selected markets from different geographical regions, in order to generalize and present results that are not specific to a country or region. Initially, we have selected a sample of two markets/country to study in each of the following geographical regions: Europe, Latin America, Africa and Asia, in addition, to studying the US for a comparative basis. As a general criterion, the selected markets or countries to study were amongst the largest economies (GDP) in their respective geographical region, since the size of the economy, or GDP, is usually an indicator of market efficiency and data availability. In addition to the GDP, the depth of each country’s debt market was our second criteria, since the most difficult variables to collect were the yield curves of each country on a historical basis, as not all countries had all yield curve points necessary for our analysis, and others had large disruptions in the data that were unreconstructible. Vela (2013) confirmed that the available yield curves historical data for Latin American countries are different from a country to another. Referring to the selected markets, the US economy accounted for 25% of the global economy, it is the world's largest economy per GDP equivalent to \$ 26 trillion, followed by the Chinese GDP equivalent to \$ 19 trillion, as of Apr 2023, according to the IMF. In fact, the US economy has a developed mixed economy, with the US dollar constituting central banks' world largest reserve currency (Amadeo, 2021). Additionally, the US dollar is the prime currency used in international trade, as well as being the reference currency for the petrodollar. Furthermore, the US has the world's largest bond market in the world standing at \$ 51 trillion, compared to \$ 20 trillion bond market for China, as of Sep 2022, according to the Bank of International Settlements. The US stock market had a market cap of \$ 44 trillion, accounting for 41% of the world's equity market value as of Mar 2023, according to the Securities Industries and Financial Markets. From Europe, the UK and the Euro Area were selected. The UK is the second financial center in the world, with a mixed economy accounting for 2.9% of the global economy, relying mainly on the services and industrial sectors, with a GDP equivalent to \$ 3.1 trillion, as of Apr 2023, according to the IMF (Jones, 2022; Ansari, 2023). The UK had an outstanding bond market equivalent to \$ 4.3 trillion, as of Sep 2022, according to the Bank of International Settlements, and its stock market value was equivalent to 2.9% of world's equity market value, as of Mar 2023, according to the Securities Industries and Financial Markets. On the other hand, we have selected the Euro Area, a monetary union of European countries that adopted the Euro as their currency, similar to Errais et al., (2015) who used "Euro Area" data when analysing the effect of yield curves on inflation. Noting that the Euro currency constitutes central banks' second world largest reserve currency, according to the European Union. The Euro Area includes 20 countries, according to the European union, with a consolidated GDP of \$ 15 trillion, as of Apr 2023, according to the IMF. The use of the Euro Area data (consolidated GDP growth rate, and inflation rate in percent) in our analysis reduces the noise or specific factor out of data co-movements, meaning that data co-movements related to events that are specific to each country were minimized, and since our objective was to identify common or general trends (not specific to a country) in data co-movements and predictability of variables, the use of the Euro Area data constituted an advantage in that matter. From Latin America, Brazil and Mexico were selected. Brazil had a GDP equivalent to \$ 2 trillion accounting for 1.9% of the global economy, compared to a GDP of $ 1.6 trillion accounting for 1.5% of the global economy for Mexico, as of Apr 2023, according to the IMF. Brazil had an outstanding bond market equivalent to $ 2.2 trillion, compared to $ 677 billion for Mexico, as of Sep 2022, according to the Bank of International Settlements. Brazil, with rich natural resources, has a mixed economy primally based on the service sector and industrial production, compared to the Mexican economy that is based on a diversified manufacturing export-oriented industry (Montoya, 2023a, 2023b). The Brazilian stock market had a market cap of $ 764 billion, accounting for 0.7% of the world's equity market value, compared to a Mexican stock market cap of $ 585 billion, accounting for 0.5% of the world's equity market value, as of Mar 2023, according to CEIC data. Africa has the smallest contribution to the global economy equivalent to 2.8%, compared to 23% for Europe and 36% for Asia, as of Apr 2023, according to the IMF. From Africa, South Africa and Egypt were selected because they were amongst the largest economies in their geographical region, and they were homogeneous in terms of GDP size. South Africa had a GDP equivalent to $ 399 billion accounting for 0.38% of the global economy, compared to a GDP of $ 387 billion accounting for 0.37% of the global economy for Egypt, as of Apr 2023, according to the IMF. South Africa had an outstanding bond market equivalent to $ 317 billion, compared to $ 56 billion for Egypt, as of Sep 2022, according to the Bank of International Settlements. South Africa has one of the most industrialized and diversified economies in Africa based on agriculture and mining with abundant natural resources, compared to the Egyptian economy that has moved to a market economy during the last decade based on agriculture, natural gas and tourism (Egypt Country Commercial Guide, 2022; Economy of Egypt, 2022; Marais & Ntsoane, 2023; South Africa Country Commercial Guide, 2023). The South African stock market had a market cap of $ 1.3 trillion (as of Jan 2023), compared to an Egyptian stock market cap of $ 38 billion (as of Mar 2023), according to CEIC data. From Asia, China and Indonesia were selected. China has the largest economy in Asia and the second in the world, and Indonesia constituted a very interesting country to select, since it has a great future potential for growth, and it is expected to become the 4th largest economy in the world, in the next decade, according to the IMF. China had a GDP equivalent to $ 19 trillion, compared to a GDP of $ 1.3 trillion for Indonesia, as of Apr 2023, according to the IMF. China had an outstanding bond market equivalent to $ 20 trillion, compared to $ 391 billion for Indonesia, as of Sep 2022, according to the Bank of International Settlements. China has an export oriented socialist market economy mainly relying on industrial production. Although, China has the second largest economy in the world, many sectors in its economy are still being controlled by the government (Hwa, 2018; Bada, 2019; Yang W., 2023). On the other hand, Indonesia has an industrialized diversified market economy that has moved from exporting crude oil and natural resources to a manufacturing industry (Indonesia Country Commercial Guide, 2022; Economy of Indonesia, 2023; Indonesia's Economic Growth to Moderate, 2023). In terms of stock markets, China had a market cap of $ 12 trillion, compared to an Indonesian market cap of $ 663 billion, as of April 2023 according to CEIC data. Details on the behavior of the selected markets variables were provided in the descriptive statistics section.

In light of the above, we have analyzed and identified common trends in yield curves and macro variables co-movements by studying nine markets, from different geographical regions, in order to present results that are not specific to a country or region. We have used the Eingenvector anaylsis performed on the yield curves and macro variables together as means to analyze and visualize different forms of variables co-dependency. Then, we have used the three VAR structural analysis reports: Granger Causality, Impulse Response Function and Variance Decomposition, in order to study the direction and lead lag relation between the variables. Afterwards, we have predicted the yield curves using ANN Regression Multitask learning, and we have analyzed the data based on the average of the nine studied markets in order to generalize. In addition, we have compared between the prediction accuracy of the Multitask and Singletask learning, and we have applied an Independent Variable Contribution analysis in order to estimate the predictive power of the variables. Followingly, we have performed a sensitivity analysis on the out of sample error, and we have designed a model that measures the optimum number of hidden nodes as a function of the number of input/output nodes and forecasted horizon. Lastly, we have predicted our selected macro variables using three different Classifiers. The benefit of using three different Classifiers was to generalize and present results that are not specific to a model. Adding to the fact that we have performed a behavioral analysis on K of KNN in terms of prediction accuracy and horizon forecasted, as well as we have applied a Weighted KNN approach, and compared its perdition results to the equally weighted KNN.

1.2 Problem Statement

This research was motivated by the lack of academic studies describing common trends in yield curves and macro variables behaviors, amongst different geographical regions, in terms of co-movement and predictive power of the variables. Similar studies focused on a specific country, or a specific region such the Asian countries. Castello and Resta (2022) confirmed, while modelling the yield curves of BRICS countries (Brazil, Russia, India, China, South Africa), that studying five countries from different regions all at once, ensures that the results are not specific to a particular country or region. Adding to the fact, we were also motivated by the lack of academic research on the topic of yield curves and macro variables on less developed markets, Errais and Jouini (2015) highlighted the lack of papers covering that topic in emerging markets, as well as the poor quality of data, in addition, Sowmya and Prasanna (2018) stated that academic literature that examined the association between macro factors and yield curves were conducted mostly on developed economies, especially the US and industrialized economies. Nunes et al. (2019) emphasized the lack of academic literature in the field of machine learning yield curve forecasts.

In the absence of scientific and academic research covering financial markets on less developed markets, policy makers base their decision making process on professional insights, hence, using the research results presented in this study, central bankers will be able to visualize how a change in their policy rate will affect the yield curve and the selected macro variables, i.e., the economy, especially with the recent economic turn of events whereby central banks around the world are raising policy rates in order to control inflation. On the micro level, banks and market participants will be able to position their assets and liabilities durations based on a more informed decision. From the perspective of yield curve prediction, the reader will be able to conclude that prediction results differ significantly from one studied market to another. In addition, researchers will be able to use the model that we have designed to compute the optimum number of hidden nodes as a function of the number of input/output nodes and forecasted horizon. Furthermore, we have presented the predictive power of the variables, and we have assessed which variables have the best short/long term prediction accuracies.

1.3 Research Questions (RQ)

All research questions, listed below, were answered explicitly in the three summary sections of the empirical results chapter:

- **RQ1:** What are the most common identifiable trends of yield curves and macro variables behavior in terms of co-movement?
- **RQ2:** Can ANN Regression Multitask learning be used in forecasting yield curves, in contrast to the Singletask learning currently applied by academic scholars?
- **RQ3**: How does the number of hidden nodes affect the training and out of sample error?
- **RQ4:** Can we design a scientific model that computes the optimum number of hidden nodes, rather than relying on the ad-hoc techniques currently applied by academic scholars?
- **RQ5:** Can the Independent Variable Contribution analysis provide useful insights on the predictive power of the variables?
- **RQ6:** Does the K-Fold Cross Validation improve the prediction accuracy?
- **RQ7:** Does the application of Weighted KNN improve the prediction results, compared to the equally weighted KNN?
- **RQ8:** How does K of KNN behave in terms of the prediction accuracy and forecasted horizon?
- **RQ9:** What are the most common identifiable trends of yield curves and macro variables behavior in terms of predictive power?

1.4 Research Objective

Our objective was to identify common trends in variables behaviors and present a comprehensive study, using machine learning, on the yield curves and macro variables, from two perspectives: first, the perspective of co-movement or the interaction between the variables, and second from the perspective of prediction. Castello and Resta (2022) studied the yield curves of five countries, BRICS countries, from different regions, in order to ensure that results are not specific to a particular country or region. Our intention was to cover nine markets, from different geographical regions, and we have based our analysis on observable common trends/behavior of variables amongst these selected markets. Studying markets from different geographical regions ensures that the findings are not exclusive to a specific country or region. For that purpose, we have used standard statistical techniques as well as Artificial Neural Networks: Regression and Classifier models. And since these two topics are interrelated, we have established the link between the findings in the interaction and prediction sections.

1.5 Research Methodology

In this research, we have applied a variety of different research techniques aimed at identifying yield curves and macro variables common trends in terms of interaction and predictive power of the variables. Initially, we have analyzed the interaction/co-movement between the yield curves and macro variables by use of the Eigenvectors and three VAR structural analysis reports: Granger Causality, Impulse Response Function and Variance Decomposition. Afterwards, we have predicted yield curves based on ANN Regression Multitask learning, and lastly, we have predicted our five macro variables based on three different ANN Classifiers, in order to generalize and present results that are not country, nor region, nor model specific.

1.6 Research Scope

Our objective was to identify common trends in yield curves and macro variables behaviors, from two perspectives: first, the perspective of interaction between the variables, and second from the perspective of prediction. In light of the above, we have studied the yield curves and macro variables of nine selected markets, based on different geographical regions, in order to ensure that results are not specific to a particular country or region. As our purpose was to identify common trends in different geographical regions, we were limited to studying two markets per geographical region, in addition to the US market. This research was based on a sample collected data from the period of March 2006 till March 2019 for the yield curves and five selected macro variables, extracted from Bloomberg and Reuters on monthly basis. This sample of data captured different economic cycles and yield curve shapes, along with the mortgage crisis in 2008-2009, as well as the European recession in 2012-2013. Taking into consideration that the GDP growth rates data were quarterly, not monthly, we had to transform the GDP into monthly data in order to keep the sample uniform. Transforming all the data into quarterly, would have caused a substantial reduction in the size of the sample. On the other hand, portions of the data had to synthetically be reconstructed, since we have faced a disruption in the data, in some of the selected markets. Hence, portions of the analysis were based on reconstructed data. Vela (2013) confirmed that the available yield curves historical data for Latin American countries are different from a country to another. Errais et al. (2015) stated that the "absence of a liquid secondary bond market implied that the published yield curves are built on the price of primary market auctions" for some developing markets. Although, for yield curves and macro variables predictions, we have used non-linear techniques based on neural networks, linear standard techniques were used to capture the interaction between yield curves and macro variables, since currently there are no neural network non-linear technique available for that purpose.

1.7 Significance of the Study

We have contributed to academic literature by analyzing common trends in the selected variables behaviors, and by providing a study on markets from different geographical regions, thus, our results are less bias to a country or region. More specifically, our contributions in each section of this study were as follows:

- On the topic of yield curves and macro variables interaction:
    - We have included an analysis of the Eigenvectors performed on the yield curves and macro variables as a measure of co-dependency, and we have defined plausible scenarios of variables co-movements. This analysis is similar somehow to analyzing different plausible correlation matrices between the variables at time (t), not a lead lag relation like the Causality, or shocks to the error like the Impulse Response Function. This type of analysis was not provided before in academic literature on the same topic.
    - We have included a new variable ordering mechanism for the Cholesky Decomposition based on the predictive power of variables, measured from the Granger Causality section.
- On the topic of yield curve prediction using ANN Multitask learning:
    - We have filled in the gap in academic literature on the use of Multitask learning for yield curve prediction, taking into consideration that academic researchers

mainly focus on Singletask learning for yield curve prediction. Nunes et al. (2019) emphasized the lack of academic literature in the field of ANN Multitask learning for the predictions of yield curves.

- We have analyzed how the model error term is explicitly affected by the hidden/output nodes, and horizon forecasted based on sensitivity and regression analysis.
- We have designed a scientific model that computes the optimum number of Sigmoid hidden nodes as a function of: the number of input/output nodes, and forecasted months ahead. Taking into consideration that academic researchers mainly use ad-hocs or trial and error techniques as their selection criteria for the optimum number of ANN hidden nodes. The application of our model is simple and could be used by academic researchers.
- We have measured the Independent Variable Contribution in order to estimate the predictive power of the variables. To the best of our knowledge, this technique was not applied before on the topic of yield curve prediction, as most academic literature on that topic focus on achieving the highest prediction accuracy, rather than accessing the predictive power of the variables.

- On the topic of macro variables prediction using three Classifiers:
  - We have predicted five macro variables using three different Classifiers, in order to generalize and present results that are not specific to the choice of model, i.e., common observable results/behaviors irrespective of the choice of model. In addition, our analysis was one of our contributions, as it was not focused on choosing the Classifier with the highest prediction accuracy, as most academic scholars do, but rather we were focused on the predictive power of the variables (behavior).
  - We have filled in the gap in academic literature for the prediction of the monetary policy rate variable, since academic work on that topic is scarce.
  - We have conducted a behavioral analysis on K of KNN versus the horizon forecast and prediction accuracy. This type of analysis was not provided before in academic literature on the topic of KNN.

- To the best of our knowledge, Weighted KNN was not applied before for macro variables predictions, thus, the application of this method is one of the contributions of this study.

1.8 Structure of this Dissertation

This empirical research, was divided into five chapters. The first chapter is the introduction, followed by literature review. In the third chapter, we have presented our methodologies for: the interaction between yield curves and macro variables, the prediction of yield curves, and lastly the prediction of our macro variables. In the fourth chapter, we have presented the results. In the fifth chapter, we have summarized the results and included concluding remarks.

2 Theoretical Framework and Literature Review

2.1 Theoretical Framework

This study is founded on the theories highlighted in this section, and based on our objective to identify common trends in variables behaviors and co-dependencies. In other words, we have presented in this section the theories explaining the co-movement and behavior of yield curves and macro variables, as they have laid the foundations for this study. We have tested in this study the general trends identifiable amongst the studied markets from different geographical regions, in contrast to academic scholars' theories, highlighted in this section, whether it is in terms of interaction or predictive power.

2.1.1 Yield Curve Shapes and Theories

The yield curve has three common shapes. An **upward-sloping yield curve** is the most common shape and market participants refer to it as the **normal yield curve**, where long term yields are higher than shorter-term ones. It is caused by market expectations for higher yields as the maturity of bond increases, since long-term bonds are considered to be riskier than shorter-term bonds due to the uncertainty in interest rates and yields (Koenig, 2004). Upward slopping yield curves generally indicate an economic expansion, which will cause inflation to rise in the future, thus, long-term yields are higher than short-term ones. Stronger economic growth is indicated by the steepness of the yield curve Slope. The second most common yield curve shape is the **inverted yield curve**, which occurs when bonds with long-term maturities have lower yields than bonds with short-term maturities (Koenig, 2004). An inverted yield curve generally indicates an upcoming economic recession, which will cause inflation to fall in the future, thus, long-term yields are lower than short-term ones. The third yield curve shape is unusual and rare, it's the **humped yield curve**, which initially Slopes up and then it becomes inverted (Koenig, 2004). Humped yield curves generally indicate changing economic conditions, when the economy is transitioning from expansion to recession and vice versa.

There are primarily four theories used to explain the shape of the yield curve. The first theory is the **Pure Expectations** hypothesis that assumes that the yield curve shape is based on the forward rate, which is the best predictor of the expected short rate. The Pure Expectations hypothesis can be used to explain any yield curve shape. For example, if the market expects rates to rise in the future, then the yield curve will be upward sloping and vice versa. In addition, expectations of future interest rates are highly dependent on the market's expectations of inflation (Koenig, 2004; Cernauskas, 2015). Therefore, the shape of the yield curve is a function of the market's expectations of future interest rates and inflation, according to the Pure Expectations hypothesis. However, the Pure Expectations hypothesis does not account for the risk imbedded in holding long term rates (Cernauskas, 2015). Fuhrer (1996) proved that the Pure Expectations hypothesis is a very good approximation of long-term bonds behavior, and changes in the Fed's behavior over time can reconcile with the Pure Expectations hypothesis. Musti & D'Ecclesia (2008) used Italian data to prove the Pure Expectations hypothesis for the entire Euro Area, based on a cointegration analysis of the short and long-term interest rates that was specified by an error correction mechanism. Nath et al. (2021) used cointegration and VECM to test the Pure Expectations hypothesis in India and the authors found out that the hypothesis is accepted for the very short-term maturity only, but rejected for the rest of short-term maturities. Other academic scholars rejected the Pure Expectations hypothesis in China and the US (Fan & Zhang, 2006; Corte et al., 2008). Li & Davis (2017) argued that the Pure Expectation hypothesis cointegration tests conducted by academic researchers on the yield curve term spread are not appropriate for all levels.

The second theory is the **Liquidity Preference** hypothesis, which is an extension of the Pure Expectations hypothesis by factoring in investor risk aversion and uncertainty, through a risk premium that can vary across time. Researchers found evidence that this risk premium is usually positive, suggesting that the market requires a higher yield in order to invest for longer maturities (Koenig, 2004). Therefore, if the Liquidity Preference hypothesis holds, an upward-sloping yield curve does not always mean that the market expects interest rates to rise in the future. From that perspective, an upward yield curve could actually indicate a flat yield curve, after considering the liquidity premium, as well as an inverted yield curve could indicate a drop in future rates more than the liquidity premium, and finally, a flat yield curve could indicate an expected drop in rates exactly equivalent to the liquidity premium over all the tenors (Koenig, 2004; Cernauskas, 2015). Fan & Zhang (2006) tested the term premium in China and proved that the term premiums are positive and increase with the length of the term. Ornelas & Silva Jr. (2015) used an innovative technique and found evidence supporting the Liquidity Preference theory in Brazil. Contrary to results from academic literature regarding the violation of the Liquidity Preference theory, Boudouk et al. (1999) used the US bond returns to provide evidence consistent with the theory.

The third theory is the **Market Segmentation**, which states that investors maturity preferences are determined based on their future need for liquidity and their risk preferences. According to the Market Segmentation theory, the supply and demand dynamics determine the yield curve shape (Koenig, 2004). Rhodes & Aazim (2011) stated that the monetary policy impact on the yield curve is better explained by the Market Segmentation hypothesis. The fourth theory is the **Preference Habitat**, which is an extension of the Market Segmentation theory. According to this theory, investors prefer a certain investment horizon, and to change their preferences they will require a premium. This theory explains the reason behind long-term yields being greater than short-term yields, and investors preferences are mostly geared towards shorter term investments (Cernauskas, 2015). Aazim (2011) found evidence that during financial and economic uncertainties the Preferred Habit explained the yield curve better.

The Liquidity Preference and Preference Habitat theories can explain the upward sloping yield curve by identifying the rise in the liquidity premium with bonds maturities because of investors preferences for short-term maturities (Mishkin, 2004). In addition, the Liquidity Preference and Preference Habitat theories, can explain as well the unusual inverted yield curves, based on the assumption that when short-term interest rates are expected to fall in the future so that the average of the expected short-term rates is below the current short-term rate, even though the liquidity premium is positive and it's added to this average, the resulting long-term rate will still be below the current short-term interest rate (Mishkin, 2004). The Liquidity Preference and Preferred Habitat theories are in general the most recognized because they combine features of both the Pure Expectations theory and the Market Segmentation theory by proclaiming that long-term interest rates will be the sum of a liquidity premium and the average of the short-term interest rates that are expected to materialize over the life of the bond (Mishkin, 2004).

2.1.2 Efficient Market Hypothesis

The Efficient Market Hypothesis (EMH) states that stock market prices reflect all information, and trade at their fair value, hence, investments should be directed towards passive portfolios. However, some argue that it is possible to beat the market, since stock prices do not always reflect their fair value. "If capital markets are sufficiently competitive, then simple microeconomics indicates that investors cannot expect to achieve superior profits from their investment strategies" (Dimson & Mussavian, 1998, p.91). In fact, "Expectations in financial markets are equal to optimal forecasts using all available information" and the EMH "is just an application of rational expectations to the pricing of securities" (Mishkin, 2004, p.150). Though, the EMH is mainly applied to stocks, it could as well be applied to foreign exchange rates, like stock prices, as they should in general follow a random walk (Mishkin, 2004).

There are mainly three types of EMH. The **Weak Form EMH** that assumes that prices adjust immediately on new market information, thus, investors will not be able to earn abnormal returns on the basis of previous information or past price patterns such as technical analysis. Weak form efficiency is associated with the Random Walk, and it is measured by the autocorrelation among returns or by testing the impact of different trading rules on stock prices (Naseer & Tariq, 2015). The **Semi-Strong Form EMH** that assumes that current stock prices fully reflect, not only historical price information, but also publicly available information relevant to the company's stock price (announcement regarding earnings, dividends, stock splits, new issues, and other economic or political events) (Naseer & Tariq, 2015). And finally, the **Strong Form EMH** that assumes that all available information is incorporated in stock prices, and investors have no access to private information, adding to the fact that there is a perfect reflection of all private information into the current price, thus, investors are unable to earn above average risk-adjusted profit by anticipating the information (Naseer & Tariq, 2015).

The evidence in favor of EMH was based on the performance of mutual funds, on whether stock prices reflect publicly available information or not, the random-walk behavior of stock prices, and the failure of technical analysis (Mishkin, 2004). More precisely, since mutual fund managers are unable to beat the market and earn an abnormal return, greater than the equilibrium return, then all prices today would reflect all available information. In addition, the EMH implies that stock prices should in general follow a random walk, meaning future stock prices are unpredictable (Mishkin, 2004). On the other hand, evidence against EMH is based on the small firm effect earning abnormal returns, the January Effect in stocks being predictable and conflicting with the random walk, and market overreaction to news (Mishkin, 2004). Plihal (2016) did not find any violation of EMH indicating that the stock market in Germany is informational efficient. Kan & Callaghan (2007) found evidence that supports the Efficient Market hypothesis for the foreign exchange rates of Asian countries. Andrianto & Mirza (2019) proved that the Indonesian stock market is characterized as a Weak Form Efficiency. Granero et al. (2020) used an innovative technique to prove that emerging markets' stock markets are conform to a Weak Form Efficiency. Lee et al. (2010) proved that stock markets from many developed and developing countries are inconsistent with the EMH. Titan (2015) argued that testing for market efficiency is a difficult task because of changes in market conditions.

2.1.3 Fisher Effect

The Fisher equation assumes that the nominal interest rate is equal to both: real interest rate, and expected inflation rate. Hence, according to the Fisher effect the nominal interest rate will adjust itself to mirror any changes in the expected inflation (Mishkin, 2004). In fact, economists disagree about the direction of the Causality relationship between the inflation and interest rates, some stated that there is a
positive causal relationship from the inflation to the nominal interest rate, others argued that any increase in interest rates causes the inflation to rise due to cost-push inflation (Karahan & Yılgor,

2017). James & Webber (2001) stated that the 10-year bond yield is a good guide to expected inflation. Coppock & Poitras (2000) did not find evidence supporting the Fisher effect. Fahmy & Kandil (2003) results did not support the Fisher effect in the short-run since short-term interest rates are not associated with the expected inflation. The authors stated that the inflation and nominal interest rates exhibit common stochastic trends in the long run, as the correlation between nominal interest rates and inflation rates increases with the maturity until they become fully associated for longer term horizons. Incekara et al. (2012) found evidence supporting the Fisher effect in the long term for the Turkish economy. Panopoulou & Pantelidis (2016) provided evidence supporting the existence of a long-run Fisher effect in which interest rates move in tandem with inflation rates in most OECD countries. Djuranovik (2014) estimated the correlation between the yield curve Level and the inflation forecasts to be quite high equivalent to +0.65, since the Level is represented as the long-run inflation expectation.

2.1.4 The Monetary Policy

Monetary policy is a combination of instruments used by central banks around the world to control money supply, and regulate economic variables such as the inflation. The monetary policy has three main objectives: inflation, unemployment, and the foreign exchange rate. Contractionary monetary policy is used to reduce money supply and control inflation. In addition, the monetary policy can affect the level of unemployment in the economy by adopting an expansionary monetary policy which would stimulate the economy and create jobs. Bringing stability to the foreign exchange market is also one of the monetary policy's goals, since an expansionary monetary policy leads to a depreciation of the currency exchange rate which makes the economy more competitive. To implement its objective, the monetary policy has three different tools: first, by open market operations through buying and selling government securities to affect money supply, second, by changes to its policy rates, the central bank can increase the cost of borrowing for customers and contract the money supply, and third, by changing its reserve requirements, the central bank can contract or expand its money supply as well (Mishkin, 2004; Conducting Monetary Policy, n.d.; Loo, 2023).

Tayssir & Feryel (2018) proved that there is a significant impact of monetary policies on the level of financial development over the studied countries. Ryan-Collins et al. (2016) found out that short and long-term interest rates did not affect the GDP, however, credit growth did, thus, policy makers need to specifically target bank credit to stimulate the GDP. Hameed (2011) proved that the interest rate has minor impact on the GDP, but the growth in money supply greatly affected the GDP of Pakistan. Amaral et al. (2022) demonstrated that the US monetary policy did have a positive impact on economic growth in the short term, but not in the long term. On the other hand, in the long term, inflation was affected by the expansionary monetary policy, thus, the expansion of money supply leads to long-term inflationary pressures. Lee & Werner (2018) tested whether lower interest rates resulted in higher growth and vice versa in the US, UK, Germany and Japan, using the relationship between the 3-month and 10-year benchmark yields and the GDP growth rate, and the authors concluded that interest rates follow the GDP, and are consistently positively correlated with economic growth. In fact, the impact of monetary policy on the economy differs across countries, and macro variables co-movements behave differently from a country to another. Cachanosky & Hoffman (2016) studied the effects of monetary policy at the industrial level in 10 European countries during a period of expansionary monetary policy, and the study found out that short-term elasticities differ across countries for similar industries. In addition, the authors suggested that a monetary policy targeting price stability may not necessarily lead to economic and financial stability in the long run. It is worth mentioning that in West African countries foreign exchange rates play a dominant role in determining the behavior of the monetary policy, adding to the fact that the money supply is the major transmitter of all the interactions to economic growth (Olamide & Maredza, 2019). On the other hand, the relationship between the monetary policy and the economy might be more ambiguous than some academic scholars stated. Twinoburyo & Odhiambo (2017) argued that there is no impact of the monetary policy on economic growth in the long term whether the proxy for monetary policy is money supply or interest rate, however, when money supply is used to measure the monetary policy, a negative relationship between the monetary policy and economic growth prevails. The authors concluded that the monetary policy may not be a solution for economic growth in Tanzania.

Academic literature highlighted the role of the monetary policy in defining the behavior of the yield curve spread, thus, yield spreads changes are dominated by the overreaction of short-term yields. Accordingly, the short end of the yield curve responds promptly to the monetary policy. Adding to the fact that expansionary supply shocks cause a drop in all yield maturities, short and long, while real demand shocks increase them (Chirinos-Leañez & Pagliacci, 2015). Chirinos-Leañez & Pagliacci (2015) stated that in the short run, short and long-term yields move according to the monetary conditions of the economy, which might depend on other factors that affect the money market, meaning that even long-term yields changes are in harmony with the monetary conditions. In the medium/long run, long-term yields are positively correlated with inflationary expectations, due to the fact that it takes around six months for this association to appear as inflationary expectations take time to be formed (Chirinos-Leañez & Pagliacci, 2015). Some authors analyzed the monetary policy relationship with the yield curve under different regimes, such as Shang (2022) who proved that in a low uncertainty regime, monetary policy shocks have more effects on the shorter end of the yield curve than the longer end, while the opposite is true in a high uncertainty regime. Furthermore, other scholars found out that the monetary policy can influence the whole yield curve, not just short-term yields alone. Rhodes & Aazim (2011) findings support the existence of a monetary policy impact across the whole yield curve, but the direction and magnitude of impact is not typical for advanced economies. The authors added that short-term yields drop as a reaction to an expansionary monetary policy, and medium/long-term yields tend to move in the opposite direction with a heterogenous way. On the same train of thought, Aazim (2011) stated that the monetary policy impacts the whole yield curve, however, this influence weakens along the different yield curve maturities. In addition, the author confirmed that, during unstable economic conditions, the monetary policy impact is significant towards the short end of the yield curve. Djuranovik (2014) stated that a shock to the monetary policy rate raises the Level factor persistently, since inflationary pressure causes the central bank to tighten economic conditions. Sowmya & Prasanna (2018) found out that a hike in the monetary policy rate increases the Level as proposed by the EH theory in Asian markets, except in the case of China, Japan and Hong Kong. The author stated that the Chinese monetary policy rate doesn't affect their yield curve effectively because of the weak monetary policy transmission mechanism. On the other hand, when the economy faces inflationary pressures, central banks adopt a contractionary monetary policy to curb inflation, which in turn lowers the

Level (Sowmya & Prasanna, 2018). In fact, the results of Sowmya & Prasanna (2018) reflect the strength of the monetary policy in controlling the inflation in Asian countries.

Monitory policy targeting inflation, rather than economic output, provides better macroeconomic outcomes in the case of less developed economies, in fact, central banks should follow a policy coherent with inflation targeting (Mayandy & Middleditch, 2022). Moreover, targeting inflation reduces overall volatilities in financial markets, promotes financial development, and improves the transmission of monetary policy signals. Hence, central banks of less developed economies should focus on inflation in order to endorse their objectives and bring financial stability (Mayandy & Middleditch, 2022). Vasicek (2010) studied the monetary policy of recently joined twelve EU new members, and the author found out that central banks in countries with flexible exchange rates responded mainly to inflation, however, countries with fixed exchange rates seem to apply an interest rate peg with the Euro. Inflation is hard to predict because it is affected by several non-monetary factors, more precisely supply shocks, which complicates the monetary transmission mechanism, as these factors are not controllable. Often central banks in emerging markets find it difficult to account for supply shocks when determining the monetary policy (Mohanty & Klau, 2007). However, it is argued that these non-monetary factors affect the inflation only in the short run, but in the long run, monetary variables determine the inflation rate. Thus, central banks should focus on the aggregate demand in the economy (Mohanty & Klau, 2007). Shocks to food prices are the main cause of inflation in almost all emerging markets, followed by the foreign exchange rate, noting that oil price shocks do not have a major influence on the inflation. The inability of the monetary policy in emerging markets to accommodate these shocks has caused it to become ineffective. The role of the monetary policy is more transparent and its impact more effective when inflation is primarily driven by demand shocks (Mohanty & Klau, 2007). As a final note, Mohanty & Klau (2007) stated that inflation persistence is rather high in many emerging markets which makes it more difficult to control inflation. Gregorio (2012) stated that the monetary policy should target headline inflation, and the main reason for the rise in emerging markets inflation was food prices, more than energy prices. Watt (2009) found sufficient evidence to support the negative relationship between the monetary policy and inflation, when the monetary policy is proxied by a given nominal interest rate. Kumar & Dash (2020) found out that, in India, the effectiveness of a contractionary monetary policy in controlling inflation has improved due to better transmission through credit and asset price channels.

The monetary policy has a significant impact on the country's foreign exchange rate. As a matter of fact, a hike in the policy rate leads to an appreciation in the country's foreign exchange rate, as it becomes more lucrative compared to other currencies offering lowering interest rates. The monetary policy relationship with the foreign exchange rate differs based on the country's currency system. In a floating exchange regime, an expansionary monetary policy increases money supply by reducing the policy rate and capital outflows, leading to a depreciation in the country's exchange rate. However, if the currency system is fixed, the central bank intervenes using its reserves not to allow the currency to fall. Thus, the monetary policy does not have efficiency in the system of fixed exchange rates (Dilmaghani & Tehranchian, 2015). Based on a study conducted on four countries, Kearns & Manners (2005) confirmed that changes in the policy rate are rapidly transmitted into the foreign exchange rate. The authors added that a policy rate tightening of +0.25% causes an appreciation of the foreign exchange rate by +0.35% on average, which indicates that monetary policy changes account for only a small part of the observed variability in exchange rates in the studied countries. On the other hand, the country's exchange rate is also affected by other macro variables such as the inflation and GDP. Dilmaghani & Tehranchian (2015) indicated that the money supply, as a proxy to the monetary policy, relationship to the foreign exchange rate is negative in the studied developing countries, the coefficient of this variable is about 0.04, meaning if the money supply increases by 1%, the country's exchange rate decreases by about 0.04%, caused by central banks implementing expansionary monetary policies, and reducing interest rates, and causing capital outflows. In addition, the authors stated that the GDP has a significant and positive effect on the country's exchange rate. Accordingly, if the GDP increases by 1%, the country's exchange rate rises by 0.05%, as a rise in the domestic income creates additional demand for domestic money. Furthermore, inflation has a negative effect on the country's exchange rate, as an increase in the domestic price level makes local goods relatively more expensive than foreign goods, leading to an increase in imports resulting in the depreciation of the country's exchange rate. Moreover, the authors found out a significant positive effect of the exports of goods and services on the country's exchange rate, meaning if the exports of goods increase by 1%, the country's exchange rate appreciates by 0.08%. Finally, the authors noted that the increase of the country's exchange rate in the previous period increases the exchange rate in the current period, i.e., the Autoregressive process. Following shocks to a country's exchange rate, central banks need to be careful in adopting the appropriate strategy, as sometimes wrong policy choices have been selected, as it happened in several other countries (Dilmaghani & Tehranchian, 2015). Mohanty & Klau (2004) found out that interest rates respond strongly to the foreign exchange rates in emerging economies with different degrees, noting that in some countries the response is even higher than the inflation rate or the output gap change, adding to the fact, central banks' reactions in the studied countries following a negative inflation shock might be smaller in magnitude than to a positive shock. Skibinska (2017), studying Eastern European countries, found out that a currency depreciation shock leads to a fall in foreign currency lending and in loans denominated in the domestic currency, as central banks react to a weaker exchange rate by hiking their policy rates.

The monetary policy has a negative relationship with the stock market or stock prices, as a hike in the policy rate depresses the equity market. As a matter of fact, a higher policy rate means higher cost of borrowing for companies, inflationary pressures, and a slowing economy, which leads to lower stock prices. On the other hand, stock price valuations are based on the present value of the expected cash flows, and an increase in the policy rate, leads to higher discount rates used to discount cash flows, which lowers the present value of the expected cash flows. Ioannidis & Kontonikas (2006) studied the relationship between the stock market and the monetary policy in OECD countries, the authors found out that in 80% of the countries under investigation contractionary monetary policies caused a decline in stock prices, since investors require higher returns to invest in the stock market. The authors added that this relationship holds across a variety of countries with different monetary policy frameworks. Suhaibu et al. (2017) studied the relation between the monetary policies and the stock markets of African countries, and they found out that the stock markets are affected by their respective monetary policies through interest rates, and in the long term this relation is bidirectional. Fausch & Sigonius (2018) found out that the changes in the German excess stock returns mainly reflect future dividends expectations, and the stock market response to the ECB monetary policy shocks. Adding to the fact that a substantial stock market reaction to surprise changes in the monetary policy is related to only real negative interest rates regime prevailing in an economic recession. Bissoon et al. (2016) proved the negative relationship between the interest rate and the stock market both in the short and long run, in fact, the authors stated that a direct link between the money supply and the stock market exists. In fact, monetary policies of global economies can also have a spillover effect on other markets. In an interesting study, Hung et al. (2022) tested the economic integration of the Chinese monetary policy with other global equity markets, and the authors found out that there is a long-term cointegration relationship between the Chinese monetary policy and Asian stock markets. However, the authors found little evidence of advanced economies response to the Chinese monetary policy. Furthermore, Chiang (2021) found spillover effects from the US monetary policy to international stock markets, the author stated that unexpected monetary growth and changes in the US monetary policy have significant negative impacts on stock returns, with a one-month lag, adding to the fact that similar effects extend to Europe, Latin America, and Asians stock markets. However, the relation between the monetary policy and the stock market is not as apparent, even in developed markets. In a comparative study, Laopodis (2013) examined the relation between the monetary policy and the stock market in the US during three monetary regimes. The author stated that in the 1990s the association between the federal funds rate and the stock market was not high, and the impact of inflation on the stock market did not appear as important in the 80s and the 90s. The author concluded that his results suggest that the relationship between the monetary policy and the stock market was not consistent, and the dynamics of this relation was different in each of the three monetary regimes. Similarly, Hu & Lai (2020) found out that the relation between the interest rate and the stock price is dynamic and changes over time. By examining this relation in China for 20 years, Hu & Lai (2020) proved that the impact of interest rates on stock prices has moved from a period of low correlation to positive correlation to negative correlation, adding to the fact that China's monetary policy has an effect in the short term, but not in the long-term.

2.1.5 Yield Curve association with Macro Variables

The yield curve association with macro variables has been studied extensively from academic scholars, as the information is bidirectional, it flows from the yield curve to the macro variables and vice versa (Diebold et al., 2006; Sowmya & Prasanna, 2018). These studies have been revolving around the shape of the yield curve, more precisely the Slope and its predictive capabilities over the economy. As a matter of fact, an upward slopping yield curve indicates a future growth in the economy, and a downward sloping yield curve indicates a future economic recession. Jamriska (2008) examined this relationship, in the UK, Germany, and France, and he concluded that the Slope was able to predict the probability of recession. Similarly, Hannikainen (2017) was also able to prove this relationship in the US. In addition, academic scholars also developed several innovative techniques in order to improve the results and capture the effect of the yield curve Slope over the GDP (Abdymomunov, 2011). However, some other scholars were not able to prove this relationship, Chinn and Kucko (2010) argued that the prediction power of the yield curve has deteriorated over time, and models on European countries performed better than models on non-European countries. In addition, Kaya (2013) was unable to prove the Slope and GDP growth rate relationship. In fact, other yield curve factors also affect macro variables. Djuranovik (2014) stated that as a shock to the Level could signal future inflationary pressures it led to: a positive response in the inflation variable, a positive response from the policy rate in the form of the central bank hiking its rate to fight inflation, and a negative response in industrial production. In addition, the author did not find evidence of the Slope effect on industrial production, though, it had a slight positive effect on the inflation in the short run only. Shocks to the industrial production caused a positive response in the Level, suggesting a rise in economic activity which could trigger inflationary pressures, and shocks to the inflation caused a positive response in the Slope and the policy rate. The author finally stated that shocks to the policy rate raised the Level, due to economic tightening actions, and affected the Slope and Curvature in the short run, positively and negatively respectively. Compared to Shareef and Shijin (2017) that stated that a shock to the policy rate caused a negative response in the Level, and the Slope, and a positive one in the Curvature, similar to findings from Ang and Piazzesi (2003). On the other hand, shocks from the Level and Curvature caused a positive response in the policy rate, however, a shock from the Slope caused a negative response in the policy rate (Shareef and Shijin, 2017).

Sowmya & Prasanna (2018) studied the bidirectional relationship between yield curves and macro variables in Asian markets. The authors found out that a monetary policy rate shock caused an increase in the Level in most Asian economies, which is conform to the Expectation

Hypothesis, except for three countries where the relation was negative, among them was China where the monetary policy transmission mechanism was weak. Furthermore, a rise in the inflation reflected a mixed response, positive and negative, on the yield curve Level of Asian countries. Theoretically, when the central bank adopted a contractionary monetary policy to lower the inflation, it caused the Level to drop which in turn reflected the efficiency of the monetary policy in controlling inflation (Diebold et al., 2006).

In general, a rise in the economic growth increased the Level, a higher output suggests the possibility of inflationary pressures, accordingly, Shareef and Shijin (2017) proved that the exchange rate was Granger Caused by the economic output. On the other hand, the authors found out that the Level had a leading effect on macro variables. A rise in the Level preceded higher inflation, which caused a rise in the policy rates of most studied Asian countries, similarly, Shareef and Shijin (2017) found out that the inflation was Granger Caused by the Level, indicating that the Level factor can capture the long-term inflation outlooks. Therefore, the Level led inflation and the policy rate. The opposite of this relationship exists only in Japan due to slow inflation adjustments since the country had very a low inflation rate over a long period of time. The authors noted that the effect of the Level on the economy's output growth and the currency's exchange rate was not significant. Although, Shareef and Shijin (2017) found out that the economic growth was Granger Caused by the Level.

Sowmya & Prasanna (2018) studied as well the effects of macro variables on the Slope. The authors indicated that a rise in the policy rate was reflected in the short end of the yield curve, causing a rise in the Slope, which is economically consistent since central banks influence the policy rate through the short end of the yield curve. Moreover, the economic output and inflation did not seem to have a significant effect on the Slope. Adding to the fact that the depreciation of the country's exchange rate increased next period Slope in only three of the studied countries, though, for the rest of the countries the impact was not significant. On the other hand, the Slope led the policy rates and inflation in most studied countries. More precisely a rise in the Slope led a rise in the policy rate, though, the responses of inflation and exchange rates were mixed. Finally, the economic output response was not significant in general, noting that Shareef and Shijin (2017) found out that the economic growth was Granger Caused by the Slope.

The yield curve Curvature is the third latent factor that was studied in academic literature, defined by a humped yield curve shape. An increase in the policy rate caused a positive response in the Curvature of just few countries, but in general the response was mixed and insignificant according to Sowmya & Prasanna (2018). Similarly, the inflation and output caused a positive response in the Curvature in also few markets, thus, for the rest of the studied countries the response was not significant. Finally, the country's exchange rate had a non-significant response on the Curvature. Furthermore, Sowmya & Prasanna (2018) stated that the Curvature had a lead effect on the policy rate, causing a positive response in the policy rate, though, the inflation and output responses were mixed amongst the studied countries, while the country's exchange rate response was not significant. Shareef and Shijin (2017) proved that the Level and Curvature have a bidirectional relationship.

2.2 Literature Review

2.2.1 The Interaction between Macro variables and Yield curves

An understanding of the yield curves and macro variables interactions is crucial for economists, policy makers and financial market participants. Academic scholars have studied the matter considerably and presented valuable insights on the co-dependency between the variables, and their connections to economic or financial theories. We have presented in this literature review, the methodologies applied by academic scholars, in addition to similar key findings and their discrepancies. Rather than focusing on a specific country or region, we have studied the interaction between the yield curves and macro variables based on different geographical regions in order to identify common/general trends in variables co-movements.

Most techniques used to study the interaction between macro variables and yield curves were similar somehow, with few variations (Rudebusch & Wu, 2003; Ang & Piazzesi, 2003; Diebold et al., 2006; Pooter et al., 2010; Kaya, 2013; Coroneo et al., 2014; Djuranovik, 2014; Yan & Guo, 2015; Shareef & Shijin, 2017; Sowmya & Prasanna, 2018; Stona & Caldeira, 2019; Rubin, 2020). Basically, researchers extracted the first three yield curve latent factors, more precisely, the Level (yield curve parallel shifts), the Slope (Slope of the yield curve) and the Curvature (the hump in the yield curve), by using Principal Component or Dynamic Nelson Seigel, since the first three yield curve latent factors account for more than 95% of yield curves movements, as per most academic scholars. Afterwards, these first three yield curve latent factors would be fitted along with the macro variables into a VAR framework. Finally, researchers would use the VAR three structure analysis reports: Granger Causality, Impulse Response Function and Variance Decomposition, in order to interpret the data. Though, few scholars based their analysis, on the interaction between yield curves and macro variables, on just one of the VAR structural analysis reports, such as Granger Causality. Plihal (2016) was able to prove that the German stock market is a leading indicator, as it Granger Caused industrial production and interest rate; Coroneo et al. (2016) proved that economic growth Granger Caused the Slope and the Curvature, while the real interest rate Granger Caused the Level; Jammazi et al. (2017) proved that a bidirectional Granger Causal relation exists between the movements in the US 10-year bond yield and the stock market; Ahmed et al. (2017) used the Granger Causality to study the relationship between the Pakistan stock market and macro variables such as the foreign exchange rate, inflation, and interest rates.

Conform to most academic literature, the yield curve Level accounts for 70% to 80% in yield curve movements, hence, it is considered as the most important determinant of yield curves responses to macro variables shocks, as it is the yield curve factor with the most effect on other macro variables (Sowmya & Prasanna, 2018). As a matter of fact, the association of the Level to inflation has been emphasized by economic theory. According to the Fisher effect the nominal interest rate will adjust itself to mirror any changes in expected inflation (Mishkin, 2004). In fact, scholars proved that the inflation had a more pronounced effect on longer term yields maturity, a proxy for the Level, rather than shorter maturities (James & Webber, 2001; Rubin, 2020).

Panopoulou & Pantelidis (2016) provided evidence supporting the existence of a long-run Fisher effect in which interest rates move in tandem with inflation rates in most OECD countries. Kaya (2013) stated that the Level has the highest correlation with inflation equivalent to 0.61, in addition, Ang and Piazzesi (2003) stated that the inflation is highly correlated with yields. Economically, a growth in the economy leads to higher income and demand, which causes inflationary pressures that will trigger a rise in the yield curve in the form of a parallel shift (the

Level), prompting the central bank to hike its policy rate (Rudebusch & Wu, 2003; Ang and Piazzesi, 2003; Diebold et al., 2006; Djuranovik, 2014; Shareef and Shijin, 2017; Coroneo et al., 2016). However, some scholars argued that a rise in the inflation reflected a mixed response, positive and negative, on the yield curve Level of Asian countries, according to Sowmya & Prasanna (2018), although in theory when the central bank adopted a contractionary monetary policy to lower inflation it caused the Level to drop which in turn reflected the efficiency of the monetary policy in controlling inflation (Diebold et al., 2006). Additionally, the Level did have a substantial impact on the economic growth, since a rise in the Level is considered an indication of future inflation expectations, and causes a hike in the policy rate, the economic output is negatively affected by a higher borrowing cost for companies causing a reduction in output (Rudebusch & Wu, 2003; Diebold et al., 2006; Djuranovik, 2014; Shareef and Shijin, 2017). Contrarily, Sowmya & Prasanna (2018) argued that the effect of the Level on the economy output growth was not significant, and Ang and Piazzesi (2003) stated that real activity is weakly correlated with yields, in fact, the response of yields to real activity shocks is smaller than the response to inflation shocks. Finally, the relationship between the Level and the foreign exchange rate was debated with controversy in academic literature. Theoretically, the economy is expected to have an effect on the country's exchange rate (Shareef & Shijin, 2017). Kaya (2013) stated that the correlation between the foreign exchange rate and the Level is negative. However, few scholars argued that, although the depreciation of the country's exchange rate increased the next period Level in just few of the selected countries, the effect of the Level on the country's exchange rate was mostly not significant (Ahmed et al., 2017; Sowmya & Prasanna, 2018). It is noteworthy that in west African countries foreign exchange rates had a key role in determining the monetary policy (Olamide & Maredza, 2019). It would have been interesting if these authors took different subsamples, and the dynamics of the estimated relationship was tested.

The yield curve Slope is the second most important latent factor, as it accounts for 15%-20% of yield curves movements, and on a cumulative basis the first and second yield curve latent factor accounts for 90%-95% of yield curves movements. There is extensive academic literature on the topic of the yield curve Slope predictive capabilities over future economic growth. In fact, an upward slopping yield curve shape signals a growing economy, as the short rate is low, representing a low borrowing cost and a low current inflation, which will stimulate the economy in the future. Noting that an inverted yield curve indicates the opposite. Several academic scholars found evidence supporting this theory (Jamriska, 2008; Abdymomunov, 2011; Hannikainen, 2017; Lee & Werner, 2018). On the other hand, Kaya (2013) and Ryan-Collins et al. (2016) were unable to prove this relationship, and Chinn and Kucko (2010) argued that the prediction power of the yield curve has deteriorated over time, and models on European countries performed better than models on non-European countries. As we have previously mentioned that shocks to inflation, economic output, and the policy rate caused a positive response in the yield curve Slope, researchers also found out that the short end of the yield curve was affected more by the monetary policy, and inflation affects more longer-term maturities (Coroneo et al., 2014; Shang, 2022). Alternatively, Sowmya & Prasanna (2018) demonstrated that a rise in the Asian countries' yield curves Slopes caused a rise in the policy rate, and a mixed response in the inflation and the exchange rate, meaning that the effectiveness in controlling the inflation differs from a country to another. Finally, the economic output response, in Asian countries, was not significant in general. It would have been interesting if these scholars had differentiated between the magnitude of the policy rate shock that caused the change in Slope and not the Level.

On a different course of action, it has been argued that the policy rate has the ability to influence the whole yield curve, not just the short end of the yield curve (Rhodes & Aazim, 2011; Djuranovik, 2014; Sowmya & Prasanna, 2018; Tayssir & Feryel, 2018). Although, as per economic theory, the monetary policy has a substantial influence on the future economic pathway, more precisely, a contractionary monetary policy causes the economy to slow down, several academic scholars argued that the monetary policy effect on the economy differs from a country to another (Hameed, 2011; Cachanosky & Hoffman, 2016; Twinoburyo & Odhiambo, 2017; Lee & Werner, 2018; Amaral et al., 2022). Furthermore, Shang (2022) analyzed the monetary policy relationship with the yield curve under different regimes, and the author proved that in a low uncertainty regime, monetary policy shocks have more effects on the shorter end of the yield curve than the longer end, while the opposite is true in a high uncertainty regime. Additionally, the monetary policy has a negative relationship to inflation, and the effectiveness of a contractionary monetary policy in controlling inflation has improved due to better transmission through several price channels in different countries (Watt, 2009; Kumar & Dash, 2020). In addition, it is important for monetary authorities to target headline inflation in emerging markets, since the main reason for inflation was food prices (Gregorio, 2012). Evidence has been provided on the monetary policy significant impact on the country's foreign exchange rate, according to Kearns & Manners (2005) changes in the policy rate are rapidly transmitted into the foreign exchange rate. On the other hand, the country's exchange rate is also affected by other macro variables such as the inflation and GDP (Dilmaghani & Tehranchian, 2015). In fact, the foreign exchange rates in emerging markets have a substantial impact on the interest rates, with a higher degree of influence than the inflation and economy (Mohanty & Klau, 2004). Lastly, the monetary policy has a negative relationship with the stock market or stock prices, as a hike in the policy rate, depresses the equity market of countries with different monetary policy frameworks (Ioannidis & Kontonikas, 2006; Suhaibu et al., 2017; Fausch & Sigonius, 2018). Arguments have been presented as well by several scholars stating that the relationship between the monetary policy and the stock market was dynamic and not consistent (Laopodis, 2013; Hu & Lai, 2020). It would have been interesting if markets, from different geographical regions, were selected in the above scholars' analysis, in order to compare between the different monetary policies effectiveness using the same time frame, and model specifications, so that the results are comparable.

In this context, there is a substantial amount of academic literature on the topic of yield curve and macro variables interactions covering the US market (Rudebusch & Wu, 2003; Ang and Piazzesi, 2003; Diebold et al., 2006; Pooter et al., 2010; Coroneo et al., 2014; Coroneo et al., 2016; Jammazi et al., 2017; Stona & Caldeira, 2019; Rubin, 2020; Fromentin, 2022). Other scholars have covered as well, the same topic, on different specific countries, for example, Kaya (2013) studied Turkey; Djuranovik (2014) studied Indonesia; Yan & Guo (2015) studied China; Plihal (2016) studied Germany; Shareef and Shijin (2017) studied India; and Ahmed et al. (2017) studied Pakistan. Rather than presenting a study on a specific country, some other scholars opted to study a specific region, such as Sowmya & Prasanna (2018) who studied Asian markets.

The purpose of this review was to present the academic literature on the topic of yield curves and macro variables interactions, in terms of models used and findings. One major disadvantage of these models is their linearity. Thus, they will not be able to capture any non-linear behavior or co-dependency between the variables. As you will be able to conclude that most of these studies were conducted on a specific country or even a specific region. In light of the above, we have analyzed the interaction between the yield curves and macro variables, in different geographical regions, by identifying the general trends in variables co-movements, not country nor region specific.

2.2.2 Yield Curves and Macro Variables Predictions

The topic of yield curves and macro variables predictions has been extensively studied in academic literature. Models and methodologies applied by academic scholars have evolved during the last decade, especially due to the developments in machine learning techniques, and technology in general. We have presented, in this literature review, academic work on the topic of yield curves and macro variables predictions, in terms of models' developments, architecture of the network, and its performance compared to traditional linear models. In our application of yield curves and macro variables predictions, we have filled in the gap in academic literature, as it was clearly presented in this review, and we have generalized and identified common trends in variables predictive powers, rather than presenting results specific to a country, or model.

At the basis of forecasting yield curves comes linear regression models and Affine models, such as Nelson and Siegel. The popularity of these models was caused by their performance and simplicity. Academic scholars have used linear regression models such as VAR on a standalone basis, or combined with Affine models such as Nelson and Siegel, to forecast yields (Ang & Piazzesi, 2003; Diebold et al., 2006; Pooter et al., 2010; Vereda et al., 2014; Yan & Guo, 2015). The inclusion of macro variables data into the forecasting model, improves the prediction accuracy as most academic literature affirmed. Although, academic researchers are still developing traditional yield curve prediction techniques such as Shang & Zheng (2018) who applied a mixed-frequency affine model, or Feng & Qian (2018) who used a dynamic natural cubic spline model, ANN models have drawn much attention from academic researchers, due to their capabilities of mimicking most linear and non-linear functions, and their design flexibility, hence, their popularity in the field of economic times series predictions. In fact, academic scholars used the flexibility in ANN architecture and further developed models for yield curve prediction. Although, the US yield curve was vastly studied in academic literature, several academic scholars decided to revisit the US yield curve prediction based on different neural network methodologies, for example, Sambasivan and Das (2017) revisited the prediction of the US yield curve, using a combination of machine learning and Gaussian processes, which performed better towards the longer end of the yield curve, and Puglia & Tucker (2020) revisited the predictive power of the US yield curve based on Classifiers novel methodology. Other scholars like Leite et al. (2010) and Kauffmann et al. (2022) have moved away from studying developed markets, and focused on markets less covered by academic literature, such as Brazil. In fact, Kauffmann et al. (2022) used a very intuitive approach based on neural networks for the prediction of the yield curve factor decomposition in Brazil, however, the authors never mentioned their selection criteria for the two hidden layers structures and large number of hidden nodes. Rather than focusing on a specific country, some scholars decided to study a specific region, such as Latin America. For example, Vela (2013) applied neural networks to predict yield curves of Latin American countries, and compared his results to other traditional models. The author stated that his contribution was to study yield curves of Latin American countries, and he specified that the neural network predictions did not outperform traditional models, as the results depended on the studied country. Taking into consideration that historical data were not available or complete for all Latin American countries. Finally, the author mentioned that some countries, such as Colombia, were most difficult to forecast and other countries, such as Mexico, had better prediction results. This study provided a good comparative basis for the behavior of yield curves predictions using neural networks in different countries. From another perspective, Castello & Resta (2022) did not focus on a specific country nor a specific region, but rather used neural networks to study the yield curves of the BRICS (Brazil, Russia, India, China, South Africa) countries. The authors confirmed that their sample of countries is less bias to a country or region but it rather generalizes. This research is interesting, but it focusses more on the technqiue rather than providing a good comparative basis amongst the studied countries as presented by Vela (2013). It is worth mentioning that all these studies used Singletask learning to predict the yields and none of them attempted at applying Multitask learning.

The use of ANN in predictions focuses mainly on Singletask learning vs Multitalsk learning. Multitask is an ANN learning many objectives at the same time, or being able to predict several outputs all at once, compared to Singletask whereby the network uses the data to predict only one output. A detailed description of Multitask learning vs Singletask learning is provided by Caruana (1997). Multitask learning is an interesting technique that could be used effectively to forecast yield curves or correlated variables. In a Multitask learning environment the hidden layer is shared by all output targets, hence, the learning occurs at the same time, which could be an advantageous property for modelling variables such as yield curves since several hidden nodes could focus on specific targets, such as the short or long end of the yield curve. Multitask learning has been successfully applied in engineering, the health industry, image processing and many other fields. Nunes et al. (2019) presented an interesting work on Multitask neural networks to forecast European yield curves. Their paper was very intuitive because the writers explained extensively their techniques and results, and they highlighted the lack of academic literature in the field of Multitask yield curve forecasting.

The predictive capability of the yield curve Slope over the GDP has been extensively studied in the academic world (Jamriska, 2008; Chinn & Kucko, 2010; Hannikainen, 2017). Other innovative techniques also emerged in studying the predictive power of the Slope over the GDP, by fitting the GDP along with the yield curve with a Dynamic Nelson Siegel model, yielding better results than term spread models as it used information from the entire yield curve, such as the three latent factors (Abdymomunov, 2011). Furthermore, the yield curve was also proven to have predictive powers over the inflation as well (Errais & Jouini, 2015). On the other hand, macro variables were also proven to have predictive powers over the yield curve; Pooter et al. (2010) found out that adding macroeconomic info, through PCA, improved the forecasting accuracy for yields, especially during recessions, though, models without macro factors performed well during periods of low volatility.

Classifiers techniques have proven to be reliable and more stable than Regression ones for the prediction of macro variables, since it makes more sense to forecast the direction/cycle of the economy, rather than a continuous variable (Estralla et al., 2003). Academic scholars used and still use binary (Classifier) models, such as Probit regression, in order to predict macro variables (Jamriska, 2008; Lange, 2018; Alexiou & Trachanas, 2020). As a matter of fact, academic scholars noted the superior prediction accuracy of Classifiers over linear statistical techniques. For example, the results of Priambodo et al. (2019) showed that their Classifier was able to predict the GDP using a small dataset better than multiple linear regression models and neural network regression. In addition, Maccarrone et al. (2021) found out that the Classifier prediction performed better than traditional linear models, and Ogundunmade & Adepoju (2022) chose machine learning Classifiers to predict the Nigerian stock market. Furthermore, scholars also used more advanced techniques based on Classifiers to predict macro variables, for example, Ballings et al. (2015) compared between Ensemble Methods (Random Forest, AdaBoost and Kernel Factory) and single Classifier models (Neural Networks, Logistic Regression, Support Vector Machines and KNN), for the purpose of stock market predictions, and Puglia and Tucker (2020) used a combination of machine learning and Probit regression (binary model) to predict the US recession. We have noted that most of these academic scholars' aim was to select the model that produced the best prediction results, however, most of these researches are specific to the country/market selected, and in some instances to the model. In addition, the predictive power of the variables was not accessed adequately in these studies.

ANN modules used for forecasting economic times series can be designed in many different forms and level of complexity, however, complexity does not necessarily mean better performance. In fact, ANN simple designs have proven to be as good as complex ones, if not better, thus, many researchers used a simple architecture or one hidden layer in their network, since one layer was found sufficient enough to approximate any complex non-linear function (Tkacz, 2001; Dunis and Morrison, 2007; Badea, 2013; Vela, 2013; Jahn, 2018; Nunes et al., 2019; Castello & Resta, 2022). One of the most ambiguous topics, in ANN prediction, is setting the hidden nodes parameters. In fact, academic scholars recognized the difficulty in setting the number of hidden nodes, as there are no single agreed upon technique to solve that problem, it is rather based on trial and error. In fact, a significant magnitude of nodes leads to inadequate results in the optimization and increases the probability that the parameters converge to a local optimum (Hamzacebi et al., 2009). For example, Moshiri & Cameron (2000) selected the number of hidden neurons based on a trial &

error basis and the training error variance. Tkacz (2001) tested from one to four hidden neurons, on a trial & error basis, and the author finally selected three hidden neurons, without providing clear evidence of his selection criteria. Badea (2013) set the number of hidden neurons based on trial & error in order to forecast foreign exchange rates. Shah & Debnath (2017) stated that the number of neurons in the hidden layer is determined by a trial & error procedure. Jahn (2018) used four hidden neurons, based on a trial & error basis, and the author further noted that the choice of hidden neurons number was related to his model selection. Nunes et al. (2019) used sensitivity analysis, and trial & error to test the impact of changing the number of hidden neurons on the out of sample error as a selection criterion. Chuku et al. (2019) noted that the selection criteria of the number of hidden nodes is a difficult and complex problem, and there are no agreed upon technique in academic literature that tackles that matter. Castello & Resta (2022) stated that there is no precise rule in academic literature to select the best combination of hidden nodes.

In times series predictions, most researchers have noted the outperformance of ANN models compared to the traditional linear ones, although, in some situations the ANN models were unable to outperform linear ones. Moshiri and Cameron (2000) compared the performance of ANN with traditional econometrics approaches to predict the inflation rate for Canada, over a horizon of one, three and twelve months, their results showed that ANN models performed as well as traditional ones for the horizons of 1 and 3 months, and outperformed them for the twelve-months horizon. Tkacz (2001) reduced the forecasting error of the Canadian GDP over the 1-year horizon when compared to linear and univariate models, however, for shorter horizons predictions, such as quarterly, the error did not differ from other linear models, the opposite is true for the long-run, due to asymmetries between interest rates and real economic activities that is captured by neural networks. Badea (2013) used an ANN in order to forecast EUR/RON and CHF/RON exchange rates one step ahead, the writer was able to reach lower Mean Squared Error when compared to ARIMA results. In his one-month predictions of Latin American yield curves countries, using an ANN model, Vela (2013) found out that the neural networks showed better results than the Autoregressive and Random Walk, however, for longer forecasting horizons the results are not decisive, in fact, the results are dependent on the studied yield curve. Sambasivan & Das (2017) was able to improve yield curves predictions, when compared to standard techniques, especially for the long-term region of the yield curve. Jahn (2018) used ANN to predict the GDP of fifteen countries, the ANN results were more accurate than the corresponding linear models. Chuku et al. (2019) used ANN based on macro variables inputs to predict the GDP of African countries, and compared the results to standard econometrics techniques. The writers noted that the superior performance of the ANN models was caused by their non-linear twist. Maccarrone et al. (2021) found out that the KNN Classifier performed better than traditional linear models when predicting the US GDP. Hence, ANN will not necessarily be superior in every situation. Prior to their analysis, it would have been interesting if these researchers could have tested the linearity/non-linearity assumptions in variables in order to comprehend whether or not the non-linearity is the cause behind the higher performance of ANN models.

Hybrid and other methods are emerging in the field of prediction, and their performance have mostly outperformed traditional ANN models. For example, Shah and Debnath (2017) used a Wavelet neural network on yield spreads to forecast the GDP. This paper is interesting because it illustrated the use of an innovative technique, i.e., Wavelet families, used to decompose the data and then feed them into an ANN model. Due to their flexibility in architecture designs, several scholars have combined different machine learning techniques to outperform the traditional ANN models, such as Sambasivan & Das (2017) who used a combination of machine learning and Gaussian processes in order to the improve the yield curve forecasts for longer term maturities when compared to statistical techniques results, and Hiransha et al. (2018) who used four types of deep learning techniques for predicting different stock markets, and his results outperformed the linear ARIMA model. Alternatively, other scholars used Ensemble techniques for their times series predictions. Ensemble methods are techniques that uses multiple independent models to solve a problem, later these models are combined to produce improved results. Thus, usually Ensemble methods produce more accurate solutions than single models. For example, Nti et al. (2020) used Ensemble Regressors and Classifiers in stock market predictions, using different combination techniques. Alotaibi (2021) introduced a new prediction model, based on a Classifier Ensemble technique like Support Vector Machine, Random Forest, and optimized neural network, that outperformed traditional models. We believe that in the future further developments will take place in the design of hybrid models, based on ANN, as the flexibility in their design is a very appealing property.

The purpose of this review was to present the academic literature on the topic of yield curves and macro variables predictions, in terms of models' developments, architecture of the network, and its performance compared to traditional linear models. In light of the above, we have filled in the gap in academic literature for yield curve prediction based on ANN Multitask learning, and we have designed a model that computes the optimum number of hidden nodes to fill in the gap in academic literature for the hidden nodes' selection methodology. Furthermore, we have predicted macro variables based on three Classifiers in order to generalize and present results that are not specific to a model or country. Adding to the fact, that our analysis was based primarily on the predictive power of the variables, rather than selecting the Classifier with the highest prediction accuracy.

3 Methodology

3.1 Data Sources and Analysis

3.1.1 Data Type & Frequency

We have conducted in this study a behavioral analysis on yield curves and macro variables, from different geographical regions, and we have identified common trends in yield curves and macro variables behaviors. Our aim was to study the co-movements of yield curves and macro variables together, as well as the predictability of variables. By choosing markets from different geographical regions, we have ensured that the findings are not specific to a country or region, similar to Castello and Resta (2022) that modelled the yield curves of BRICS countries (Brazil, Russia, India, China, South Africa), five countries from different regions to ensure that the results are not explicit to a particular country or region. Similar studies were conducted mainly on more developed markets, such as the US, or a specific region only, such as Asian countries and Latin American countries for example. We were consistent on the data selected for each studied market, and we took into consideration the availability and scarcity of information, noting that we were collecting several variables for each studied market. Vela (2013) confirmed that the available yield curves historical data for Latin American countries are different from a country to another. Errais et al. (2015) mentioned that yield curves data is scarce for several African countries, such as Egypt and Morocco, since the "absence of a liquid secondary bond market implied that the published yield curves are built on the price of primary market auctions".

In our study on the yield curves and macro variables, we have selected markets from different geographical regions, in order to generalize and present results that are not specific to a country or region. Initially, we have selected a sample of two markets to study in each of the following geographical regions: Europe, Latin America, Africa and Asia, in addition to studying the US for a comparative basis. As a general criterion, the selected markets or countries to study were amongst the largest economies (GDP) in their respective geographical region, since the size of the economy or GDP is usually an indicator of market efficiency and data availability. In addition to the GDP, the depth of each country's debt market was our second criteria, since the most difficult variables to collect were the yield curves of each country on a historical basis, since not all countries had all yield curve points necessary for our analysis, and others had large disruptions in the data that were unreconstructible. Vela (2013) confirmed that the available yield curves historical data for Latin American countries are different from a country to another. Referring to the selected markets, the US economy is the world's largest economy with a GDP equivalent to $ 26 trillion, followed by the Chinese economy with a GDP equivalent to $ 19 trillion, as of Apr 2023, according to the IMF. From Europe, the UK and the Euro Area were selected. The UK is the second financial center in the world, with a GDP equivalent to $ 3.1 trillion, as of Apr 2023, according to the IMF. On the other hand, we have selected the Euro Area, a monetary union of European countries that adopted the Euro as their currency, similar to Errais et al. (2015) who used "Euro Area" data when analyzing the effect of yield curves on inflation. Noting that the Euro currency constitutes central banks' second world largest reserve currency, according to the European Union. The Euro Area includes 20 countries, according to the European union, with a consolidated GDP of $ 15 trillion, as of Apr 2023, according to the IMF. The European Central Bank (ECB) is in charge of the Euro Area monetary policy and it defines the monetary policy for the whole Euro Area. Although, within the Euro Area, economic policy remains mostly the responsibility of the member countries, respective economic policies must be coordinated in order to achieve joint objectives such as growth and inflation. The Euro Area releases consolidated GDP growth rates, and inflation figures (annual inflation rate in percent), for the Euro currency (Euro Area) member countries. In our analysis, we have used the Euro Area GDP growth rates and inflation figures, in addition to the Euro yield curve (not a specific yield curve of any of the member countries). Moreover, since Euro Area countries have a single currency, the times series of the Euro currency foreign exchange rate was used in the analysis, in addition, to the ECB policy rate. Finally, the Euro Area does not report a consolidated equity index, thus, we had to make an assumption and use the Germany equity index as a proxy, taking into consideration that Germany has the highest GDP among all Euro Area countries, hence, its financial market is stable and its stock market is information efficient, adding to the fact that in general there is a high degree of correlation between equity indices in developed markets (Plihal, 2016). Furthermore, Fausch & Sigonius (2018) stated that the German stock market responds to the ECB monetary policy shocks effectively. The use of the Euro Area data in our analysis reduces the noise or specific factor out of data co-movements, meaning that data co-movements related to events that are specific to each country were minimized, and since our objective was to identify common or general trends (not specific to a country) in data co-movements and predictability of variables, the use of the Euro Area data constituted an advantage. From Latin America, Brazil and Mexico were selected. Brazil had a GDP equivalent to $ 2 trillion, compared to a GDP of $ 1.6 trillion for Mexico, as of Apr 2023, according to the IMF. From Africa, South Africa and Egypt were selected because they were amongst the largest economies in their geographical region, and they were homogeneous in terms of GDP size. South Africa had a GDP equivalent to $ 399 billion, compared to a GDP of $ 387 billion for Egypt, as of Apr 2023, according to the IMF. From Asia, China and Indonesia were selected. China has the largest economy in Asia and the second in the world, and Indonesia constituted a very interesting country to select, since it has a great future potential for growth, and it is expected to become the 4th largest economy in the world in the next upcoming decade, according to the IMF. China had a GDP equivalent to $ 19 trillion, compared to a GDP of $ 1.3 trillion for Indonesia, as of Apr 2023, according to the IMF. Details on the behavior of the selected markets variables were provided in the descriptive statistics section, and additional details on the markets selected were provided in the background information section.

In terms of macro variables selection, the GDP growth rates in percent (GDP) and INF (annual inflation rate in percent) were chosen for their importance, as one cannot study the behavior of the yield curves and macro variables, without including these two variables. The central bank policy rate (POLRATE) was included, since this variable has a major influence on the behavior of the GDP, INF, FX, EQUITY and the yield curve. Furthermore, equity indices were selected since they are considered a leading indicator for the economy, as well as their association with the yield curve latent factors, as per academic literature, in addition, portfolio managers and market participants would be interested in the behavior/predictability of the stock market. The foreign exchange rate (FX) was added to our study, because of its influence on the economy, according to academic literature. Furthermore, the FX has a major impact on the central bank's monetary policy, as well as being one of the main reasons of inflation surge in several studied markets. Noting that FX trading daily turnover was around $ 7.5 trillion as of Oct 2022 according to the Bank of International Settlements. Modelling these five macro variables along with yield curves satisfied our objective to identify general trends in variables co-movement behavior and predictive powers. For example, our analysis identified the influence of each variable on the rest of the variables. This type of analysis would not have been possible if we have chosen for the analysis the GDP and INF alone to study. In addition, based on our analysis, we were able to better visualize how a change in the policy rate (monetary policy) affected the INF, GDP and the yield curve for example, especially with recent events, where central banks around the world have been trying to curb inflationary pressures. Our choice of macro variables was similar to the macro variables chosen by Sowmya and Prasanna (2018), with the exception of equity indices.

We have conducted our analysis on monthly basis from Mar 2006 till Mar 2019. Our period of study was mainly based on the behavior of the GDP growth rates, inflation rates, and yield curves of each studied market. At first, we have plotted the standardized data of the GDP growth rates, inflation rates and yield curve term spreads, for each market, on different graphs, and we have made sure that our selection captured different economic cycles. Moreover, we have made sure as well that yield curves changed shapes during the selected period. On the other hand, this time period captured the mortgage crisis in 2008-2009, as well as the European recession in 2012-2013. Finally, some portions of the collected data had to be trimmed to make sure the sample is uniform for all countries/markets studied. Vela (2013) confirmed that the available yield curves historical data for Latin American countries are different from a country to another.

3.1.2 Yield Curve Reconstruction Using PCA

Yield curve data, for some selected countries, namely Egypt, Mexico, Brazil, Indonesia and South Africa, were not complete, due to the fact that some of the yield curve tenors were sometimes not traded for a long duration, or the rates were simply not available, therefore, we had to synthetically reconstruct these yield rates missing points in order to proceed with our research. As illustrated in Figure 3.1, yield curves incomplete data, per tenor and per country, as per the list hereunder:

- The Egyptian yield curve following tenors: 3 Year (Y), 5Y, 7Y and 10Y
- The Brazilian yield curve for the following tenors: 3 month (m), 6m, 3Y, 5Y & 10Y
- The Indonesian yield curve for the following tenors: 3m & 6m
- The Mexican yield curve for the following tenors: 3m, 1Y & 7Y
- The South African yield curve for the following tenors: 3m, 1Y & 7Y

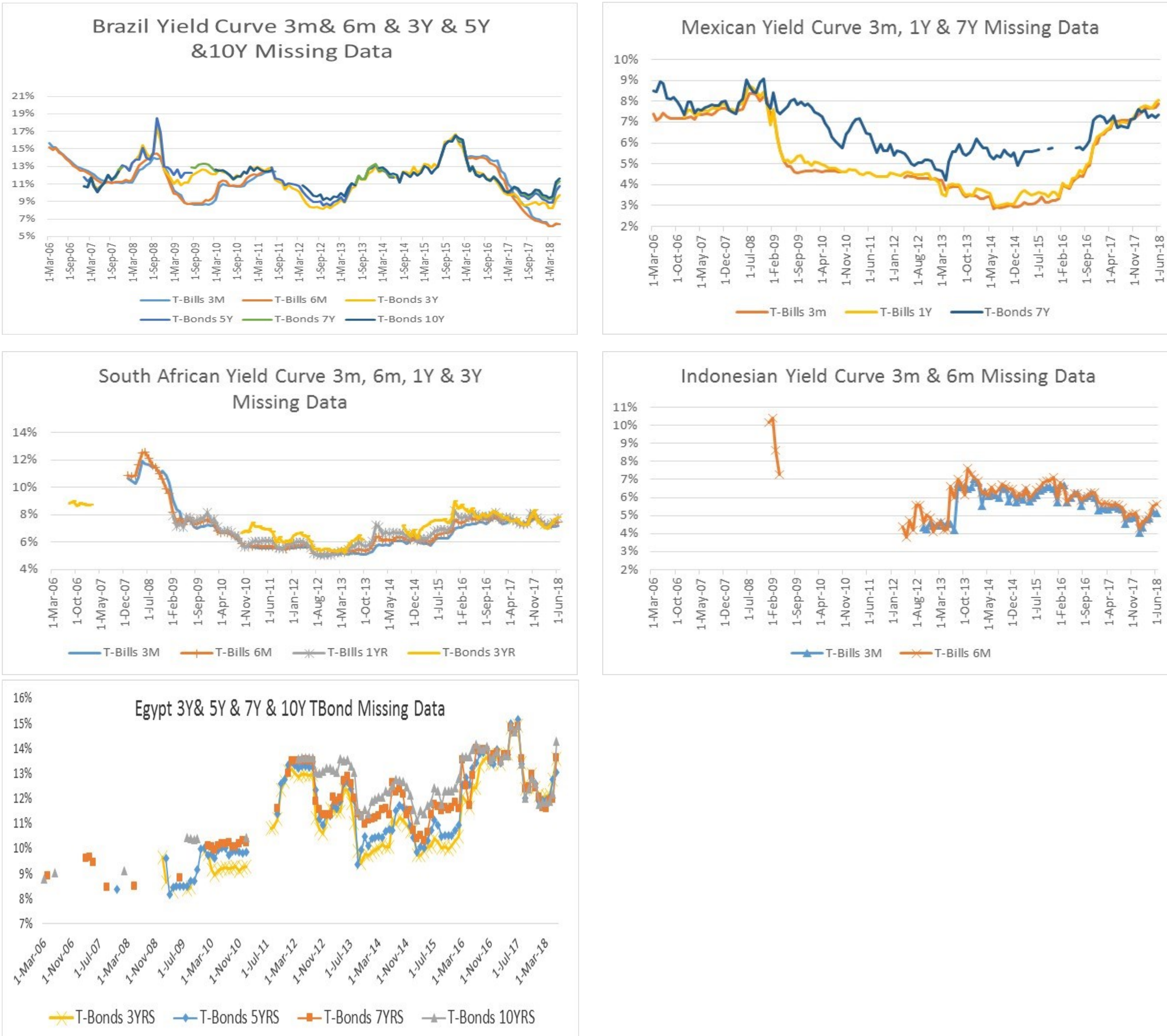


Figure 3.1 Yield curves missing data points per tenor and per country

Source: Bloomberg & Reuters

We have reconstructed all the missing data of the yield curves, using the methodology described by Alexander (2001), based on Principal Component Analysis (PCA), <u>according to the following steps:</u>

I. Perform a PCA on a period where the first simulated target tenor is available along with just few other highly correlated tenors, such as the 3m, 6m, 1Y yields to simulate the 3Y yield. Using the first difference in yields, we computed the Eigenvectors and Eigenvalues for the 3m, 6m, 1Y, and 3Y yields, based on the Covariance matrix.

II. Perform another PCA on the 3m, 6m, 1Y yields for the whole data, excluding the target yield (3Y) where the data is missing.

III. Thirdly, we used the factor weights from step 1) and multiplied it by the Principal Components computed in step 2), for example to simulate the 3Y yield: 3Y = W1 (from step1) x PCA1 (from step 2) + W2 (from step1) x PCA2 (from step 2).

IV. Using the simulated yield from step 3) (3Y yield) in addition to non-missing tenors (3m, 6m, 1Y yields), we repeated step 1) to 4) for another missing tenor and so forth until we have reconstructed all missing tenors.

Illustrated in Figure 3.2, the reconstructed yield curves, as you will be able to conclude that PCA was able to synthetically reconstruct missing data yield rates effectively, hence, we recommend this technique to be used in further empirical research on yield curves when the data is missing.

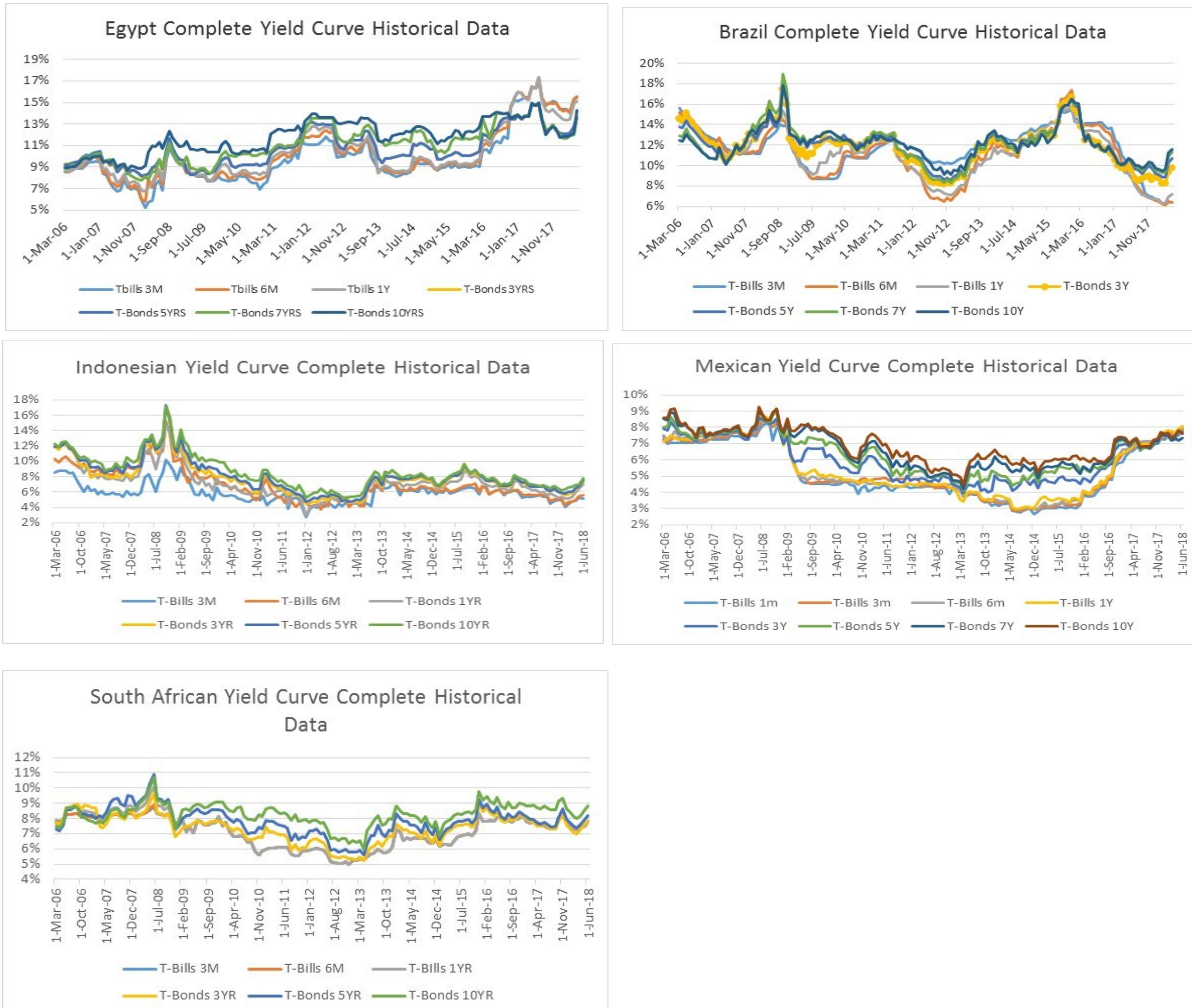


Figure 3.2 Yield curves reconstructed data points per tenor and per country

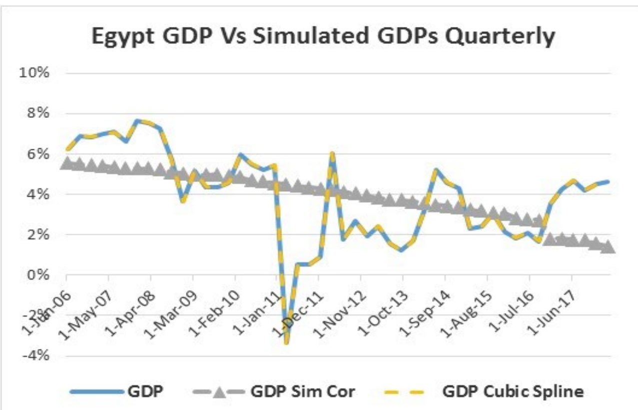
Source: Authors' own calculations

3.1.3 Transform GDP quarterly data to monthly

All observations that we have gathered were on monthly basis, except for the GDP growth rate figures, that were on quarterly basis. Hence, we needed to transform the GDP frequency from monthly to quarterly. We have tested two different techniques, in that matter, then we chose the one that performed better. The two tested techniques were:

- PCA, based on the technique highlighted in the previous section, however, this time the PCA was performed on the correlation matrix of the standardized returns of all variables, denoted in Figure 3.3 as GDP Sim Cor.
- Cubic Splines, as they performed well in the GDP monthly transformation performed by Kaya (2013), denoted in Figure 3.3 by GDP Cubic Spline.

Illustrated in Figure 3.3, the quarterly GDP for Egypt and Brazil as an example, as you will be able to conclude that the Cubic Splines perfectly mimics the GDP quarterly data and the PCA (GDP Sim Cor) was only able to capture the linear trend, therefore, we chose Cubic Splines to transform Quarterly GDP data to monthly.



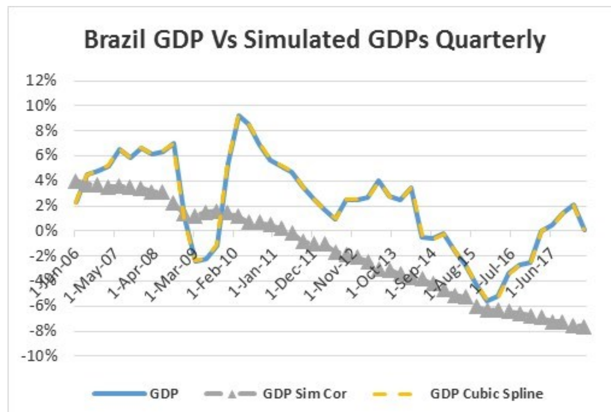


Figure 3.3 GDP transformation to monthly data
Source: Authors' own calculations

3.1.4 Descriptive Statistics

In this section, we have described some of the statistical parameters of all variables. All estimates were measured based on the monthly frequency of stationary data, since this is a study on the behavior of yield curves and macro variables, and our aim was to capture the co-movement between the different variables. Furthermore, inputs to PCA were based on the yields first difference, in order to induce stationarity (James & Webber, 2001; Alexander, 2008; McCarthy et al., 2015; Mikhaylov, 2019). In fact, stock prices and foreign exchange rates are modelled as a Geometric Brownian Motion in continuous time, with an equivalent process in discrete time in which the logarithm of the price follows a random walk (Integrated (1)), thus, the logs difference (returns) is necessary to induce stationarity (Alexander, 2008). Therefore, in our PCA and VAR computations, we have used the log returns of the EQUITY and FX, since their first differences are not in the same units/scales and does not induce stationarity, thus, the log returns were necessary to induce stationarity. On the other hand, continuous time models of other macro variables, such as interest rates, assume that there is a mean reversion process in the drift term, so that the variable is stationary, adding to the fact that these variables do not need to follow a Geometric Brownian Motion, hence, their first difference is used to induce stationarity (Alexander, 2008). These variables are then called Difference Stationary (DS) and they are transformed into a stationary times series by simply taking their first difference (Enders, 2015). Nelson and Plosser (1982) proved that macro variables are Difference Stationary rather than Trend Stationary. Fromentin (2022) stated that most of the macro variables used in his analysis were Difference Stationary. Thus, the first difference of the yields, POLRATE, GDP growth rate and INF, was enough to induce stationarity, adding to the fact that the first difference of these macro variables have the same unit/scale (percent) as the yields, making the interpretation of the results easier, for example a +1% (from 3% to 4%) change in the inflation rate, caused a +0.25% (from 5% to 5.25%) hike in the central bank policy rate, and a rise in yields by +0.30% (30bps rise). When estimating a VAR equation, we have to ensure stationarity (Brooks, 2014; Enders, 2015), in fact “a critical requirement of VAR is that the time series under consideration are stationary” (Gujarati, 2011, p. 277), in addition, “in an m-variable VAR model, all the m variables should be (jointly) stationary. If that is not the case, we will have to transform the data appropriately (e.g., by first-differencing)” (Gujarati & Porter, 2009, p. 788). One of the main challenges in VAR modelling is the specification of appropriate lag length (Gujarati & Porter, 2009). On the other hand, some authors argued that the data in the VAR environment needs not to be stationary in order to capture the effect of unit roots (Harvey, 1990; Cuthbertson, 2002). On the topic of yield curves and macro variables, academic scholars used different data transformation methodologies in their models. Ang & Piazzesi (2003) studied the yield curve latent factors and macro variables using VAR and Impulse Response Function based on different forms: yields in levels form, and log returns of macro variables. Plihal (2016) studied the Causality between the stock market and macro variables, based on the logs of the variables, while the interest rate was used in the levels form. Similar to our approach, Jammazi et al. (2017) studied the Causality between the US Treasury bond yield and the stock market by applying log returns to the stock market and first difference to the yields. Errais et al. (2015) used the inflation rate as an annual percent change (similar to our inflation rate), and yields along with yield spreads to study the relationship between the inflation and yield curves. Pooter (2010) in his research on the yield curve and macro variables applied different data transformation to the original series based on: no transformation (levels), log of the levels, annual first differences of the log levels, and annual first differences of the levels.

In order to test the relationship of the short-term yield to the rest of the yield curve tenors, we have measured the correlation estimates of the 3m yield to the rest of the yield curve tenors in each studied market, as illustrated in table 3.1 in Appendix A. As you will be able to conclude that the correlations estimate of the 3m yield to the rest of the yield curve tenors had a trend that is similar in almost all studied markets, with the exception of Indonesia. We have measured, in the last row of table 3.1 in Appendix A, the linear Slope for the correlation vector, representing the correlation decay rate per tenor. As it is clear that the decay rates of the 3m yield correlation to the rest of the tenors were very close in all the studied markets, with the exception of Indonesia. Illustrated in Figure 3.4, the annualized volatilities of each tenor in the yield curve compared to all countries. It is clear from Figure 3.4 that IND, BRA and EGP had the highest volatilities, on the other hand, the EUR and CHI had the lowest yield curve volatilities.

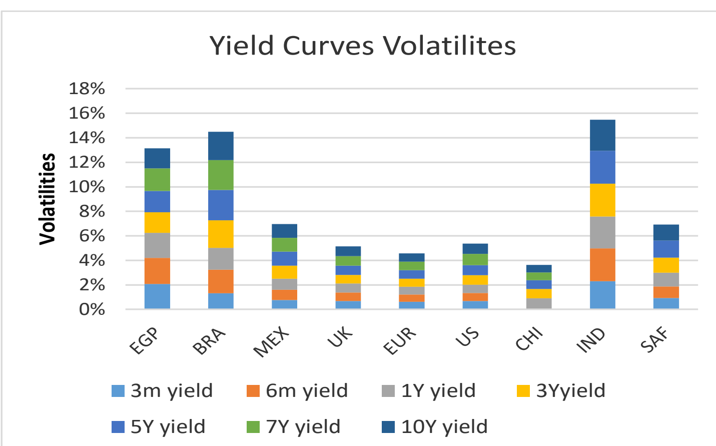


Figure 3.4: Yield curves annual volatilites per country

Source: Authors' own calculations

It is clear from table 3.2 in Appendix A that some countries had an upward slopping yield curve volatility term structure, such as MEX, SAF, and BRA, and the others had an almost flat volatility curve such as UK, EUR and US, while EGP and CHI seemed to be the only countries with a downward slopping yield curve volatility.

Illustrated in table 3.3 in Appendix A, equity indices descriptive statistics per studied market. It is clear from table 3.3 that the Egyptian equity index had the highest monthly sigma, due to two major shocks in the sample period, the 2008 credit crunch along with the 2011 Egyptian political turmoil. We have also computed the Average /Sigma ratio as a proxy for the Sharpe ratio, as it is clear that the highest ratios came from SAF and IND equity indices. All markets were categorized by negative skewness and positive excess kurtosis, the highest excess kurtosis was in IND. Finally, the highest monthly gains and losses were in Egypt, equivalent to +31% and -40%, due to the previously mentioned reasons.

Illustrated in table 3.4 in Appendix A, FX descriptive statistics per studied market. For the purpose of this analysis, we have measured the returns of each FX home rate versus the dollar, not the dollar versus the home currency rate. It is clear from table 3.4 that most FX rates were trending downward, as opposed to the US and CHI FX rates that appreciated. The highest sigma came from the EGP rate due to the devaluation of the currency in 2016, causing the EGP rate to lose 69% of its value in one day, hence, explaining the high excess kurtosis.

Illustrated in table 3.5 in Appendix A, GDP descriptive statistics per studied markets. It is clear from table 3.5 that CHI, IND and EGP benefited from the highest GDP on average. GDP changes were all symmetric or mean reverting. The highest sigma of GDP changes came from the EGP due to the political crisis. The skewness' of GDP changes were all positive, except for the EUR and the EGP that also exhibited high excess kurtosis, caused by high negative changes. The highest positive and negative GDP monthly changes were recorded by MEX +2.26% and EGP -3.32% respectively.

Illustrated in table 3.6 in Appendix A, INF descriptive statistics per studied market. It is clear from table 3.6 that the EGP and the EUR had the highest and lowest INF averages on the variable level, 12.78% and 1.75% respectively. The high EGP INF average level was caused by the currency devaluation event. All INF changes were almost symmetric and mean reverting, except for IND and EGP. A negative skewness in the context of INF changes is a positive indicator, and IND had the highest negative skewness equivalent to -4.58.

Illustrated in table 3.7 in Appendix A, central banks' policy rate descriptive statistics per studied market. It is clear from table 3.7, in the first-row header that the central banks of BRA and IND changed rates the most, 67 and 53 times respectively, compared to the UK central bank that changed rates the least. The US, UK, EUR, BRA, IND and CHI decreased policy rates more than hiked rates in terms of total, while BRA and IND had the highest rate cuts, -23.25% and -11% respectively. As opposed to EGP and MEX who increased policy rates, by a total of +15.25% and +6.5% respectively. Finally, SAF total rate hikes and cuts were almost symmetric.

3.1.5 Yield Curves Shapes

In order to study the yield curve natural shape, we have used the linear trend function of Microsoft Excel named Slope, and regressed the yields against the maturity (t) of each yield curve at each time interval, rather than using the term spread (term spread=10Y yield - 3m yield). Illustrated in Figure 3.5, the time varying behavior of yield curves Slopes. It is evident that most yield curves have been upward slopping, during the sample period, since their Slopes were above the red dotted line, representing the zero threshold, except for the Brazilian and Egyptian yield curves. These findings are consistent with academic literature, where an upward-sloping yield curve is the most common shape, and it's referred to as the normal yield curve shape, mainly caused by market expectations for higher yields as the maturity of bond increases, since long-term bonds are considered to be riskier than shorter-term bonds due to the uncertainty in interest rates and yields (Koenig, 2004).

In order to differentiate between a flat yield curve and an upward or downward slopping yield curve, we chose the Slope threshold of +/-0.10%, above or below which the yield curve in question would be identified as upward or downward slopping. As illustrated in table 3.8 in Appendix A, the US Slope coefficient was 78.85% of the times above the +0.10% threshold, meaning that the US yield curve has been 78.85% of the times upward sloping approximately, and was 21.15% (1-78.85%=21.15%) of the times flat. Most yield curves have been upward slopping, except for the case of Brazil and Egypt, their respective yield curves were upward slopping 51% and 73% of the times, while their yield curves were downward slopping by 16% and 15% of the times. Meaning the Brazilian and Egyptian yield curves flattened by 32.05% (1-(51%+16%) = 32.05%) and 10.90% respectively (1-(73.7%+15.3%) = 10.9%) of the times. It is worth noting that the Chinese yield curve was upward slopping 41.03% of the times, and flat for 58.97% of the times (1-41.03% = 58.97%).

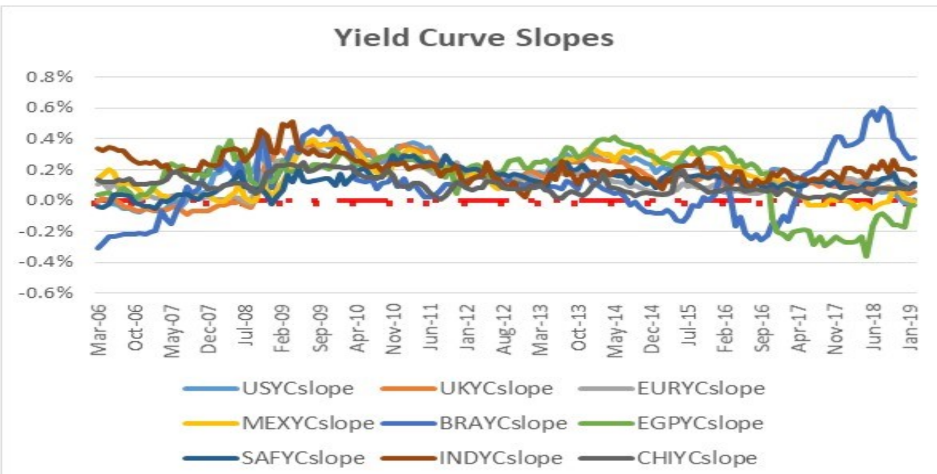


Figure 3.5 Yield curve Slopes per country

Source: Authors' own calculations

3.1.6 Yield Curves Eigenvectors Analysis

For the purpose of yield curve analysis, we have estimated the Eigenvector/values based on the Variance-Covariance matrix of yields, for each country, computed by taking the first difference. For the sake of simplicity, we have considered only the first three weights vectors. As it is illustrated in Figure 3.6, the W1 for all countries that represented the parallel shift or the Level factor, which covered around 70%-80% of all yield curves variations, compared to W2 for all countries that represented the Slope factor, which cumulatively covered 90%-95% of all yield curves variations, and finally W3 for all countries that represented the Curvature factor, which cumulatively covered 95%-98% of all yield curves variations, noting that the Curvature factor for the US and BRA yield curves looked like a humped yield curve, while the rest of the yield curves looked like the inverse of a humped yield curve. You will find in the Appendix A the Eigenvectors/values tables for all countries.

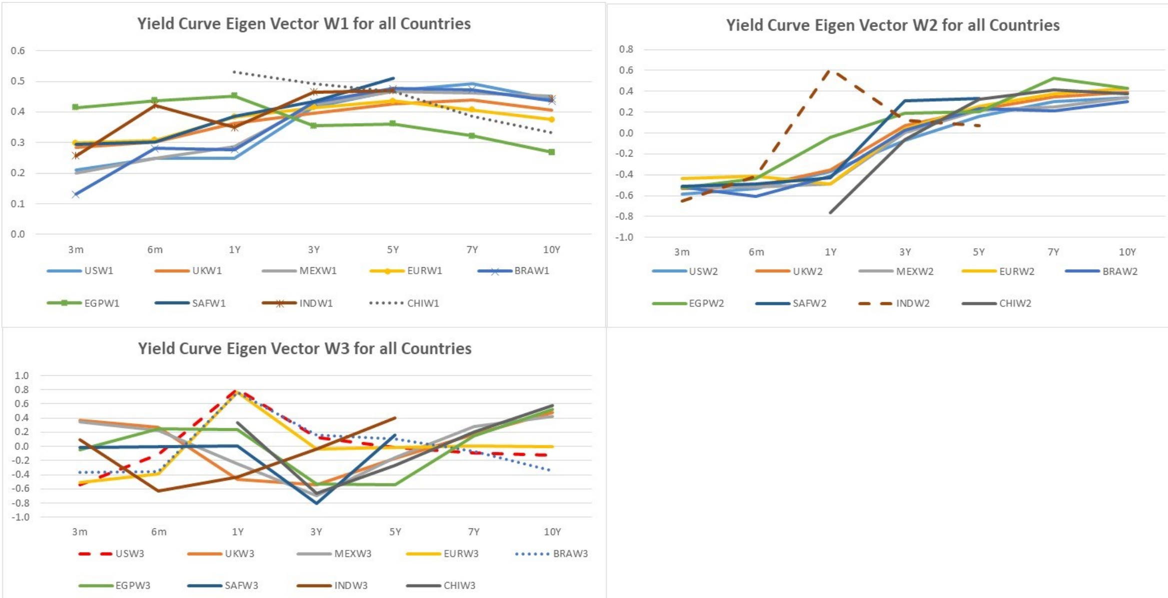


Figure 3.6 Yield curve eigenvectors for all countries

Source: Authors' own calculations

3.2 Yield Curves and Macro Variables Interactions

3.2.1 Principal Component Analysis (PCA)

Principal component analysis (PCA) is a technique for reducing the dimensionality of data, and improving the interpretation in the form of factors that describes the co-movement of data, hence, we have used Principal Component Analysis (PCA) in order to measure the variation and co-movement between yield curves and macro variables (Jolliffe & Cadima, 2016). PCA is appropriate for correlated data and systems that have similar economic drivers, such as the stock market, yield curves, futures prices…(McCarthy et al., 2015). PCA can be applied to both the Covariance matrix or the Correlation matrix of the standardized returns, both techniques are similar since the Correlation matrix is the Covariance matrix of the standardized returns (Tsay, 2010; Jolliffe and Cadima, 2016). The Correlation matrix of standardized returns is used when computing PCA on variables with different scales, meaning if we were computing PCA on yield curves alone, we would use the Covariance matrix, but since we have multiple variables with different scales, the Correlation matrix of standardized returns was used in order to neutralize the effect of different volatilities levels (Alexander, 2008; Jolliffe and Cadima, 2016). Otherwise, the

Eigenvectors would be dominated by the variable with the highest volatility, according to Alexander (2008). For example, using the Covariance matrix on our variables for the purpose of PCA would cause the equity index weight to dominate entirely the Eigenvectors. The drawback of using the Correlation matrix is that we have captured the co-movements of variables while ignoring the volatilities according to Alexander (2008), which was not a major disadvantage since we were only interested in the co-movements of variables for the purpose of that analysis. Another disadvantage of PCA is the linear combination performed on the original variables to compute the latent factors. In other words, PCA is only able to capture linear co-movements (Jolliffe & Cadima, 2016). Furthermore, PCA could lead in some instances to a loss of accuracy, if few Principal Components are selected, adding to the fact that the addition of too much Components could lead to increasing the noise in the data.

3.2.2 Granger Causality (GC)

VAR models are difficult to analyze due to their parameters and complex variable interactions, meaning that their lagged variables, coefficients and different signs makes them difficult to interpret. Therefore, VAR is often interpreted using various types of structural analysis reports. The three main types of structural analysis reports are: Granger Causality, Impulse Response Functions, and Variance Decomposition (Zivot & Wang, 2006; Brooks, 2014). Hence, these three statistical test/reports complement each other. Granger Causality Block Exogeneity Wald Test helps to identify the effect of each variable on each dependent variable (Brooks, 2014). In fact, Granger Causality detects the effects of past values of one variable on the current value of another variable (Gujarati & Porter, 2009; Gujarati, 2011; Brooks, 2014; Enders, 2015). One of the main limitations of the Granger Causality is its sensitivity to the lag length used in the model (Gujarati & Porter, 2009). The existence of the effect of variables over the dependent variable does not precisely mean that these variables are causing the dependent variable, which is another limitation of the VAR (Davidson & MacKinnon, 2004; Gujarati, 2011). Clearly, Granger Causality does not infer true Causality as stated by Zivot & Wang (2006). In fact, Granger Causality actually means that there is a lead lag relationship between a variable, or a group of variables, with another, meaning that a correlation between the current value of one variable and the past values of others exist (Brooks, 2014). Based on Granger Causality extracted from VAR, Plihal (2016) was able to prove that the stock market is a leading indicator, and can be used for predicting the economy, since it Granger Caused industrial production and interest rate. Furthermore, the author added that there is a bi-directional Granger Causality between money supply and the stock market. Shareef & Shijin (2017) used Granger Causality/Block Exogeneity Wald test, along with the Impulse Response Function, and Variance Decomposition, to test the relationship between the yield curve three latent factors: the Level, the Slope and the Curvature, with the macroeconomic factors in the Indian financial markets. Coroneo et al. (2016) studied the relation between the US yield curve and macroeconomics factors, and they proved that economic growth, Granger Caused the Slope and the Curvature, while real interest rate Granger Caused the Level. Jammazi et al. (2017) used Granger Causality to study the relation between the US 10-year Treasury Bond and the stock market, and they proved that a bidirectional Granger Causal relation exists between the movements in the 10-year Treasury Bond and the stock market. Ahmed et al. (2017) used the Granger Causality, Impulse Response Function and Variance Decomposition to study the relationship between Pakistan's stock market, and macro variables, such as the foreign exchange rate, inflation, and interest rates. The Authors were able to prove that interest rates Granger Caused the stock market, and based on the Impulse Response Function they concluded that the stock market was mainly affected by the variable own shock. Additionally, an impulse from the interest rate caused responses in the foreign exchange rate and inflation. Moreover, the Variance Decomposition demonstrated that changes in the stock market were mainly caused by the variable own shock. Thus, foreign exchange rates, inflation, and interest rates mainly affected the future value of the stock market. Using Granger Causality, Fromentin (2022) proved that there is a bi-directional Causality between the US stock market and macro variables. In light of the above, we have examined the lead lag relationship between co-movements in the yield curves and macro variables, based on the Unrestricted VAR Granger Causality Block Exogeneity Wald Test performed on the three yield curve latent factors (Level, Slope and Curvature) and the selected macro variables. The VAR optimum lag length criteria were chosen based on AIC, while the Wald Exclusion test was used to remove non-significant legs, as recommended by most researchers.

3.2.3 Impulse Response Function (IRF) and Variance Decomposition

As we have mentioned, in the previous section, that the Granger Causality, Impulse Response Function (IRF), and Variance Decomposition are the three structural analysis VAR reports, complementing each other (Zivot & Wang, 2006; Brooks, 2014). Several academic scholars used these three reports in conjunction in order to analyze the data and provide valuable insights on the topic of yield curves and macro variables interaction (Shareef & Shijin, 2017; Ahmed et al., 2017). Rudebusch & Wu (2003) studied the relationship between the US yield curve and macro variables using the IRF and Variance Decomposition. Ang & Piazzesi (2003) used the IRF and Variance Decomposition to study the interaction between the US yield curve and macro variables. Djuranovik (2014) studied the relationship between the Indonesian yield curve and macro variables, using the IRF and Variance Decomposition. Sowmya & Prasanna (2018) studied the interaction between yield curves and macro variables in Asian markets using the IRF.

Therefore, after having analyzed the Causality relationship between the variables, we have used the IRF to analyze the coefficient signs between yield curves and macro variables. In fact, IRF explains how shocks to each of the variables in the system affects the dependent variables, thus, for each variable, a unit shock is applied to the error, and the effects over time are stated (Brooks, 2014; Enders, 2015). It is important to note that since we are referring to a unit shock in the error, it suggests that the error terms of all other equations are held constant, or are not correlated. However, this is not correct since the error terms are correlated and not independent. Assuming that the error term are independent leads to misrepresentations (Tsay, 2010; Brooks, 2014). Thus, we need to generate the Orthogonalized IRF that removes the correlation from the error being shocked and the rest of the errors in the system. One likely restriction of the IRF and Variance Decomposition is to impose a particular ordering of the variables, since if the variables are highly correlated, then some of the results might differ, or not. However, if the variables are not highly correlated, then the ordering mechanism will not differ at all (Tsay, 2010; Brooks, 2014; Enders, 2015). The ordering mechanism of variables is important in order to remove the correlation from the error being shocked and the rest of the errors in the system, thus, variables with the highest predictive power enters the system at first, and so forth. From that perspective, we have measured the Orthogonalized IRF, using the Cholesky One Standard Deviation Degrees of Freedom Adjusted, based on an order for the variables in the Cholesky Decomposition from the most to the least Exogeneous variable, taking into consideration the predictive power of each variable. In other words, variables with more predictive power entered the system at first, in addition, each country had its own order, as the dynamics of each economy is different from the other. Variables prediction powers were measured from the previous section Granger Causality Block Exogeneity Wald Test, by counting the number of times each variable Granger Caused other dependent variables.

Finally, we have examined the third structural report, the Variance Decomposition of the Unrestricted VAR, and we have only interpreted general trends. In fact, Variance Decomposition measures the proportion of the movements in the dependent variables that are attributable to the rest of the variables, in other words, what portion of the variance of the forecast error in predicting the dependent variables is caused by the structural shock to the explanatory variables (Zivot & Wang, 2006; Brooks, 2014). As we have previously mentioned, Variance Decomposition has the same restriction as the IRF, and it is often used in academic research alongside the IRF (References provided in IRF).

3.3 Yield Curves Predictions using ANN Regression Multitask Learning

Multitask learning is an interesting ANN technique that could be used effectively to forecast yield curves or correlated variables. The lack of academic literature on the use of Multitask learning to predict yield curves, was our prime motive. Though, academic scholars have recently started adopting Multitask learning along with other machine learning methodology for stock market predictions (Park et al., 2022; Yuan et al., 2023). The ANN Multitask learning network is a model with many output targets, compared to only one output target for the Singletask learning model. More precisely, in a Multitask learning environment, the hidden layer is shared by all output targets, hence, the learning occurs at the same time, which could be an advantageous property for modelling variables such as yield curves, since several hidden nodes could focus on specific targets, such as the short or long end of the yield curve. In addition, Multitask learning could be useful to forecast a variable over different horizons at the same time by means of generalization. In fact, Multitask learning was successfully used in the health industry, and speech/image recognition. For example, by modelling the air pollution link to health problems, the study found out that analyzing several outputs at the same time, improved the results of the model. As a final note, Multitask learning processing time is less than the total processing time of modelling each target on a Singletask learning basis, hence, it saves considerable time for the researcher. From that perspective, we have used an ANN Feedforward Regression Multitask learning model in order to predict all points in the selected yield curves at once. Although, the attempt at designing a forecasting model is a difficult task, neural network regression models have proven to be better than more traditional models due to their design flexibility and non-linear twist.

3.3.1 Neural Network Structure

We have used the typical and most common ANN Feedforward Regression structure/topology, whereby the network is composed of three vectors: an input vector, a hidden vector, and an output vector. In fact, the structure/topology that we have used is similar to the network mostly used by academic scholars for economic times series predictions (Moshiri & Cameron, 2000; Gradojevic & Yang, 2000; Dunis & Morrison, 2007; Bal & Demir, 2017; Jahn, 2018; Chuku et al., 2019). Illustrated in Figure 3.7, the neural network yield curve topology, whereby the network was subdivided into three layers. The **first layer** is the ***input layer*** which received the input data and transferred them to the next layer. This layer was composed of different nodes/neurons for every model tested, as it will be explained later, more preciously the input nodes varied from three to seven nodes/inputs. As suggested by the academic literature, the inputs needed to be normalized in order to have a smooth convergence of the cost function, and in order to avoid that one variable might dominate the others in magnitude so the model is unable to obtain the contribution of smaller scaled variables (Singh & Singh, 2020). Normalizing techniques varies, and we have opted to use a z-score methodology based on the coefficients estimated from the training data, as this method has yielded smoother results for our data, according to Al-Faiz et al. (2019) z-score normalization reduces the training time. Furthermore, we have tested out models on raw data, without normalization, and we concluded that when optimizing based on normalized data the processing time was less, and the convergence of the cost function was less likely to be caught in local minimums. In terms of end results, the normalized data optimization only slightly improved the cost function compared to the raw data optimization, due to the fact that inputs and outputs are yields already scaled on the same level.

On the hand, we have tested on a sample of our data, a different normalizing technique, the MinMax method, however, the results were worse when compared to the results with the z-score method.

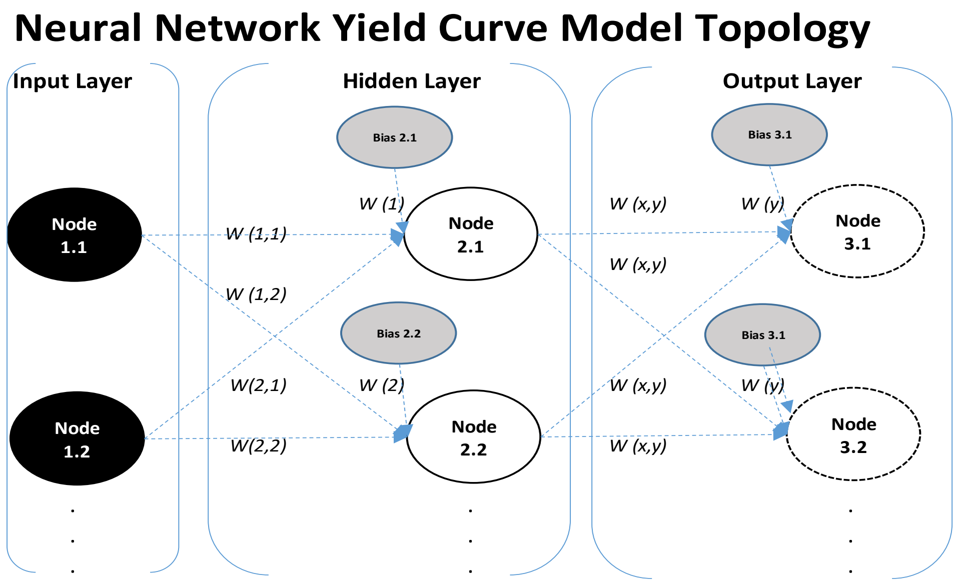


Figure 3.7 Neural network topology for yield curve prediction

Note: Author's own diagram based on the ANN Multitask structure, similar to Bilgehan & Turgut (2010), Younsi (2015), and Nunes et al. (2019) illustrations

The **second layer** is the ***hidden layer*** which received the inputs from the previous layer and squashed them into intervals using an activation function. The inputs were multiplied by weights W(x,y) , where y corresponded to the number of the nodes in the current layer and x corresponded to the number of nodes in the previous layer, then added the bias at each node and transferred the value to an activation function. We have used **one hidden layer**, as per most academic literature, one hidden layer is sufficient enough to approximate complex non-linear functions. We have experimented by adding another hidden layer on a sample of our data, however, the prediction results did not improve much, similar to Tkacz (2001) who experimented with two hidden layers but the results were not noticeably better. Dunis & Morrison (2007) stated that one hidden layer is normally sufficient to approximate any complex nonlinear function. Badea (2013) forecasted foreign exchange rates using one ANN hidden layer. Shah & Debnath (2017) used one hidden layer to forecast yield spreads. Bal & Demir (2017) forecasted foreign exchange rates, namely USD/EUR-GBP-JPY-NOK, based on one hidden layer, as it is sufficient enough to forecast economic times series. Jahn (2018) used one ANN hidden layer to predict the GDP of fifteen countries. Nunes et al. (2019) used one hidden layer in their ANN Multitask model to forecast yield curves. Castello & Resta (2022) used one hidden layer in their BRICS countries yield curves forecasts.

On the other hand, **the selection criteria of hidden nodes/neurons** number was most unsettled, as all academic researchers noted the difficulty in setting the number of hidden nodes as there are no single agreed upon technique to solve that problem, it is rather based on trial and error. In fact, a significant number of nodes leads to inadequate results in the optimization, and increases the probability that the parameters converge to a local optimum (Hamzacebi et al., 2009). Moshiri & Cameron (2000) selected the number of hidden neurons based on a trial and error basis and the training error variance. Tkacz (2001) tested from one to four hidden neurons, on a trial and error basis, and the author finally selected three hidden neurons, without providing clear evidence on his selection criteria. Badea (2013) set the number of hidden neurons based on trial and error in order to forecast foreign exchange rates. Shah & Debnath (2017) stated that the number of neurons in the hidden layer is determined by a trial and error process. Nunes et al. (2019) used sensitivity analysis and trial and error to test the impact of changing the number of hidden neurons on the out of sample error as a selection criterion. Jahn (2018) used four hidden neurons, based on a trial and error basis, and the author further noted that the choice of hidden neurons number was related to his model selection. Chuku et al. (2019) noted that the selection criteria of the number of hidden nodes is a difficult and complex problem, and there are no agreed upon technique in academic literature that tackles that matter. Castello & Resta (2022) stated that there is no precise rule in academic literature to select the best combination of hidden nodes.

In the absence of a scientific approach that tackles the problem of hidden nodes selection criteria, there are general rules that could be taken into consideration, such as the number of the input/output nodes, amount of training data available, complexity of the function being learned, and training algorithm. Some researchers recommended that the number of hidden nodes could be:

- Somewhere between the size of the input and output nodes.
- Equal to the number of inputs.
- $N = Ns (\alpha * (Ni + No))$, Ni= number of input neurons, No= number of output neurons, Ns= number of samples in training data set, α= an arbitrary scaling factor usually 2-10.
- 2/3 the size of the input layer, plus the size of the output layer.
- Less than twice the size of the input layer.
- $N= \sqrt{I*O}$, I=input nodes and O=output nodes.
- $N=2*I+1$, I=input nodes.
- Based on the Out of Sample Error.

In order to avoid computational problems, and design a network that generalizes well and does not learn by example or overfits the data, we have decided to **set the number of hidden nodes equal to the number of output nodes at first**, more precisely equal to the number of yield curve points being predicted. Afterwards, we have conducted a thorough sensitivity analysis on the hidden nodes and analyzed their behavior and impact on the cost function, and we have designed a model that measures the optimum number of hidden neurons in section 3.3.4. Moshiri & Cameron (2000) stated that the training error decreased as the number of hidden nodes increased from one to five, after which the training error increased. Tkacz (2001) used three hidden neurons to forecast the Canadian GDP. Dunis & Morrison (2007) forecasted 10-year gov bond yields based on five hidden nodes. Jahn (2018) used three hidden neurons to predict the GDP of fifteen developed countries. Nunes et al. (2019) used ten hidden nodes in order to forecast yield curves based on Multitask learning. Chuku et al. (2019) used from three to four hidden nodes to forecast the GDP of African countries.

We have used the S-shaped **Sigmoid activation function in the hidden layer** that squashed the data in a range from 0 to 1, $S(x)= 1/(1+e(-x))$. The Sigmoid function is the most widely used in financial markets due to its appealing properties. According to McNelis (2005) the Sigmoid function behavior resembles many types of economic variation to changes in fundamental variables, for example, if interest rates are very low or very high, small changes in rates will have very little effect on consumers behavior. However, within these two extremes, small changes in rates may cause significant changes in consumers behavior. Another appealing property as mentioned by McNelis (2005), the shape of the Sigmoid function reflects a form of learning behavior, the function becomes increasingly steep until some inflection point, whereby the function becomes increasingly flat. The Sigmoid Activation Function is the most commonly used in finance for the predictions of economic times series (Moshiri & Cameron, 2000; Bal and Demir, 2017; Chuku et al., 2019). Bal and Demir (2017) and Chuku et al. (2019) did not find clear evidence that a certain activation function always improved the prediction results. In fact, the Sigmoid Activation Function was used by many academic scholars to forecast the GDP (Tkacz, 2001; Jahn, 2018; Chuku et al., 2019).

On the other hand, as its typically set in academic literature, we have used a **linear activation function in the output Layer** (Moshiri & Cameron, 2000; Gradojevic & Yang, 2000; Badea, 2013; Jahn, 2018; Bal and Demir, 2017; Chuku et al., 2019). The **Root Mean Squared Error** was used as a cost function, as its commonly used in academic literature (Moshiri & Cameron, 2000; Gradojevic & Yang, 2000; Tkacz, 2001; Dunis & Morrison, 2007; Badea, 2013; Shah & Debnath, 2017; Nunes et al., 2019; Chuku et al., 2019). Finally, the **Gradient Decent, as an Optimization Algorithm**, was used in order to minimize the **Root Mean Squared Error** on approximately 70% of the data, while 30% of the data were kept for out of sample purposes. Tkacz (2001) used the Gradient Descent algorithm to minimize the cost function. Bal and Demir (2017) tested different optimization algorithms, and they did not find evidence that one algorithm always performed better the others. Jahn (2018) used the Gradient Descent algorithm to predict the GDP. Chuku et al. (2019) forecasted the GDP of African countries using the Gradient Decent algorithm. Kauffmann et al. (2022) used the Gradient Decent algorithm and forecasted yield curves decompositions.

Illustrated hereunder, the formulas for the hidden layer and output layer activation functions (McNelis, 2005). H_L is the Sigmoid activation function of X_L which is the summation of the Inputs multiplied by the weights plus the bias at each hidden layer node. O_V is the linear activation function at the output layer which is the summation of the hidden layers' responses H_L multiplied by the weights and adding to it the bias at each output layer node.

$$X_L = \sum_{i=1}^{n} I_i W_{iL} + bias_L$$

I: Inputs

W: Weights

bias: Bias at each hidden layer node

n: Number of inputs

L: Hidden layer node number

$$H_L = \frac{1}{1+ e^{-X_L}}$$

H_L*: Hidden layer node Sigmoid function response*

$$O_v = \sum_{L=1}^{S} H_L W_{Lv} + bias_v$$

W: Weights

bias: Bias at the output layer node

v: Output layer node number

S: Hidden layer node numbers

O_v*: Output response*

3.3.2 Tested Models

For the purpose of choosing the best forecasting inputs, we have tested 13 different inputs/models, for the nine studied markets, over three forecasted horizons; 1m, 3m and 6m horizons. Illustrated in table 3.9, the thirteen inputs/models that were tested to forecast the yield curves. Our choice of forecasted horizons was similar to Kauffmann et al. (2022), except for the very short term of 1-week, as we were interested only in capturing the general trends in the data. Taking into consideration that our forecasted horizons represent a short, medium and long term, rather than focusing on the short term alone or short/medium term if we were to choose for example 1m, 2m, 3m. As per academic scholars, the yields forecast accuracy deteriorates over longer term maturities, our choice of horizon forecasted served in testing whether the properties of ANN were beneficial in capturing the non-linear behavior of variables over the medium and long-term horizons (Sambasivan & Das, 2017). Boeck & Feldkircher (2021) suggested that it takes a year or so for markets and macro variables to fully align with the monetary policy.

You will find in table 3.9 the independent variables X, the dependent variables Y (yields to be forecasted), the number of input nodes or number of inputs, the number of hidden nodes, and finally the output nodes or yield points to be forecasted. The description on the thirteen inputs/models is illustrated hereunder:

- Model 1.01 used the three standardized yield curve PCAs as inputs (PCASD).
- Model 1.02 used three standardized PCA that were based on yield curves and five macro variables (AllPCA).
- Model 1.03 combined 1.01 & 1.02 as inputs.
- Model 1.04 was an Autoregressive process; it used the most recent yield curve points to forecast the next yield curve points.
- Model 1.05 combined model 1.01 with an Autoregressive process in the form of three most recent yield curve points as inputs.
- Model 1.06 combined model 1.02 with an Autoregressive process in the form of three most recent yield curve points as inputs.
- Model 1.07 used three yield curve proxies to the entire yield curve as inputs. We have created three yield curve proxies to the entire yield curve by taking the average of:
    - First, short term maturities, 3m, 6m and 1Y
    - Second, medium term maturities, 3Y and 5Y
    - Third, long term maturities, 7Y and 10Y
- Model 1.08 combined models 1.01 and 1.07 as inputs.
- Model 1.09 combined models 1.02 and 1.07 as inputs.
- Model 1.10 used three inputs of 3m moving averages of the 3 yield curve points (MA3mYC) used models 1.05 & 1.06 as inputs.
- Model 1.11 combined models 1.01 and 1.10 as inputs.
- Model 1.12 combined models 1.02 and 1.10 as inputs.
- Model 1.13 combined models 1.07 and 1.10 as inputs.

Table 3.9 Neural network yield curve prediction inputs/models

Model number	X inputs to the model	Y outputs to the model	Number of Input Nodes	Number of Hidden Nodes	Number of Output Nodes
1.01	3 PCASD	YC	3	7	7
1.02	3 AllPCA	YC	3	7	7
1.03	3 PCASD & 3 AllPCA	YC	6	7	7
1.04	7 AR YC	YC	7	7	7
1.05	3 PCASD & 3 AR YC	YC	6	7	7
1.06	3 AllPCA & 3 AR YC	YC	6	7	7
1.07	3 YC Proxies	YC	3	7	7
1.08	3 PCASD & 3 YC Proxies	YC	6	7	7
1.09	3 AllPCA & 3 YC Proxies	YC	6	7	7
1.1	3 MA3m YC	YC	3	7	7
1.11	3 PCASD & 3 MA3mYC	YC	6	7	7
1.12	3 AllPCA & 3 MA3mYC	YC	6	7	7
1.13	3 YC Proxies & 3 MA3m YC	YC	6	7	7

3.3.3 Singletask vs Multitask

Followingly, we have compared between Multitask and Singletask learning, by removing output nodes and re-optimizing the best performing model and computing the error term in order to determine whether there was a difference between Single and Multitask learning networks in terms of prediction accuracy. Similarly, Nunes et al. (2019) compared between Multitask vs Singletask prediction accuracy for his yield curves predictions. Coller et al. (2019) compared between Singletask and Multitask for Cancer cells predictions.

3.3.4 Sigmoid Regression Hidden Layer Nodes Sensitivity and Optimum Number Selection Model Design

As we have previously mentioned, the selection criteria of the number of hidden nodes/neurons is an ambiguous topic in academic literature, as all academic researchers noted the difficulty in setting the number of hidden nodes, as there are no single agreed upon technique to solve that problem, it is rather based on trial & error and sensitivity analysis (Moshiri & Cameron, 2000; Tkacz, 2001; Badea, 2013; Shah & Debnath, 2017; Jahn, 2018; Chuku et al., 2019; Nunes et al., 2019; Castello & Resta, 2022).

We have presented in this section the methodology that we have followed in designing the model that measures the most optimum number of ANN Sigmoid hidden nodes. This methodology was divided into two steps. In the first step, we conducted a sensitivity analysis on the error term and measured the impact of changing the hidden, output nodes, and forecasted horizon, on the model performance. In the second step, we performed a regression based on the sensitivity analysis data that generalized and measured the optimum number of hidden nodes (dependent variables) as a function of (independent variables): the number of input nodes, forecasted horizon, and output nodes. The application of this model is simple and could be used by researchers to compute their optimum number of ANN Sigmoid hidden nodes.

In fact, the sensitivity analysis and trial and error were used by many researchers to test the impact of changing the hidden nodes on the error term (Moshiri & Cameron, 2000; Tkacz, 2001; Badea, 2013; Shah & Debnath, 2017; Jahn, 2018; Nunes et al., 2019). From that perspective, our first step was to perform a sensitivity analysis on the hidden nodes and error term. This sensitivity analysis was performed by changing the number of hidden nodes (H) and outputs nodes (O), and the three different horizons forecasted (F), on models 1.08, 1.07 and 1.04, and re-optimizing the models and recording their error term. Afterwards, in order to better visualize how the error term was affected by H, O, F, we have regressed these variables, as independent variables, against the following dependent variables: training error first, out of sample error second, R2[1] training third, and finally R2 out of sample. In table 3.10 in Appendix C, we have provided a simple example of the regressions that we have performed, where the dependent variable was the training error, and the independent variables were: the number of hidden nodes (denoted by H), the number of forecasted months (denoted by F), and the number of output nodes (denoted by O).

In the second step of model design, we begun by selecting the optimum number of hidden nodes that corresponded to the level at which the prediction total error was at its minimum, based on the sensitivity results data, taking into consideration that the prediction total error is non-linear.

[1] R2 Coefficient of Determination

Moshiri & Cameron (2000) used trial and error from one to ten hidden neurons and they selected the number that minimized the training error. The authors also noted that the training error decreased as the number of hidden neurons increased from one to five, and after that the error increased. Jahn (2018) used four hidden neurons, based on trial and error, and he further noted that testing revealed that the results with four hidden neurons were not worse than those with five. After having selected the optimum number of hidden nodes per model, we have performed a linear regression, where the dependent variable was the optimum number of hidden nodes (H), and the independent variables were: the number of inputs (I), number of output nodes (O), and the forecast horizon per month (F), as illustrated in table 3.11 in Appendix C. The end result was a model that estimated the optimum number of hidden nodes based on the number of input nodes, the number of output nodes, and the forecast horizon in terms of months.

3.3.5 Independent Variable Contribution Analysis

In order to measure the contribution of each input in the best performing model, we have conducted an Independent Variable Contribution analysis using the weights methodology. In other words, the Independent Variable Contribution measures the predictive power of the variables used in the ANN model or their relative importance. This type of analysis was not used before, to the best of our knowledge, in yield curves predictions, since the majority of academic work focusses on the techniques that provide the highest prediction accuracy, rather than the predictive power of the variables. Thus, the application of this method is one of the contributions of this study. We were interested to apply such a method in our analysis cause our motivation for this study was to identify common trends in terms of co-movements and variables predictive powers. Pentos (2016) used the Independent Variable Contribution to access the importance of each variable on his study of the relationship between chemical honey parameters and other parameters, comparatively, Pentos et al. (2015) used the Independent Variable Contribution as a honey quality assessment tool. Furthermore, studies on the comparison between the different techniques available to extract the contribution of independent variables in a neural network environment were presented by several researchers (Olden et al., 2004; Paliwal & Kumar, 2011).

Our computations followed the simplified weights interpretation of Gevrey et al. (2003), as summarized by the following two steps:

1. For each hidden neuron, divide the absolute value of the input hidden layer connection weight by the sum of the absolute value of the input hidden layer connection weight of all input neurons.
2. For each input neuron divide the sum for each hidden neuron by the sum for each hidden neuron of the sum for each input neuron, and multiply by 100. The relative importance of all output weights attributable to the given input variable is then obtained.

3.3.6 K-fold Cross Validation

In order to remove the selection bias of the hold out period (70% training and 30% out of sample data), we have used the K-fold Cross Validation technique on our best performing model. This method does not produce a selection bias since all observations are used for both training and validation. The technique consists on randomly splitting the data into k equal sized subsamples, then a single subsample is reserved for the validation data, and the remaining $k - 1$ subsamples are used for the training. The process is then repeated k times, with each of the k subsamples used exactly once for validation. Finally, the results are averaged to produce a single estimation. For that purpose, we have used k=3, three subsamples, in order to re-optimize the best performing model, for the nine studied markets, and three different horizons, which necessitated the re-optimization of 81 different models (9x3x3=81). In fact, k-fold Cross Validation has many advantageous: removes the bias, produces more stable results as the model is trained on split data, prevents the model from overfitting the training data, and helps the model to learn by generalization (Khandelwal, 2018; Narang, 2023). Nunes et al. (2019) compared between different Cross Validation methods, including k-fold, and the authors argued that k-fold has a disadvantage as it does not respect the order of the time series because in some cases we will be forecasting backwards, using future data to predict past data. Puglia and Tucker (2020) argued that the prediction results based on k-folds are biased optimistically, and the use of this method indicates that more advanced prediction techniques, such as neural networks, outperforms standard statistical techniques, which supports evidence from academic literature, however, the authors own Cross Validation method indicated the opposite. Agu et al. (2022) predicted the

GDP in Nigeria using multiple techniques, and the authors used k-fold Cross Validation to compare between the different models estimates. Ogundunmade & Adepoju (2022) used two different k-fold Cross Validation techniques to compare between the machine learning prediction results of the Nigerian stock market.

3.4 Macro Variables Predictions using three Classifiers: KNN, Sigmoid & Softmax

ANN Feedforward models offer a wide range of structures, that could be effectively used in economic times series forecasting, where the output of variables is either continuous (regression) or binary/multicalss (classifier). We have used in the previous section a continuous model, an ANN Multitask Feedforward Regression to predict yield curves, and we have used in this section ANN Feedforward Classifier to predict macro variables. In fact, Classifiers techniques have proven to be reliable and more stable than Regression ones for the prediction of macro variables. Estrella et al. (2003) tested Classifier (binary), and Regression (continuous) models to predict the GDP and inflation in the US and Germany, and the authors noted that Classifiers models are more stable than Regression ones. In addition, other researchers favored as well the use of binary models (Classifier) in order to predict the GDP, such as Jamriska (2008) who examined the predictive power of the yield spread over the GDP, in the UK, Germany and France, using a Classifier, Probit regression. Priambodo et al. (2019) used macro variables data to predict the Indonesian GDP based on KNN Classifier because it's a simple and easy to use technique, and its prediction accuracy was better than the results of multiple linear regression methods. Puglia and Tucker (2020) used machine learning and a Probit regression (Classifier) to predict the US recession. In addition, Maccarrone et al. (2021) found out that the KNN model captured the self-predictive ability of the US GDP and performed better than traditional linear models. Ogundunmade & Adepoju (2022) used machine learning Classifiers to predict the Nigerian stock market.

In our study, we have used three different Classifiers in order to generalize about the findings, and not present results that would be specific to a model, or country. Additionally, we have modelled five macro variables, in order to capture common predictive capabilities of the variables, i.e., which variables affected the future outcome of others. In our predictions, we have used longer forecasted horizons due to the fact that macro variables predictions improved over longer horizons, which is due to a non-linear influence of monetary variables that seems to be more relevant in the longer run, since policy actions takes time to reflect on the economy (The Transmission of Monetary Policy, n.d.; Tkacz, 2001). Chirinos-Leañez & Pagliacci (2015) stated that the relationship between inflation and long-term yields takes around six months to be formed. Boeck & Feldkircher (2021) suggested that it takes within a year until news are fully absorbed by macro variables. Maccarrone et al. (2021), using machine learning to predict the GDP, found out that the prediction results improved over longer-term horizon forecasts. Thus, neural networks are better at capturing the long-term asymmetric effects of the monetary policy on macro variables due to their non-linear twist. Moreover, predicting macro variables over longer term horizons, such as quarters, served our motivation of capturing general trends in data co-movements without capturing too much noise from monthly forecasts. From that stand point, we have forecasted macro variables over 3-month, 6-month and 12-month horizons, similar to the forecast horizons used by Feng & Qian (2018), except for the 1-mth horizon as to avoid capturing too much noise from the data. Tkacz (2001) stated that, when forecasting the GDP over a 3-mth horizon, financial variables have little information at this short-term horizon, although, when the forecast horizon is 1-year the results improve substantially.

The three different Classifiers used were: K-nearest neighbors, Sigmoid and Softmax, in order to predict/classify macro variables movements into the future. For each of these techniques, we have tested four different models with varying input components between yield curve PCA, macro variables PCA and the Autoregressive process. The data used for our macro variables predictions models were normalized using the z-score methodology, performed using the training data set parameters. Kindly find in table 3.12 the four different models that we have used to predict our five macro variables, for the nine different studied markets. Each of the tested models was based on different inputs, and the outputs (Y) were the macro variables forecasts of each studied market over the horizons of 3m, 6m and 12m separately (labelled MAC).

Table 3.12 The tested four inputs models for the three Classifiers

Model	**Component 1**	**Component 2**	**The number of inputs**	**Forecasted variable Y**
2.01	3 PCASD	0	3	MAC
2.02	3 AR	0	3	MAC
2.03	3 MAC PCA	0	3	MAC
2.04	3 PCASD	3 MAC PCA	6	MAC

The description of the four models is illustrated hereunder:

- Model 2.01 used the three standardized yield curve latent factors, extracted from PCA (PCASD), as inputs (Level, Slope, and Curvature).
- Model 2.02 used three most recent Autoregressive processes of each macro variable being predicted, labelled 3 AR, as inputs.
- Model 2.03 used the three standardized PCA of the five macro variables (MAC PCA) of each studied market, as inputs.
- Model 2.04 used both the inputs of models 2.01 and 2.03.

3.4.1 KNN Classifier

We have used K-Nearest Neighbors (KNN) Classifier in order to predict whether a macro variable will likely be classified, into the future (3m, 6m and 12m horizon), in the category of an upward or downward movement. KNN is a simple machine learning Classifier technique that was extensively applied in different fields, and references for this methodology are available widely (Harrison, 2018; Joby, 2021; Christopher, 2021; Srivastava, 2023). The training data set, of 70% of the data, was used to categorize the data into two sets: first category, data with future output higher than today's value, and second category lower than today's value. The next step was to compute the **Euclidean Distance** between each point in the testing/out of sample data (30% of the data) to the training data set categories, and rank them from the smallest (closest) to the highest (further away) (Fiori, 2020; Badole, 2021).

$$Eucilean\ Distance = \sqrt{\sum_{i=1}^{n}(X_i - Y_i)^2}$$

Where n refers to the training data points

The final step was to choose how many (K) points were optimum to decide whether macro variables will likely rise or fall in the future. The choice of K was based on the prediction accuracy of the testing/out of sample data, meaning that K was chosen based on the maximum prediction accuracy. Here, the prediction accuracy was not measured by the variance from the correct outcome, but rather whether the prediction was correct or wrong, or did the variable rise or fall.

Afterwards, we have used a variant of the KNN technique, the Weighted KNN (wKNN), and we have compared its prediction results with the equally weighted KNN approach. In the Weighted KNN approach the distance between the point of study to the nearest neighbors is a function of a weight, the further away the neighboring point, the less the weighting will be, in the form of weight=1/Euclidean Distance, compared to the KNN method where all neighboring points are used irrespective of their distance (Zhao & Chen, 2016). Academic scholars have successfully employed KNN for the prediction of times series, as its application is simple and yields a high degree of accuracy. Ballings et al. (2015) used KNN, amongst other Classifiers, to predict the stock market. Rodriguez-Vargas (2020) used KNN to predict the inflation. And other academic scholars used KNN to predict the GDP because it's a simple and easy to use technique, as they stated (Priambodo et al., 2019; Maccarrone et al., 2021). To the best of our knowledge, wKNN was not applied before in macro variables predictions, though, academic literature exists on the methodology for computing the weights, or even using wKNN performing one function in another machine learning method. Furthermore, few academic scholars have applied wKNN in the health and petroleum industries. Thus, the application of wKNN for macro variables predictions is one of this study contributions.

3.4.2 Sigmoid Classifier

The Sigmoid Classifier is used for binary Logistic regression, meaning two classes Classification, either upward or downward, while the Softmax Classifier is used for more than two classes Classification, like the multinomial regression (Wood, n.d.; Maheshkar, 2022; Kumar, 2023). The structure of the ANN Sigmoid Classifier is very much similar on all aspects to the ANN Sigmoid Regression that we have used for yield curves predictions, except for the output node that does not compute a continuous target (yields), but rather a binary (Classifier) value 1 or 0.

In fact, the Sigmoid Logistic Classifier was successfully used in many fields in order to categorize data into two classes. For example, Ballings et al. (2015) used an ANN Classifier based on a Logistic function to predict the stock market, and compared it to different Classifiers. Pitta de Jesus & Nobrega Besarria (2023) used a Sigmoid Logistic Classifier for credit scoring in Brazil, and bankruptcy prediction. On the other hand, Kumar et al. (1995) used a Logistic Classifier in the retail industry for marketing solutions. In addition, the Logistic Classifier was also used in other fields, such as the health industry, in detecting diseases, for example, Bhatia et al. (2016) for the detection of eye disease, and Khanna et al. (2015) for the detection of heart diseases.

The structure of our ANN Sigmoid Classifier is illustrated in Figure 3.8, whereby the network was subdivided into three layers (Kumar, 2023). Our ANN Sigmoid Classifier structure is similar to the ANN Sigmoid Regression, with the exception of the output value that takes only two values, 1 or 0. The **first layer** is the ***input layer*** which received the input data and transferred them to the next layer. This layer was composed of different nodes/neurons for the four tested models, where the input nodes varied from three to six nodes/inputs.

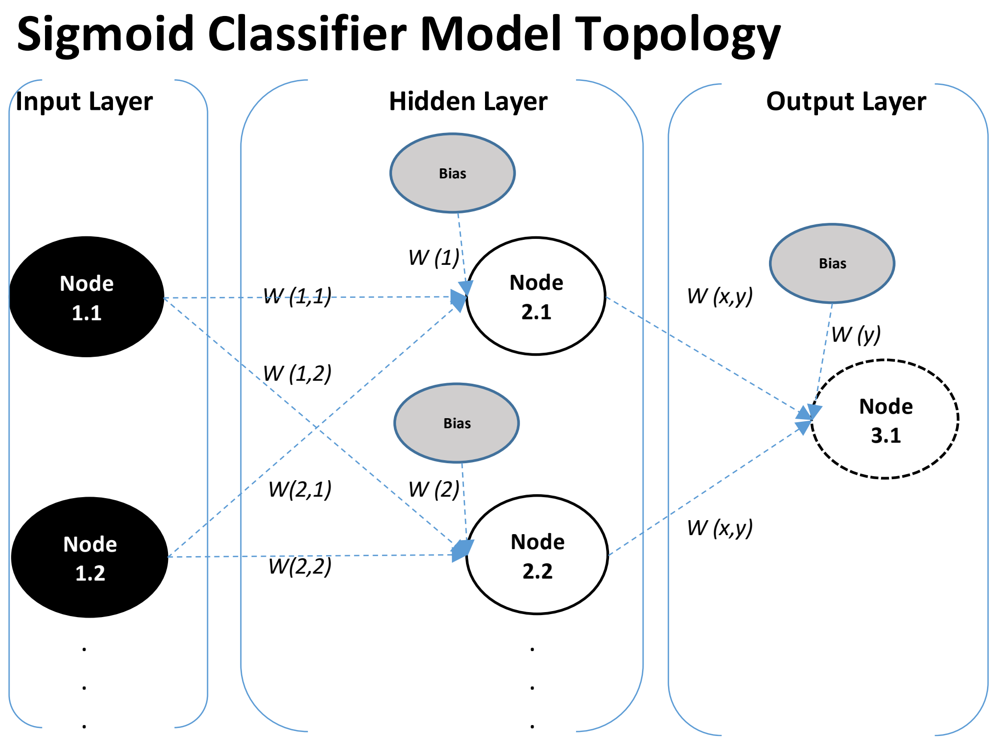


Figure 3.8 Sigmoid classifier neural network model topology

Note: Author's own diagram based on the standard ANN Sigmoid structure with one hidden layer, similar to Kumar (2023) illustration

The **second layer** is the ***hidden layer*** which holds the activation function and received the inputs from the previous layer and squashed them into intervals using an activation function. The inputs were multiplied by weights W(x,y) , where y corresponded to the number of the nodes in the current layer and x corresponded to the number of nodes in the previous layer, then added the bias at each node and transferred the value to an activation function. We have used **one hidden layer**, as per most academic literature, one hidden layer is sufficient enough to approximate complex non-linear functions, references for the one hidden layer structure were provided in section 3.3.1 for the model on yield curves predictions. More precisely, academic researchers found out that one hidden layer was sufficient to forecast macro variables. On the other hand, the **choice of hidden nodes/neurons numbers was most unsettled**, as all academic researchers noted the difficulty in setting the number of hidden nodes as there are no single agreed upon technique to solve that problem, therefore, in order to avoid computational problems, and design a network that generalized well and did not learn by example or overfits the data, we have decided to set the number of hidden nodes equal to five, taking into consideration that we have conducted, at a later stage, a thorough sensitivity analysis on the hidden nodes and analyzed their behavior and effect on the cost function. References for the selection criteria of the optimum number of hidden nodes was provided in section 3.3.1 for the model on yield curves predictions.

We have used the **S-shaped Sigmoid activation function** in the hidden layer that squashed the data in a range from 0 to 1, S(x)= 1/(1+e(-x)). The Sigmoid function is the most widely used in financial markets due to its appealing properties. According to McNelis (2005) the Sigmoid function behavior resembles many types of economic variation to changes in fundamental variables. On the other hand, we have used a **linear activation function in the output layer**, which has only one output node that takes two binary values, either 1 for function values equal and above 0.5, or 0 for function values below 0.5 (Logistic Regression, n.d.; Kumawat, 2021; Xu, 2022). Finally, the **Gradient Decent, as an Optimization Algorithm** (references for the use of the Gradient Decent was provided in section 3.3.1 for the model on yield curves prediction), was used to maximize the prediction accuracy on the training data set, similar to the KNN error term, the prediction accuracy was not measured by the variance from the correct outcome, but rather, whether the prediction was correct or wrong, or did the variable rise or fall.

Kindly find hereunder, the formulas for the hidden layer and output layer activation functions. H_L is the Sigmoid activation function of X_L which is the summation of the Inputs multiplied by the weights plus the bias at each hidden layer node. O_V is the linear activation function at the output layer which is the summation of the hidden layers' responses H_L multiplied by the weights and adding to it the bias at each output layer node.

$$X_L = \sum_{i=1}^{n} I_i W_{iL} + bias_L$$

I: Inputs

W: Weights

bias: Bias at each hidden layer node

n: Number of inputs

L: Hidden layer node number

$$H_L = \frac{1}{1+ e^{-X_L}}$$

H_L: *Hidden layer node Sigmoid function response*

$$O = \sum_{L=1}^{S} H_L W_L + bias$$

W: Weights

bias: Bias at the output layer node

S: Hidden layer node numbers

O*: Output response*

In order to test the behavior of the hidden nodes and their impact on the model error term, we have conducted a sensitivity analysis on the hidden nodes and measured the impact of changing the hidden nodes on the forecasting accuracy. We have therefore re-optimized the best performing model for the equity predictions, and we have changed the number of hidden nodes, number of inputs, and forecasting horizons, by which creating 48 different scenarios. Using these scenarios results, we have selected the optimum hidden nodes based on the behavior of the prediction total error, meaning that the selection criteria was based on the training error being at its minimum, a selection that is sometimes relative since the prediction total error was highly non-linear. After having selected the optimum number of hidden nodes per model and forecast horizon, we have performed a linear regression where the dependent variable was the optimum number of hidden nodes (H), and the independent variables were: the number of inputs (I), and the forecast horizon per month (F). Our objective was to design a model that computed the optimum number of hidden nodes for a Sigmoid Neural Network Classifier as a function of: input nodes, and forecasted horizons. This sensitivity analysis is similar to the one performed for the yield curve prediction model in section 3.3.4.

3.4.3 Softmax Classifier

We have used afterwards the Softmax Single Layer Classifier, which is an extension of the Sigmoid Logistic regression to multiple dimensions, used for Multi-Class classifications, when the outputs are mutually exclusive. The Softmax function transforms the vector of inputs into a vector of output values that sum to 1, so that they can be interpreted as probabilities, in other words, the Softmax activation function normalizes the outputs to a probability distribution over the predicted output classes (Wood, n.d.; Brownlee, 2020; Koech, 2020; Saxena, 2021; Maheshkar, 2022). The Softmax Classifier was successfully applied in facial recognition, in the agriculture industry, in attitude detection, and in actuarial sciences. The use of the Softmax Classifier for macro variables predictions is not widely spread among academic scholars, therefore, the application of this Classifier to predict five macro variables provided useful insights on the performance of this approach compared to other Classifiers. Several academic scholars used the Softmax Classifier indirectly as one layer combined with another neural network model to predict macro variables, such as inflation and stock market predictions (Bravo & Mekkaoui, 2022; Liu et al., 2022; Simeon, 2022; Jiang et al., 2023). In our model, we have classified the variables according to three classes, whether the macro variables have moved upwards, or did not move, or thirdly if the variables moved downwards, compared to the KNN and Sigmoid Classifiers, where variables were just classified whether they moved upwards or downwards. The second Softmax class is based on variables remaining constant, neither moving upwards nor downwards, taking into consideration that these macro variables are continuous, except for the POLRATE which is not adjusted continuously, therefore, we needed to define the criteria of a continuous variable being classified as constant. We have defined these boundaries in terms of 3m standard deviation (sigma), of each variable, multiplied by a threshold of +/- 0.10%, except for the POLRATE that could remain unchanged. Kindly find illustrated in table 3.13 the 3m Sigma of each of the four macro variables, in addition to the table of the Sigma multiplied by the threshold.

Table 3.13 Macro variable 3m Sigma

Studied market/Macro variable	3m Sigma				0.10% x 3m Sigma			
	EQUITY	FX	GDP	INF	EQUITY	FX	GDP	INF
BRA	12.98%	8.58%	1.86%	0.58%	1.30%	0.86%	0.19%	0.06%
CHI	19.47%	1.13%	1.00%	1.33%	1.95%	0.11%	0.10%	0.13%
EGP	18.43%	2.09%	1.96%	3.05%	1.84%	0.21%	0.20%	0.31%
EUR	10.22%	5.21%	1.01%	0.56%	1.02%	0.52%	0.10%	0.06%
IND	13.93%	5.39%	0.88%	2.15%	1.39%	0.54%	0.09%	0.21%
MEX	9.54%	6.33%	2.00%	0.67%	0.95%	0.63%	0.20%	0.07%
SAF	8.50%	8.08%	0.99%	1.16%	0.85%	0.81%	0.10%	0.12%
UK	7.25%	5.26%	1.07%	0.70%	0.73%	0.53%	0.11%	0.07%

Studied market/Macro variable	3m Sigma				0.10% x 3m Sigma			
	EQUITY	FX	GDP	INF	EQUITY	FX	GDP	INF
US	7.97%	4.85%	0.99%	1.26%	0.80%	0.48%	0.10%	0.13%

Source: Authors' own calculations

We have illustrated in Figure 3.9 the Softmax Single Layer Classifier Neural Network Topology (Yang et al., 2021; Kumar, 2022). Firstly, the inputs were normalized, based on the z-score methodology, in order to have a smooth convergence of the cost function, noting that some inputs were already normalized since they were based on the standardized PCAs, then they were transferred from (1) to (2) and multiplied by weights W(x,y) , where y correspondences to the number of nodes in the current layer (here its 3) and x correspondences to the number of nodes in the previous layer, then the bias at each node was added, and finally we have applied the **Softmax Activation Function** in (3). The number of nodes in (2) will always corresponds to the number of classes, more precisely, in our model we have three classes, the probability of a variable moving upwards in the future, and the probability of a variable not moving, and thirdly the probability of a variable moving downwards.

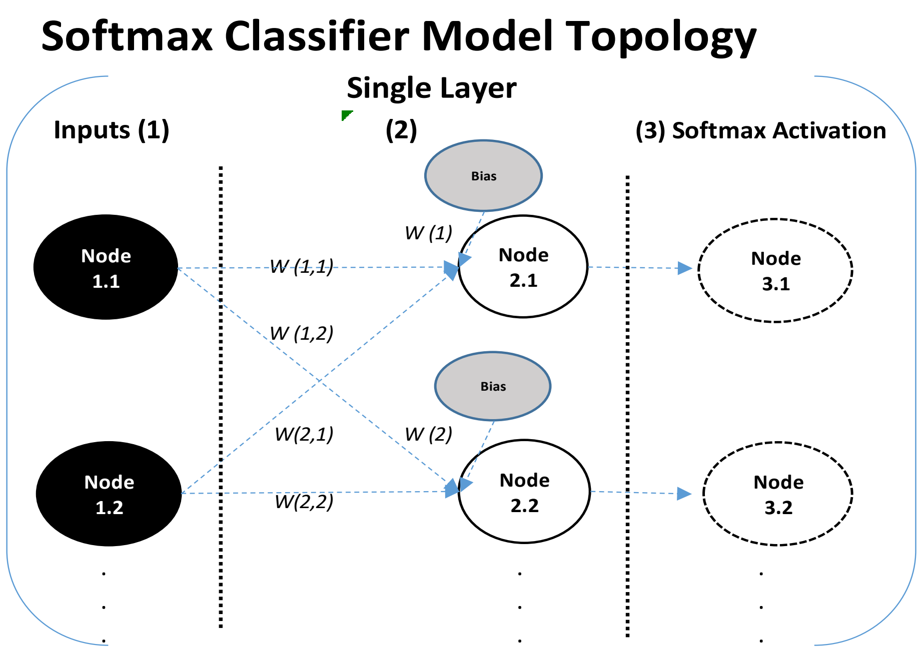


Figure 3.9 Softmax Classifier neural network model topology

Note: Author's own diagram based on the standard Softmax Single Layer structure, similar to Yang et al. (2021) and Kumar (2022) illustrations

Kindly find hereunder, the formulas for (2) weights times the inputs, in the neural network topology, and (3) the **Softmax Activation Function** that yields the probability of occurrence of each of the three classes (Wood, n.d.; Maheshkar, 2022; Kumar, 2022).

(2) $X_L = \sum_{i=1}^{n} I_i W_{iL} + bias_L$

I: Inputs

W: Weights

bias: bias at each node

n: number of inputs

L: Number of classes, here its 1 to 3

(3) $P_L = \frac{e^{X_i}}{\sum_{i=1}^{M} e^{X_i}}$

L: Number of classes, here its 1 to 3

M: total number of classes, here its 3

e: Exponential

X_i : Output of step (2) i.e the weights times the inputs

We have used as a cost function the **Cross Entropy,** since the outputs of the Softmax network ranges from 0 to 1, in addition, the Cross Entropy Function is non-linear and penalizes seriously wrong predictions (Wood, n.d.; Maheshkar, 2022). Finally, the **Gradient Decent, as an Optimization Algorithm,** was used by minimizing the total Cross Entropy.

Cross Entropy **=**$-\sum_{c=1}^{M} Observed\ Prob_c$ x $LOG(Predicted\ Prob)_C$

Where M are the total number of classes, here its 3

4 Empirical Results

4.1 Yield Curves and Macro Variables Interaction

4.1.1 Yield Curves and Macro Variables Interaction using the Eigenvectors

Based on the analysis of the first three Eigenvectors performed on the yield curve and macro variables together for all studied markets, we have identified different plausible co-movement scenarios. This analysis is similar somehow to analyzing different plausible correlation matrices between the variables at time (t), not a lead lag relation like the Causality or shocks to the error like the IRF. We have illustrated in table 4.1 the median for the factor weights of the first Eigenvectors performed on the yield curves and macro variables together. We have computed the median of these factor weights for yield curves upward and downward parallel shifts separately, along with the standard deviations of these factors. The first Eigenvectors are defined by yield curves parallel shifts or the Level, which is the most common yield curves movements. According to our calculations, the Eigenvalues median for the first Eigenvectors performed on the yield curves and macro variables together captured around 47% of the variations in all studied markets, compared to 70%-80% variations for the Eigenvectors on yield curves alone, meaning that a lot of variability cannot be attributed to common factors captured by the Eigenvectors. Pooter et al. (2010) used PCA on macro variables and their first Eigenvector captured only 35% of the variation in the data. From table 4.1 and figure 4.1, it is clear that the POLRATE, GDP and INF were positively associated with the Level or the yield curve parallel shift. For example, in an economic recession, the GDP will be contracting, which will trigger downward inflationary pressures, causing the central bank to drop its policy rate, and the yield curve to move in a negative parallel way. The opposite is also true when the economy is expanding, and the yield curve moves in a positive parallel way. These findings are consistent with academic literature, since a growth in the economy leads to higher inflationary pressures that will trigger a rise in the yield curve in the form of a parallel shift (the Level), prompting the central bank to hike its policy rate (Rudebusch & Wu, 2003; Ang and Piazzesi, 2003; Diebold et al., 2006; Djuranovik, 2014; Coroneo et al., 2016; Shareef and Shijin, 2017). It is worth mentioning that the POLRATE factor weight and its standard deviation were higher during upward yield curve parallel shifts, which might be caused by central banks inflationary target policies that would be more active during expansionary periods to control inflation. In addition, it's clear that FX movements were not aligned with movements in other macro variables, implying that FX rates are greatly affected by events that are specific to each country. According to Kearns & Manners (2005) monetary policy changes account for only a small part of the observed variability in exchange rates, adding to the fact that the relationship between the FX and the GDP converges in the long run more than the short run (Comunale, 2017). Concerning the EQUITY, it was positively associated with macro variables for yield curves upward parallel shifts, during economic expansions. Ahmed et al. (2017) proved that there is evidence of Causality from the interest rate to the stock market, in addition, Fromentin (2022) found evidence of a Causality from the industrial production to the stock market. Though, equity indices were negatively associated with macro variables for yield curves downward parallel shifts, which is probably caused by the dynamic and non-consistent relation between the monetary policy and the stock market (Laopodis, 2013). In addition, the standard deviation of the EQUITY factors weights increased, from 0.06 for upward parallel shifts to 0.18 for downward parallel shifts, implying higher uncertainty of equity indices during recessions, signifying a dynamic relation of the stock market with macro variables.

Table 4.1 Factor weights for the first Eigenvectors of yield curves and macro variables

Eigenvector	[2]Negative YC Parallel Shifts	[3]Standard Deviation of YC Negative Parallel Shifts	[4]Positive YC Parallel Shifts	[5]Standard Deviation of Positive Parallel Shifts	[6]Total Standard Deviation of Parallel Shifts Factor Weights
EQUITY	0.10	0.18	0.15	0.06	0.14
FX	0.20	0.09	0.19	0.09	0.08
POLRATE	-0.18	0.04	0.24	0.07	0.21
GDP	-0.03	0.07	0.15	0.07	0.13
INF	-0.10	0.05	0.15	0.03	0.13
Eigenvalues %	**46.93%**		**47.06%**		

Source: Authors' own calculations

[2] Factor weights for yield curves with negative parallel shifts
[3] Standard deviations of the factor weights or yield curves with negative parallel shifts
[4] Factor weights for yield curves with positive parallel shifts
[5] Standard deviations of the factor weights for yield curves with positive parallel shifts
[6] Total standard deviation of all factor weights for first Eigenvectors

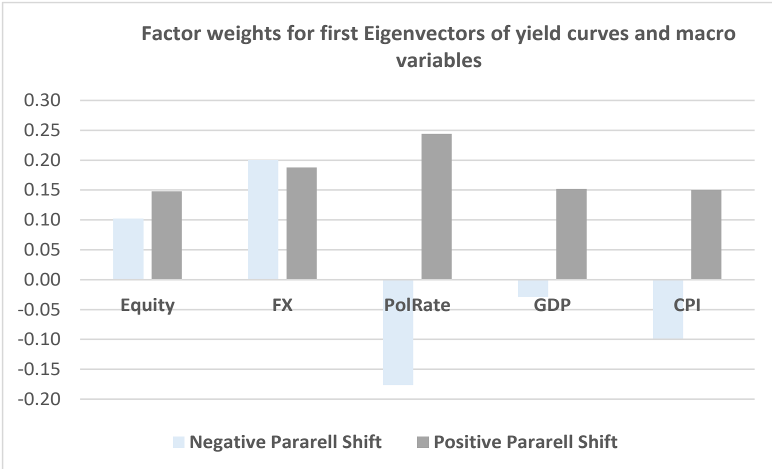


Figure 4.1 Factor weights for the first Eigenvectors of yield curves and macro variables
Source: Authors' own calculations

We have illustrated in table 4.2 and figure 4.2 the median for the factor weights of the second Eigenvectors performed on the yield curves and macro variables together. We have computed the median of these factors for yield curves that inverted (negative Slope change) and others that increased their Slopes (positive Slope change) separately, along with the standard deviation of these factors. The second Eigenvectors are defined by changes in yield curves Slopes or simply the Slope, which is a less likely movement for yield curves. The second Eigenvectors had Eigenvalues that captured approximately 15% of the variations in all studied markets, on a cumulative basis the first and second Eigenvalues captured approximately from 60% to 63% of total variations, compared to 90%-95% for the Eigenvectors on yield curves alone. Pooter et al. (2010) second Eigenvector on macro variables was able to capture 19% of the variation in the data, thus, on a cumulative basis their first and second Eigenvectors were able to capture 54% of total variation in the data. When yield curves invert or change their Slopes in the opposite direction, near the peak in an economic cycle, macro variables are positively associated, dominated by a higher magnitude change in the policy rate. While, when yield curves change their Slopes positively, Slopes become steeper, near the trough in an economic cycle, the policy rate changes are lower in magnitude, in order to stimulate a stagnant economy, and a negative GDP factor weight of -0.16 signals a depressed economy. As we have previously mentioned that economic growth is accompanied with higher inflation, leading to a positive response in the

POLRATE, leading to a negative response in the Slope as the short rate rises. Accordingly, Djuranovik (2014) stated that in response to inflationary pressures the central bank tightens economic conditions by raising its monetary policy rate. Furthermore, Chirinos-Leañez & Pagliacci (2015) found out that the short end of the yield curve responds promptly to the monetary policy. In fact, during unstable economic conditions, the monetary policy impact is significant towards the short end of the yield curve (Aazim, 2011). It is worth mentioning that the FX has very low association with both Slope scenarios (inverted and steepening), as the monetary policy relationship with foreign exchange rates differ based on the country's currency system (Dilmaghani & Tehranchian, 2015). In addition, Kearns & Manners (2005) stated that monetary policy changes account for only a small part of the observed variability in exchange rates. Although, according to findings in academic literature, the monetary policy has a negative relationship with the stock market as a hike in the policy rate depresses the equity market, the EQUITY did not seem to behave accordingly for the second Eigenvectors, or the Slope scenarios (Ioannidis & Kontonikas, 2006; Suhaibu et al., 2017). As a matter of fact, equity indices (+0.20) were positively associated with macro variables for the yield curve inversion, while for the increase in Slope they were stagnant with no association (-0.04), reflecting the state of the economy. Accordingly, Laopodis (2013) suggested that the relationship between the monetary policy and the stock market was not consistent, and the dynamics of this relation was different in each monetary regime in the same country. Reaffirming our previous statement that the relation of the EQUITY to other macro variables is dynamic.

Table 4.2 Factor weights for the second Eigenvectors of yield curves and macro variables

Eigenvectors	[7]YC Inversion	[8]Standard Deviation of YC Inversion	[9]YC Slope Increase	[10]Standard Deviation of YC Slope Increase	[11]Total Standard Deviation of Slope Factor Weights
EQUITY	0.20	0.27	-0.04	0.01	0.25
FX	0.00	0.34	0.02	0.08	0.29
POLRATE	0.47	0.09	0.02	0.61	0.30

[7] Factor weights for the yield curves that changed their Slopes negatively (inverted)
[8] Standard deviation of factor weights for yields curves that changed their Slopes negatively (inverted)
[9] Factor weights for yield curves that increased their Slopes
[10] Standard deviation of factor weights for yield curves that increased their Slopes
[11] Total standard deviation of all factor weights for second Eigenvectors

Eigenvectors	[7]YC Inversion	[8]Standard Deviation of YC Inversion	[9]YC Slope Increase	[10]Standard Deviation of YC Slope Increase	[11]Total Standard Deviation of Slope Factor Weights
GDP	0.18	0.13	-0.16	0.29	0.24
INF	0.27	0.21	0.23	0.51	0.25
Eigenvalues %	**15.14%**		**14.56%**		
Cum %	**60.41%**		**63.49%**		

Source: Authors' own calculations

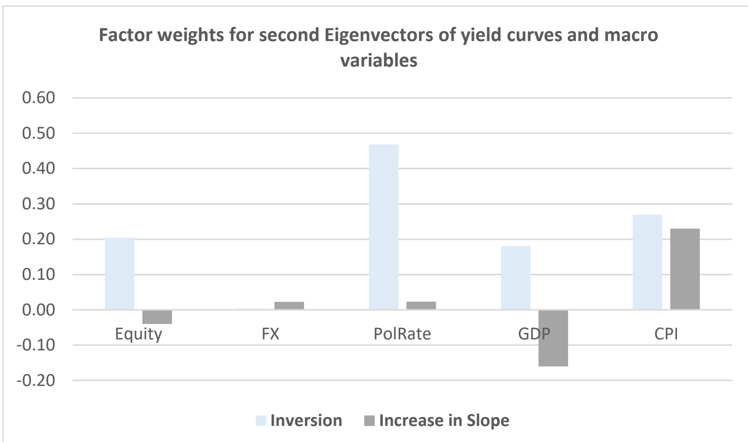


Figure 4.2 Factor weights for the second Eigenvectors of yield curves and macro variables
Source: Authors' own calculations

We have illustrated in table 4.3 and figure 4.3 the median for the factor weights of the third Eigenvectors performed on the yield curves and macro variables together. The third Eigenvectors are defined by yield curves changing in a humped way or simply the Curvature, which is an unusual movement for yield curves, even less likely than the Slope. The third Eigenvectors had Eigenvalues that captured around 10% of the variations in all studied markets, on a cumulative basis the first three Eigenvectors accounted for approximately 72% of total variations, compared to 95%-98% for the Eigenvectors on yield curves alone. Pooter et al. (2010) third Eigenvector on macro variables was able to capture 8% of the variation in the data, thus, and on a cumulative basis their first three Eigenvectors were able to capture 62% of total variation in the data. The third Eigenvectors characterized a Curvature of the yield curve accompanied by the POLRATE, the INF and the GDP being associated together, and moving in the opposite direction of the EQUITY and FX. Theoretically, the GDP, INF and POLRATE indicate an economic downturn, and the rising EQUITY and FX indicate an upturn in the economy. Accordingly, academic scholars proved that the stock market is a leading indicator for economic growth, as well as shocks to the EQUITY caused a positive response in the GDP (Plihal, 2016). On the other hand, Khandare (2017) stated that the correlation coefficient between the currency exchange rate and the GDP growth is positive. Therefore, yield curves take the form of a humped shape when the market is not sure about the future outcome of the economy, or when the economy is about to turn its direction.

Table 4.3 Factor weights for the third Eigenvectors of yield curves and macro variables

Eigenvectors	[12]Curvature	[13]Total Standard Deviation of YC Curvature
EQUITY	0.23	0.59
FX	0.30	0.35
POLRATE	-0.16	0.25
GDP	-0.05	0.50
INF	-0.13	0.34
Eigenvalues %	**10.70%**	
Cum %	**72.50%**	

Source: Authors' own calculations

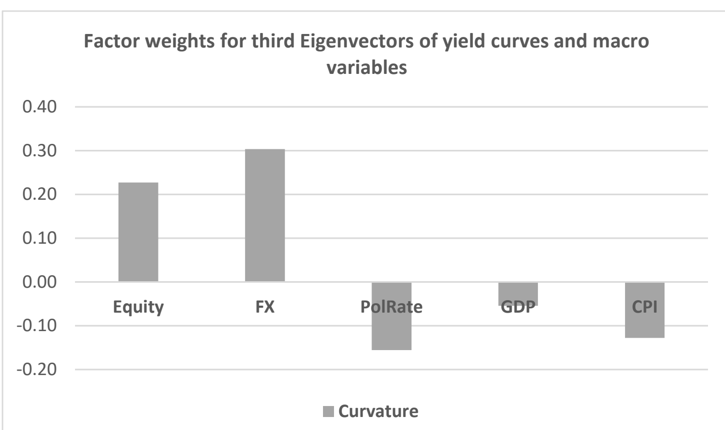


Figure 4.3 Factor weights for the third Eigenvectors of yield curves and macro variables
Source: Authors' own calculations

[12] Factor weights for the yield curves that changed their shapes into a humped form
[13] Total standard deviation of all factor weights for third Eigenvectors

Figure 4.4 shows the standard deviations of the factor weights for the first three Eigenvectors, as you will be able to conclude that the yield curve Level has the lowest standard deviations, followed by the Slope and Curvature. Lower standard deviation means less uncertainty and more common yield curves and macro variables co-movements.

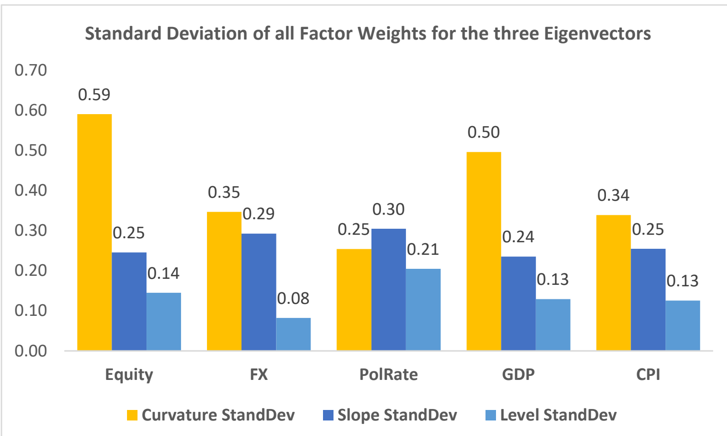


Figure 4.4 Standard deviation of all factor weights for the three Eigenvectors
Source: Authors' own calculations

4.1.2 Yield Curves and Macro Variables Granger Causality

In this section, we have presented the results of the Unrestricted VAR Granger Causality Block Exogeneity Wald Test on the yield curves three latent factors and the five macro variables. Table 4.4 shows the Level Granger Causality Block Exogeneity Wald test along with the p-value for each country, the cells highlighted in: red significant at the 5% level, and yellow at the 10% level. As you will be able to conclude that the Granger Causality differed between the studied markets for the Level. Mainly the Level is affected by the yield curve own factors, Slope and Curvature, in the US, UK, EUR, BRA and EGP, similar to Sowmya & Prasanna (2018) findings. In addition, the POLRATE led the Level in only two studied markets, the US and EGP, according to academic literature, the monetary policy impacts the whole yield curve, not just the Slope or the short rate, which is evidence of a strong monetary policy transmission mechanism, and conform to the Expectation Hypothesis (Rhodes & Aazim, 2011; Sowmya & Prasanna, 2018). Furthermore, movements in the GDP seemed to lead the Level for some studied markets such as the EUR, MEX and EGP, since a growth in the economy leads to higher income and demand, which causes inflationary pressures that will trigger a rise in the yield curve in the form of a parallel shift, prompting the central bank to hike its policy rate (Rudebusch & Wu, 2003; Ang and Piazzesi, 2003; Diebold et al., 2006; Djuranovik, 2014; Coroneo et al., 2016; Shareef and Shijin, 2017). It is worth noting that Egypt's Level is Granger Caused by most variables in the system, indicating that a lot of information was incorporated into the country's yield curve Level.

Table 4.4 Level Granger Causality/Block Exogeneity Wald Test

Dependent variable: [14]Level			**VAR Granger Causality/Block Exogeneity Wald Test**						
Excluded	US P-value	UK P-value	EUR P-value	MEX P-value	BRA P-value	EGP P-value	SAF P-value	IND P-value	CHI P-value
[15]Slope	[16]0.9%	[16]1.7%	[16]0.1%	11.1%	[17]8.9%	[16]1.7%	98.5%	86.0%	84.2%
[18]Curvature	10.3%	11.5%	[16]1.2%	60.7%	[16]1.1%	20.7%	57.3%	11.9%	10.7%
EQUITY	19.0%	21.7%	12.6%	32.7%	25.0%	[16]1.5%	58.8%	[16]0.9%	90.1%
FX	13.2%	26.9%	88.6%	69.0%	15.5%	[16]1.0%	70.0%	[17]5.5%	33.7%
POLRATE	[16]3.0%	11.5%	76.9%	13.8%	88.6%	[16]3.9%	35.5%	11.0%	65.4%
GDP	23.8%	13.6%	[17]5.0%	[16]0.3%	45.5%	[16]4.7%	96.5%	47.6%	46.2%
INF	57.1%	50.1%	54.8%	92.4%	86.0%	14.8%	46.9%	66.7%	14.8%

Source: Authors' own calculations

Table 4.5 shows the Slope Granger Causality Block Exogeneity Wald test. As you will be able to conclude that the Slope was more of an Exogenous variable than the Level. In fact, the Level led the Slope in only three studied markets, similar to findings from Sowmya & Prasanna (2018). However, we were not able to find evidence that the POLRATE affects the Slope, since the POLRATE led the Slope in only two studied markets. In fact, Shang (2022) proved that, in a low uncertainty regime, monetary policy shocks have more effects on the shorter end of the yield curve than the longer end, while the opposite is true in a high uncertainty regime.

[14] Level signifies Yield curve Level
[15] Slope signifies Yield curve Slope
[16] Highlighted in red are significant at the 5% Level
[17] Highlighted in yellow are significant at the 10% Level
[18] Curvature signifies Yield curve Curvature

Table 4.5 Slope Granger Causality/Block Exogeneity Wald Test

Dependent variable: Slope			**VAR Granger Causality/Block Exogeneity Wald Test**						
Excluded	US P-value	UK P-value	EUR P-value	MEX P-value	BRA P-value	EGP P-value	SAF P-value	IND P-value	CHI P-value
Level	[16]1.2%	32.2%	16.8%	49.7%	[16]4.3%	73.4%	[16]0.3%	18.1%	53.5%
Curvature	56.0%	19.5%	[17]5.1%	45.5%	[16]0.3%	63.1%	13.8%	16.7%	27.4%
EQUITY	80.5%	54.6%	24.1%	53.2%	44.0%	24.0%	11.6%	[16]0.1%	73.1%
FX	70.2%	60.1%	23.2%	68.8%	[16]3.2%	36.6%	18.7%	52.1%	98.0%
POLRATE	30.0%	15.7%	78.5%	43.3%	21.9%	25.5%	[16]2.3%	22.5%	29.5%
GDP	76.3%	47.6%	52.4%	17.3%	[16]1.2%	61.9%	[16]0.2%	[17]6.0%	23.6%
INF	81.4%	67.5%	76.8%	35.5%	[16]0.2%	67.3%	[16]0.0%	48.6%	62.2%

Source: Authors' own calculations

Table 4.6 shows the Curvature Granger Causality Block Exogeneity Wald test. As you will be able to conclude that the Curvature was a highly Endogenous variable Granger Caused by most variables, similar to findings from Sowmya & Prasanna (2018), and contrary to other academic scholars who did not find the Curvature highly responsive to other macro variables (Djuranovik, 2014; Shareef and Shijin, 2017).

Table 4.6 Curvature Granger Causality/Block Exogeneity Wald Test

Dependent variable: Curvature			**VAR Granger Causality/Block Exogeneity Wald Test**						
Excluded	US P-value	UK P-value	EUR P-value	MEX P-value	BRA P-value	EGP P-value	SAF P-value	IND P-value	CHI P-value
Level	[17]8.1%	[17]6.8%	12.3%	54.4%	[16]1.5%	[16]0.0%	91.8%	19.1%	59.1%
Slope	[16]0.0%	[16]4.3%	[16]0.1%	51.4%	15.7%	[16]0.0%	49.2%	90.1%	92.8%
EQUITY	45.7%	[17]7.6%	56.7%	51.3%	23.8%	38.4%	48.2%	42.5%	81.7%
FX	[17]6.5%	59.1%	[17]7.4%	[17]8.2%	63.4%	[16]0.0%	[17]7.2%	70.4%	90.1%
POLRATE	[17]9.0%	[16]0.1%	[16]1.2%	13.4%	[16]1.2%	[16]0.0%	73.4%	40.1%	82.7%
GDP	[16]3.5%	46.2%	[16]0.8%	61.1%	22.1%	[16]3.3%	48.9%	83.6%	[16]3.9%
INF	[16]0.2%	54.9%	[17]8.1%	30.9%	21.7%	[16]0.8%	60.6%	22.6%	61.3%

Source: Authors' own calculations

Table 4.7 shows the EQUITY Granger Causality Block Exogeneity Wald test. As you will be able to conclude that the Level and Curvature, had a leading effect on the EQUITY. According to Ahmed et al. (2017) interest rates Granger Caused the stock market. In contrast and similar to Plihal (2016) findings, we did not find any violation of the weak form of the Efficient Market Hypothesis, with the exception of the EUR, as most macro variables seemed to be independent of equity indices, meaning that they already contained all information about macro variables.

Table 4.7 EQUITY Granger Causality/Block Exogeneity Wald Test

Dependent variable: EQUITY			VAR Granger Causality/Block Exogeneity Wald Test						
Excluded	US P-value	UK P-value	EUR P-value	MEX P-value	BRA P-value	EGP P-value	SAF P-value	IND P-value	CHI P-value
Level	51.6%	62.6%	[17]7.4%	[35]9.2%	25.8%	[34]0.1%	56.0%	[34]0.3%	66.5%
Slope	72.1%	84.5%	[34]0.6%	77.2%	20.3%	93.7%	49.7%	84.4%	73.1%
Curvature	16.3%	30.9%	54.5%	47.3%	[34]4.5%	[35]5.7%	[34]0.1%	81.5%	37.4%
FX	77.0%	45.0%	80.8%	[34]4.0%	20.0%	52.0%	56.6%	37.0%	78.7%
POLRATE	72.1%	24.2%	42.8%	15.9%	75.8%	18.8%	25.4%	[34]1.9%	27.2%
GDP	22.4%	28.9%	[35]5.5%	82.3%	41.7%	16.8%	39.9%	67.8%	58.0%
INF	94.8%	80.1%	[35]5.1%	70.6%	98.0%	81.3%	14.7%	12.9%	39.2%

Source: Authors' own calculations

Table 4.8 shows the FX rate Granger Causality Block Exogeneity Wald test. As you will be able to conclude that the FX was strongly influenced by information coming from the Level, Slope and POLRATE. According to Ahmed et al. (2017) interest rates cause a slight appreciation in the country's exchange rate. Though, Shareef and Shijin (2017) noted that the effect of the Level on the currency exchange rate was not significant. Ang and Piazzesi (2003) argued that the relationship between the Level and the foreign exchange was debated with controversy in academic literature. On the other hand, Kearns & Manners (2005) confirmed that changes in the policy rate are rapidly transmitted into the foreign exchange rate. The FX was also Granger Caused by the GDP in two studied markets, and the INF in just one market. Consequently, Dilmaghani & Tehranchian (2015) stated that the country's exchange rate is also affected by other macro variables such as the inflation and GDP. On a final note, FX rate movements of developed markets, US, UK and EUR encompassed more info, more Endogenous than the rest of the selected markets.

Table 4.8 FX Granger Causality/Block Exogeneity Wald Test

Dependent variable: FX			VAR Granger Causality/Block Exogeneity Wald Test						
Excluded	US P-value	UK P-value	EUR P-value	MEX P-value	BRA P-value	EGP P-value	SAF P-value	IND P-value	CHI P-value
Level	[16]1.1%	[17]7.9%	76.9%	[17]9.3%	[17]9.3%	71.4%	19.5%	17.3%	78.7%
Slope	[16]3.1%	[16]3.5%	[16]0.0%	23.4%	45.2%	46.3%	51.3%	50.3%	77.9%
Curvature	34.5%	51.9%	[16]0.2%	26.1%	33.3%	25.7%	52.3%	[16]2.9%	84.6%
EQUITY	36.2%	42.8%	11.6%	87.0%	21.3%	20.0%	83.4%	[16]0.8%	97.5%
POLRATE	[17]5.9%	59.4%	[16]4.3%	10.3%	61.0%	53.6%	82.6%	[16]2.7%	66.8%
GDP	47.7%	19.0%	[16]2.7%	27.1%	[16]2.5%	74.0%	29.1%	76.4%	86.1%
INF	20.3%	[17]6.7%	50.5%	21.8%	83.0%	99.6%	78.8%	23.5%	56.7%

Source: Authors' own calculations

Table 4.9 shows the POLRATE Granger Causality Block Exogeneity Wald test. As you will be able to conclude that the POLRATE is an Endogenous variable affected by other variables in the system, adding to the fact that the POLRATE of the UK, EUR and SAF are more Endogenous, since movements in the majority of variables in the system led the policy rate, implying that the monetary policy rates of these markets are more effectively set. Mainly, the POLRATE is affected by yield curve factors, such as the Level and Slope, as per academic literature, we have previously mentioned that the Level leads the POLRATE. In addition, the POLRATE was Granger Caused by the EQUITY in three studied markets, similar to Suhaibu et al. (2017) who found out that the stock markets are affected by their respective monetary policies through interest rates, and in the long term this relation is bidirectional. Finally, the FX led the POLRATE in four studied markets, as a matter of fact, the foreign exchange rates play a dominant role in determining the behavior of the monetary policy (Olamide & Maredza, 2019). Skibinska (2017) stated that central banks react to a weaker exchange rate by hiking their policy rates. It is interesting to note that the FX is the only variable that Granger Caused the POLRATE in Egypt, highlighting the high influence of the FX on setting the monetary policy, similar to Mohanty & Klau (2004) who proved that interest rates responded strongly to the foreign exchange rates.

Table 4.9 Policy Rate Granger Causality/Block Exogeneity Wald Test

Dependent variable: POLRATE			**VAR Granger Causality/Block Exogeneity Wald Test**						
Excluded	US P-value	UK P-value	EUR P-value	MEX P-value	BRA P-value	EGP P-value	SAF P-value	IND P-value	CHI P-value
Level	[16]0.0%	[16]0.0%	[16]0.0%	[16]0.3%	[16]1.0%	38.6%	40.0%	13.3%	[16]4.8%
Slope	[16]0.0%	[16]0.0%	[16]0.1%	[16]4.4%	[16]1.9%	20.8%	4.1%	67.6%	54.6%
Curvature	31.9%	[16]0.1%	30.1%	62.1%	22.3%	76.9%	19.5%	45.6%	[16]0.1%
EQUITY	61.5%	[16]0.1%	[16]3.2%	65.0%	52.7%	33.3%	[17]7.3%	44.6%	49.7%
FX	21.2%	[16]3.5%	[17]5.8%	77.6%	46.7%	[16]2.5%	[16]0.2%	79.0%	80.7%
GDP	74.8%	28.1%	61.4%	11.4%	94.4%	62.4%	[16]4.0%	90.0%	[16]0.1%
INF	100.0%	29.4%	30.3%	35.9%	13.8%	52.1%	[16]0.2%	76.9%	86.1%

Source: Authors' own calculations

Table 4.10 shows the GDP Granger Causality Block Exogeneity Wald test. As you will be able to conclude that the GDP was a highly Endogenous variable Granger Caused by most variables in the system whether yield curves or macro variables. As we previously highlighted the association between the Level and the GDP, we found out that the Level Granger Caused the GDP in four studied markets, similar to findings by Shareef and Shijin (2017). As the predictive power of the Slope over the GDP was extensively studied in academic literature, we were able to prove this relationship in three studied markets (Jamriska, 2008; Abdymomunov, 2011; Hannikainen, 2017). On the other hand, academic scholars like Kaya (2013) did not find evidence of such a relationship, and Chinn and Kucko (2010) argued that the prediction power of the yield curve has deteriorated over time. The Curvature was found to have a strong predictive power over the economy in five studied markets, similarly Moller (2014) used the Curvature to predict the GDP and suggested that the Curvature had more predictive power than the Slope. Moreover, equity indices seemed to lead the GDP in most countries. Plihal (2016) was able to prove that the stock market is a leading indicator, as its Granger Caused the economy. The FX and INF led the GDP in three studied markets. According to Dilmaghani & Tehranchian (2015) inflation has a negative effect on the country's exchange rate, as an increase in the domestic price level makes local goods relatively more expensive. Furthermore, the POLRATE leads the GDP in the majority of the studied markets. Amaral et al. (2022) demonstrated that the monetary policy did have a positive impact on economic growth in the short term, and not in the long term. Lee & Werner (2018) tested whether lower interest rates resulted in higher growth and vice versa, and the authors concluded that interest rates follow the GDP growth and are positively correlated. Contrarily, Hameed (2011) argued that the interest rate has a minor impact on the GDP, and Ryan-Collins et al. (2016) found out that short and long-term interest rates did not affect the GDP.

Table 1.10 GDP Granger Causality/Block Exogeneity Wald Test

Dependent variable: GDP			**VAR Granger Causality/Block Exogeneity Wald Test**						
Excluded	US P-value	UK P-value	EUR P-value	MEX P-value	BRA P-value	EGP P-value	SAF P-value	IND P-value	CHI P-value
Level	[16]0.0%	[16]0.2%	20.6%	[17]8.9%	[16]0.0%	59.6%	29.8%	56.8%	73.5%
Slope	11.3%	12.1%	[17]7.5%	47.6%	[16]0.1%	[17]5.5%	55.7%	76.9%	17.7%
Curvature	[16]0.0%	73.5%	17.2%	[17]9.2%	[16]0.9%	[16]3.7%	39.9%	95.0%	[17]6.3%
EQUITY	[16]4.7%	[16]0.3%	[17]7.5%	53.5%	[17]5.7%	45.1%	39.8%	37.9%	[16]4.2%
FX	71.7%	[16]0.0%	[17]6.8%	39.4%	[16]2.2%	44.6%	73.8%	29.3%	95.1%
POLRATE	[16]0.9%	[17]7.8%	[16]0.0%	33.5%	[16]0.6%	95.3%	[16]0.3%	83.6%	[16]0.3%
INF	10.4%	55.7%	21.2%	35.0%	[16]2.2%	66.9%	[17]6.4%	[16]0.8%	12.0%

Source: Authors' own calculations

Table 4.11 shows the INF Granger Causality Block Exogeneity Wald test. As you will be able to conclude that we found evidence of a one-way direction Fisher effect in two studied markets, in the EUR and SAF, where the INF was Granger Caused by the Level (Everaert, 2014; Phiri, 2022). Djuranovik (2014) estimated the correlation between the yield curve Level and the inflation forecasts to be quite high equivalent to +0.65. Accordingly, Incekara et al. (2012) found evidence supporting the Fisher effect in the long term, and Panopoulou & Pantelidis (2016) provided evidence supporting the existence of a long-run Fisher effect in which interest rates move in tandem with inflation rates. Contrarily, Coppock & Poitras (2000) did not find evidence supporting the Fisher effect, and Fahmy & Kandil (2003) results did not support the Fisher effect in the short-run since short-term interest rates are not associated with the expected inflation. In addition, the EQUITY Granger Caused the INF in four studied markets, similar to Pradhan et al. (2015) who found Causality from both economic growth and the stock market to the inflation, in the short and long run, and Chiang (2023) who found evidence of negative correlation between the stock market and inflation, although, Plihal (2016) did not find evidence of the stock market effect on the inflation rate. Finally, the GDP Granger Caused the INF in the majority of the studied markets, since as we have previously mentioned that economic growth leads inflation, as the economy cannot grow without inflationary pressures, causing the Level and the policy rate to respond accordingly (Rudebusch & Wu, 2003; Ang and Piazzesi, 2003; Diebold et al., 2006; Djuranovik, 2014; Coroneo et al., 2016; Shareef and Shijin, 2017).

Table 4.11 INF Granger Causality/Block Exogeneity Wald Test

Dependent variable: INF			**VAR Granger Causality/Block Exogeneity Wald Test**						
Excluded	US P-value	UK P-value	EUR P-value	MEX P-value	BRA P-value	EGP P-value	SAF P-value	IND P-value	CHI P-value
Level	90.3%	11.0%	[17]5.2%	36.6%	92.1%	84.1%	[17]8.0%	61.4%	99.5%
Slope	95.7%	22.1%	16.6%	63.9%	96.0%	49.8%	12.9%	10.4%	[16]1.5%
Curvature	62.9%	[16]0.7%	47.9%	78.5%	34.1%	10.0%	10.8%	27.8%	48.1%
EQUITY	92.9%	[17]6.2%	85.0%	40.9%	84.7%	75.4%	[16]0.0%	[17]8.0%	[16]1.1%
FX	84.7%	38.5%	97.7%	45.0%	88.5%	62.6%	61.3%	[16]1.9%	89.8%
POLRATE	69.1%	34.2%	19.3%	38.1%	80.9%	28.2%	13.0%	11.8%	13.6%
GDP	93.3%	[17]5.7%	[16]0.1%	[16]1.8%	13.4%	82.2%	81.1%	[16]1.1%	[16]2.5%

Source: Authors' own calculations

In order to emphasize which of the data variables have the most predictive power or Granger Caused most variables in the VAR system, we have counted how many times each variable was significant as an independent variable in the Granger Causality/Block Exogeneity tables. Table 4.12, and table 4.13 in Appendix B shows the results of the Granger Causality variable counting per variable and per country. It's clear from table 4.12 that the Level had the most predictive power, as it has significantly preceded or Granger Caused 27 variables, followed by the Slope and the GDP. These results do make sense economically as movements in the yield curve, Level and Slope, do have an effect on the whole economic process. In addition, the Level and the Slope had the most predictive power in the US and UK economy, compared to the Slope and GDP for the EUR, as it's illustrated in table 4.13. It is worth mentioning that the Euro Area (27 significant variables), Brazil (21 significant variables), and the UK (20 significant variables), were the markets with the most statistically significant interactions between the variables.

Table 4.12 Leading variables Granger Causality per variable counted

Variables	Granger Causes
Level	27 variables
Slope	23 variables
GDP	20 variables
POLRATE	18 variables
Curvature	17 variables
EQUITY	17 variables
FX	17 variables
INF	11 variables

Source: Authors' own calculations

In order to highlight which of variables were more Endogenous in the VAR system, we have counted how many variable Granger Caused each dependent variable in the Granger Causality/Block Exogeneity tests, in table 4.14. It's clear that 29 variables Granger Caused the GDP, followed by the Curvature and POLRATE, as being the most Endogenous variables. Thus, the GDP reacted to most variables in the economy, adding to the fact that central banks take into consideration the GDP, INF and other factors prior to POLRATE hikes or cuts. Therefore, the GDP and POLRATE were the first and third most Endogenous variables. It is interesting to note that the Curvature was the second most Endogenous variable, meaning that it comprised a lot of information. For example, the Curvature and GDP were the most Endogenous variables in the US, compared to the POLRATE, Curvature, and GDP, for the UK, as illustrated in table 4.15 in Appendix B.

Table 4.14 Sorted Endogenous variables

Variables	Endogenous
GDP	29 variables
Curvature	26 variables
POLRATE	24 variables
Level	16 variables
FX	16 variables
INF	14 variables
Slope	13 variables
EQUITY	12 variables

Source: Authors' own calculations

4.1.3 Yield Curves and Macro Variables Impulse Response Function

In this section, we have presented the results of the Impulse Response Function of the Unrestricted VAR system estimated in the previous sections, on the yield curves three latent factors and the five macro variables. The purpose of this section was to study how each variable responded to impulses from other variables, i.e., the direction of this relationship, whether it is positive or negative. We have analyzed only the general trends of the variables' directional relationship, among the studied markets. In order to facilitate the illustration of the variables shocks and their responses, we have computed in the tables, presented in this section, the number of markets with positive/negative responses to each variable.

Table 4.16 Response of the Level to shocks from other variables

Response of the Level to:	Slope	Curvature	EQUITY	FX	POLRATE	GDP	INF
Countries with Negative Response	6	4	1	4	2	4	4
Countries with Positive Response	3	5	8	5	7	5	5

Source: Authors' own calculations

Table 4.16 shows the Accumulated Impulse Response Function for the Level. As we have previously mentioned, in the previous section, that the Level is mainly affected by the yield curve factors, the Slope and Curvature, similar to Sowmya & Prasanna (2018) findings, the Slope caused a negative response in the Level in six studied markets, though, the Curvature response was mixed. Shocks to the EQUITY caused a positive response in the Level in most studied markets, as we have mentioned in the previous section that the stock market is a leading indicator of economic performance, thus, a rise in the GDP would be accompanied by inflationary pressures, leading eventually to an increase in the Level. Hence, shocks to the GDP and INF mainly caused positive responses in the Level (Diebold et al., 2006; Djuranovik, 2014; Coroneo et al., 2016; Shareef and Shijin, 2017). In response to higher inflation expectations, the central bank responds by hiking its policy rate, thus, shocks to the POLRATE caused a positive response in the Level in most studied markets, according to academic literature, the monetary policy can affect the whole yield curve, not just the short rate, which is evidence of a strong monetary policy transmission mechanism, and conform to the Expectation Hypothesis (Rhodes & Aazim, 2011; Sowmya & Prasanna, 2018). As Dilmaghani & Tehranchian (2015) stated that the country's exchange rate is also affected by other macro variables such as the inflation and GDP, subsequently, shocks to the FX caused a positive response in the Level in most studied markets, because an appreciation in the FX rate of the country is due to a higher demand in the country's currency, signaling higher investments inflows and a growing economy. Though, it is worth mentioning that the FX caused a negative response in four studied markets. Ang and Piazzesi (2003) argued that the relationship between the Level and the foreign exchange was debated with controversy in academic literature.

Table 4.17 Response of the Slope to shocks from other variables

Response of the Slope to:	Level	Curvature	EQUITY	FX	POLRATE	GDP	INF
Countries with Negative Responses	8	3	6	5	6	5	7
Countries with Positive Responses	1	6	3	4	3	4	2

Source: Authors' own calculations

Table 4.17 shows the Accumulated Impulse Response Function for the Slope. Shocks to the Level caused a negative response in the Slope, in most studied markets, meaning an upward parallel shift could be followed by a reduction in the Slope, similar to findings from Sowmya & Prasanna (2018). The reduction of the Slope is the response of the central bank hiking its rate and affecting the short rate, as a reaction to higher inflation. Thus, a shock to the POLRATE caused a negative response in the Slope in most studied markets. Accordingly, the short end of the yield curve responds promptly to the monetary policy (Chirinos-Leañez & Pagliacci, 2015). As we have previously mentioned that economic growth is accompanied by higher inflation, leading to a positive response in the Level and POLRATE, a shock to the GDP and INF leads to a negative response in the Slope, as the short rate rises. Academic scholars found out evidence of a relationship between the stock market and inflation, hence, a shock to the EQUITY leads to a negative response in the Slope, caused by the reaction of the short rate to higher inflation expectations (Pradhan et al., 2015; Chiang, 2023). Akturk (2016) stated that ex-ante inflationary expectations and stock returns are positively related, whereas ex-post inflationary realizations are negatively related. Similar to the response of the Level, shocks to the FX caused a mixed response in the Slope.

Table 4.18 Response of the Curvature to shocks from other variables

Response of the Curvature to:	Level	Slope	EQUITY	FX	POLRATE	GDP	INF
Countries with Negative Responses	7	3	6	5	5	7	5
Countries with Positive Responses	2	6	3	4	4	2	4

Source: Authors' own calculations

Table 4.18 shows the Accumulated Impulse Response Function for the Curvature. Shocks from the Level and the Slope caused a negative and positive response in the Curvature respectively for the majority of the studied markets. Although, a shock to the EQUITY caused mostly a negative response in the Curvature, a shock to the POLRATE caused a mixed response, since five out of the nine studied markets had negative responses, similar to findings by Djuranovik (2014), and four out of the nine studied markets had positive responses, similar to findings by Sowmya & Prasanna (2018). A shock to the GDP and INF caused mostly a negative response in the Curvature, conform to findings by Sowmya & Prasanna (2018). Finally, a shock to the FX caused a mixed response, in contrast, Sowmya & Prasanna (2018) did not find evidence of the country's exchange rate response on the Curvature.

Table 4.19 Response of the EQUITY to shocks from other variables

Response of the EQUITY to:	Level	Slope	Curvature	FX	POLRATE	GDP	INF
Countries with Negative Responses	5	5	4	5	4	3	6
Countries with Positive Responses	4	4	5	4	5	6	3

Source: Authors' own calculations

Table 4.19 shows the Accumulated Impulse Response Function for the EQUITY. Most of the variables seemed to have mixed effects on the EQUITY. Shocks to the Level and Slope caused a negative response in the EQUITY, in five out of nine studied markets, as these two yield curve factors react according to higher inflation expectations. According to Ahmed et al. (2017) interest rates Granger Caused the stock market. On the same train of thought, as one would expect, the GDP caused a positive response in the EQUITY, in fact, a growing economy leads to higher income, which in turn increases the investment and spending. Fromentin (2022) found evidence of a Causality from the industrial production to the stock market. In addition, a shock to the INF caused a negative response in the EQUITY, as it points to future policy rate hikes. Bissoon et al. (2016) proved the negative relation between the interest rate and the stock market both in the short and long run. The relationship of the POLRATE with the EQUITY was ambiguous, as one would expect that the hike in the policy rate would cause equity indices to fall, a shock to the POLRATE caused a negative response in four studied markets, and a positive one in five markets. One possible explanation could be that the monetary policy is not transmitted effectively to the stock market. Laopodis (2013) suggested that the relationship between the monetary policy and the stock market was dynamic and not consistent. The FX shock caused a mixed response in the EQUITY, positive in four studied markets, meaning an appreciation of the exchange rate is a sign of capital inflows causing the stock market to rise. Ahmed et al. (2017) found a Causality relationship from the exchange rate to the stock market, in fact, an appreciating exchange rate causes a slight positive response in the stock market.

Table 4.20 Response of the FX to shocks from other variables

Response of the FX to:	Level	Slope	Curvature	EQUITY	POLRATE	GDP	INF
Countries with Negative Responses	6	5	1	1	5	4	3
Countries with Positive Responses	3	4	8	8	4	5	6

Source: Authors' own calculations

Table 4.20 shows the Accumulated Impulse Response Function for the FX. The FX was strongly influenced by information coming from the Level, Slope, and Curvature. A shock to the Level causes a negative response in the country's exchange rate, as it is an indication of inflationary pressures. Similarly, Ahmed et al. (2017) proved that interest rates cause a slight appreciation of the country's exchange rate. Although, a shock to the Slope caused a mixed response in the FX, since five out of nine studied markets had a negative response in the FX, as a positive shock to the Slope is caused by a decrease in the policy rate, causing a negative response of the FX. Kearns & Manners (2005) confirmed that changes in the policy rate are rapidly transmitted into the foreign exchange rate. A shock to the POLRATE caused a mixed response in the FX, as the relationship between the monetary policy and the economy might be more ambiguous than some academic scholars stated (Twinoburyo & Odhiambo, 2017). Kearns & Manners (2005) confirmed that monetary policy changes account for only a small part of the observed variability in exchange rates. As we have previously mentioned that the EQUITY is a leading indicator of economic growth, a shock to the EQUITY caused an appreciation of the FX in almost all studied markets, consequently, a positive shock to the GDP caused an appreciation of the FX as well in five out of the nine studied markets. Although, a shock to the INF caused a positive response in the FX, the response was not predominantly high. Dilmaghani & Tehranchian (2015) stated that the country's exchange rate is also affected by other macro variables such as the inflation and GDP.

Table 4.21 Response of the POLRATE to shocks from other variables

Response of the POLRATE to:	Level	Slope	Curvature	EQUITY	FX	GDP	INF
Countries with Negative Responses	0	7	5	2	4	1	2
Countries with Positive Responses	9	2	4	7	5	8	7

Source: Authors' own calculations

Table 4.21 shows the Accumulated Impulse Response Function for the POLRATE. As we have previously mentioned, and conform to results from academic literature, economic growth leads to a positive response in the Level, POLRATE and INF, a shock to the Level, GDP and INF caused a positive response in the POLRATE for almost all studied markets. On the other hand, a shock to the EQUITY leads to a positive response in the POLRATE. Suhaibu et al. (2017) found out that the stock markets are affected by their respective monetary policies through interest rates, and in the long term this relation is bidirectional. Additionally, Pradhan et al. (2015) found evidence of Causality from the stock market to the inflation, which would explain the positive response of the POLRATE to a shock in the EQUITY. In fact, the foreign exchange rates play a dominant role in determining the behavior of the monetary policy (Olamide & Maredza, 2019). Skibinska (2017) stated that central banks react to a weaker exchange rate by hiking their policy rates. A shock to the FX caused a mixed response in the POLRATE, highlighting different monetary policy mechanisms, and specific reactions to countries' foreign exchange rate shocks. Vasicek (2010) studied the monetary policy of recently joined twelve EU new members, the author found out that central banks in countries with flexible exchange rates responded mainly to inflation, comparatively, Mohanty & Klau (2004) found out that interest rates respond strongly to the foreign exchange rates in emerging economies with different degrees, noting that in some countries the response is even higher than the inflation rate.

Table 4.22 Response of the GDP to shocks from other variables

Response of the GDP to:	Level	Slope	Curvature	EQUITY	FX	POLRATE	INF
Countries with Negative Responses	1	5	5	1	2	5	5
Countries with Positive Responses	8	4	4	8	7	4	4

Source: Authors' own calculations

Table 4.22 shows the Accumulated Impulse Response Function for the GDP. As we previously highlighted the association between the Level and the GDP, shocks to the Level led to a positive response in the GDP in almost all studied markets, similar to findings by Shareef and Shijin (2017). As the predictive power of the Slope over the GDP was extensively studied in academic literature, shocks to the Slope caused a mixed response in the GDP (Jamriska, 2008; Abdymomunov, 2011; Hannikainen, 2017). Kaya (2013) did not find evidence of the relationship between the Slope and GDP, and Chinn and Kucko (2010) argued that the prediction power of the yield curve has deteriorated over time. Since the stock market is a leading indicator for the economy according to Plihal (2016), shocks to the EQUITY caused a positive response in the GDP. Shocks to the INF and the POLRATE caused a mixed response in the GDP, however, five out of nine studied markets had a slightly negative impact on the GDP in the long run, since central banks react to higher inflation rates by hiking their policy rates, which will increase the borrowing cost and slow down the economy. Amaral et al. (2022) demonstrated that the monetary policy did have a positive impact on economic growth. Lee & Werner (2018) concluded that interest rates follow the GDP growth, and are consistently positively correlated with the economy. Contrarily, Hameed (2011) argued that the interest rate has a minor impact on the GDP. Although, shocks to the FX did not cause substantially high responses in the GDP on most studied markets, as this relationship converges in the long run more than the short run, the response was positive for three studied markets, Brazil, Mexico and Egypt, as the FX induces inflation in these countries, in addition, their respective central banks reacts immediately towards a depreciating exchange rate, thus, the exchange rate regime plays a determinant role in their respective monetary policies (Mohanty & Klau, 2007; Comunale, 2017; Khandare, 2017). Khandare (2017) stated that the correlation coefficient between the currency exchange rate and the GDP growth is positive and equivalent to +0.16, but not significant though, in addition, the interest rate and inflation rate have an inverse effect on economic growth. The author further added that today's exchange rate affects tomorrow's economic growth rate negatively by -0.087, but the elasticity is not significant as well, and different results between countries are affected by their respective exchange rate regime. On the other hand, Pramanik (2021) found out currency exchange rates depreciations are accompanied by economic growth in several studied countries, though, this relationship was not apparent for a country like Mexico, and could differ between countries. In addition, Comunale (2017) concluded that the currency exchange rate misalignments caused a decline in the GDP in the long-run, but not in the short run.

Table 4.23 Response of the INF to shocks from other variables

Response of the INF to:	Level	Slope	Curvature	EQUITY	FX	POLRATE	GDP
Countries with Negative Responses	2	4	4	1	8	2	2
Countries with Positive Responses	7	5	5	8	1	7	7

Source: Authors' own calculations

Table 4.23 shows the Accumulated Impulse Response Function for the INF. Referring to the association between the GDP, Level, POLRRATE, and the INF, shocks to the Level, GDP and POLRATE caused a positive response in the INF, conform to findings in academic literature (Diebold et al., 2006; Djuranovik, 2014; Coroneo et al., 2016; Shareef and Shijin, 2017). The positive reaction of the INF to the POLRATE shows the persistence of the inflation, as markets needs time to adjust and absorb the new policy rates. It is worth mentioning that the association between the Level and INF is evidence of a one-way direction Fisher effect. Djuranovik (2014) estimated the correlation between the Level and the inflation forecasts to be quite high equivalent to +0.65. Accordingly, Incekara et al. (2012) found evidence supporting the Fisher effect in the long term, and Panopoulou & Pantelidis (2016) provided evidence supporting the existence of a long-run Fisher effect in which interest rates move in tandem with inflation rates. Contrarily, Coppock & Poitras (2000) did not find evidence supporting the Fisher effect, and Fahmy & Kandil (2003) results did not support the Fisher effect in the short-run since short-term interest rates are not associated with the expected inflation. Shocks to the EQUITY caused mostly positive responses to the INF, as the EQUITY is a leading indicator for economic growth, which will lead eventually to inflationary pressures. Accordingly, Pradhan et al. (2015) found Causality from the stock market to inflation, in the short and long run, although, Plihal (2016) did not find evidence of the stock market effect on the inflation rate. Conform to academic literature, positive shocks to the FX caused mostly negative responses in the INF, as a currency exchange rate depreciation (negative shocks) is likely to cause inflationary pressures (positive response) as import prices become more expensive, which leads to higher demand for domestic products locally and internationally, since exports become cheaper, therefore, causing an increase in domestic aggregate demand, leading to a demand-pull inflation (Whitten, 2016; Pettinger, 2019; Lowry, 2022). In addition, Monfared & Akın (2017) found out that the foreign exchange rate Granger Causes the inflation, and an appreciating currency rate leads to a negative response in inflation. It is worth mentioning that this relationship is substantially high for a country like Egypt.

4.1.4 Yield Curves and Macro Variables Variance Decomposition

In this section, we have presented the results of the Variance Decomposition of the VAR system, where we have only interpreted general trends, and we have not discussed the proportion of the variation in forecast error variance that was attributed to innovations of the dependent variable in the VAR system.

Level: apart from the variable own shocks, shocks to Slope had the strongest percent variation for the Level, ranging from 13% to 21% of the forecast error variance, conform to academic literature findings the Level is affected by the yield curve own factors (Sowmya & Prasanna, 2018). The GDP, EQUITY and FX seemed to also have explanatory power over the Level for some studied markets, as we have previously mentioned and conform to academic literature, a growth in the economy causes inflationary pressures that will trigger a rise in the yield curve in the form of a parallel shift (Diebold et al., 2006; Djuranovik, 2014; Coroneo et al., 2016; Shareef and Shijin, 2017). Adding to the fact that the stock market is a leading indicator of economic performance, thus, a rise in the GDP would be accompanied by inflationary pressures, leading eventually to an increase in the Level (Plihal, 2016). Furthermore, for a country like IND, the EQUITY explained up to 24% of the variation in the Level, and for MEX none of the variables (apart from own shock) had significant explanatory power.

Slope: apart from the variable own shocks, shocks to the Level and Curvature had the strongest percent variation for the Slope, similar to findings from Sowmya & Prasanna (2018), ranging from 14% to 28% of the forecast error variance. It is worth noting that for EGP, the FX alone could explain 25% of the variation in the Slope.

Curvature: apart from the variable own shocks, shocks to the Level and Slope had the strongest percent variation for the Curvature, ranging from 23% to 44% of the forecast error variance, for the US, UK and EUR, similar to findings from Sowmya & Prasanna (2018), where the Curvature was highly responsive to the yield curve and other macro variables, and contrary to Shareef and Shijin (2017) who found out that the Curvature was not highly responsive. The EQUITY and POLRATE seemed to exhibit some explanatory powers, ranging from 19% to 29% for BRA, EGP and IND, conform to findings in academic literature (Djuranovik, 2014; Sowmya & Prasanna, 2018). It is worth noting that for EGP, the FX explained 14% of the variation in the Curvature.

EQUITY: apart from the variable own shocks, shocks to the Level had the strongest percent variation for the EQUITY, ranging from 8% to 20% of the forecast error variance, while shocks to Slope accounted for 13% to 30% of the variation, similar to Ahmed et al. (2017) who proved that interest rates Granger Caused the stock market. The FX and GDP exhibited as well some forecasting significance for some countries, especially the FX accounted for 32% and 25% of the variations for MEX and BRA respectively. According to Fromentin (2022) there is Causality from the industrial production to the stock market.

FX: apart from the variable own shocks, shocks to the Level, Slope and Curvature accounted for 20% to 39% of the forecast error variance, while shocks to the EQUITY accounted for 13% to 24% of the variation for EGP, SAF and IND, similar to Ahmed et al. (2017) who stated that interest rates caused a slight appreciation in the country’s exchange rate. In addition, the

POLRATE accounted for 9% to 13% of the variability in the US and EUR, similarly, Kearns & Manners (2005) confirmed that changes in the policy rate are rapidly transmitted into the foreign exchange rate. The FX and GDP exhibited as well some forecasting significance in some countries, especially the FX accounting for 32% and 25% of the variations for MEX and BRA respectively, similarly, Dilmaghani & Tehranchian (2015) stated that the country's exchange rate is also affected by other macro variables such as the GDP.

POLRATE: since the POLRATE is mainly affected by yield curve factors, shocks to the Level and the Slope accounted for more variation than the POLRATE own shock for the US, UK and MEX. As we have previously mentioned, and conform to academic literature, the Level leads the POLRATE. For example, the Level accounted for 20% of the variation in the POLRATE, and the Slope for 37%, compared to the dependent variable own shock (POLRATE) of 19% of the forecast error variance. Noting that for CHI, the GDP accounted for 31% of the variation in the POLRATE, which was close to the variable own shock. In addition, the FX accounted for 37% of the variation in the POLRATE, more than the variable own shock for EGP. According to Skibinska (2017) central banks react to a weaker exchange rate by hiking their policy rates. Furthermore, the GDP seemed to have some explanatory power for the UK, MEX and IND. As we have previously mentioned, and conform to results from academic literature, economic growth leads to a positive response from the Level, POLRATE and INF. Finally, the EQUITY and INF were able to explain a portion of the variation in some countries as well. According to Suhaibu et al. (2017) stock markets are affected by their respective monetary policies through interest rates, and in the long term this relation is bidirectional. It's clear that the POLRATE dynamics were different from a country to another, since in some studied markets only the FX had a high explanatory power over the POLRATE, while in others it was the GDP, adding to the fact that in some countries it was the Level and the Slope that had explanatory power. According to Olamide & Maredza (2019) the foreign exchange rates play a dominant role in determining the behavior of the monetary policy.

GDP: apart from the variable own shocks, shocks to the EQUITY accounted from 14% to 21% of the variation in the GDP in five studied markets, according to Plihal (2016) the stock market is a leading indicator for the economy. As we previously highlighted the association between the

Level and GDP, the Level accounted from 10% to 26% of the variation in four studied markets, compared to the Slope which accounted from 9.8% to 14% of the variation in three studied markets, hence, we were unable to prove that the Slope had explanatory power over a 12-month period ahead, similarly Kaya (2013) did not find evidence of such a relationship (Shareef and Shijin, 2017).

INF: apart from the variable own shocks, shocks to the EQUITY accounted from 12% to 29% of the variation in the INF in four studied markets. Accordingly, Pradhan et al. (2015) found Causality from both economic growth and the stock market to the inflation, in the short and long run, and Chiang (2023) found evidence of a negative correlation between the stock market and inflation. In addition, the POLRATE accounted for almost 10% variation in the INF in four studied markets. Furthermore, the GDP accounted from 9% to 14% of the variation in the INF in three studied markets. Finally, the Level and the Slope seemed to have explanatory power over the INF for the US, UK and EUR, meaning that yield curve movements in more developed countries seemed to contain a lot of information about the state of the economy. As we have previously mentioned, and conform to academic literature, economic growth leads to inflation, as the economy cannot grow without inflationary pressures, causing the Level and the policy rate to respond accordingly (Diebold et al., 2006; Djuranovik, 2014; Coroneo et al., 2016; Shareef and Shijin, 2017). It is worth mentioning that the FX accounted for 29% of the variation in the INF for EGP.

4.1.5 Summary of Yield Curves and Macro Variables Interactions Findings

The findings presented here, provide the detailed answer to **RQ1**, the synopsis of the answer was presented at the end of this section.

Level

- Based on the analysis of the first Eigenvectors performed on the yield curves and macro variables together, characterized by yield curves parallel shifts or the Level, we have made the following conclusions:
    - The GDP and the INF were positively associated with the Level or yield curve parallel shifts. These findings are consistent with academic literature, since a

growth in the economy leads to higher inflationary pressures that will trigger a rise in the yield curve in the form of a parallel shift (the Level), prompting the central bank to hike its policy rate (Rudebusch & Wu, 2003; Ang and Piazzesi, 2003; Diebold et al., 2006; Djuranovik, 2014; Coroneo et al., 2016; Shareef and Shijin, 2017).

  - FX movements were not aligned with movements in other macro variables, implying that FX rates are greatly affected by events that are specific to each country. According to Kearns & Manners (2005) monetary policy changes account for only a small part of the observed variability in exchange rates, adding to the fact that the relationship between the FX and GDP converges in the long run more than the short run (Comunale, 2017).
  - Equity indices were positively associated with macro variables for yield curves upward parallel shifts, during economic expansions. Academic scholars proved that there is evidence of Causality from the interest rate to the stock market (Ahmed et al., 2017). Though, equity indices were negatively associated with macro variables for yield curves downward parallel shifts, which is probably caused by the dynamic and non-consistent relation between the monetary policy and the stock market (Laopodis, 2013).

- The Level is affected by the yield curve own factors, Slope and Curvature, in the US, UK, EUR, BRA and EGP, similar to Sowmya & Prasanna (2018) findings.
- The POLRATE led the Level in few studied markets, and shocks to the POLRATE caused a positive response in the Level, conform to findings in academic literature, whereby the monetary policy impacts the whole yield curve, not just the Slope or the short rate, which is evidence of a strong monetary policy transmission mechanism, and conform to the Expectation Hypothesis (Rhodes & Aazim, 2011; Sowmya & Prasanna, 2018).
- The GDP seemed to lead the Level for some markets such as EUR, MEX and EGP, since a growth in the economy leads to higher income and demand, which causes inflationary pressures that will trigger a rise in the yield curve in the form of a parallel shift (the Level) prompting the central bank to hike its policy rate (Rudebusch & Wu, 2003; Ang and Piazzesi, 2003; Diebold et al., 2006; Djuranovik, 2014; Coroneo et al., 2016; Shareef

and Shijin, 2017). Shocks to the GDP and INF mainly caused positive responses in the Level (Diebold et al., 2006; Djuranovik, 2014; Coroneo et al., 2016; Shareef and Shijin, 2017).

- Shocks to the EQUITY caused a positive response in the Level in most studied markets, since the stock market is a leading indicator of economic performance.
- Shocks to the FX caused a positive response in the Level in most studied markets, because an appreciation in the FX rate is due to a higher demand in the country's exchange rate, signaling higher investments inflows and a growing economy. Dilmaghani & Tehranchian (2015) stated that the country's exchange rate is also affected by other macro variables such as the inflation and GDP.

Slope

- We were not able to find evidence that the policy rate affects the Slope, since the POLRATE led the Slope in only two studied markets. In fact, Shang (2022) proved that in a low uncertainty regime, monetary policy shocks have more effects on the shorter end of the yield curve than the longer end, while the opposite is true in a high uncertainty regime.
- We were able to prove the predictive power of the Slope over the GDP in three studied markets, as this relationship was extensively studied in academic literature (Jamriska, 2008; Abdymomunov, 2011; Hannikainen, 2017). On the other hand, academic scholars like Kaya (2013) did not find evidence of such a relationship, and Chinn and Kucko (2010) argued that the prediction power of the yield curve has deteriorated over time.
- Shocks to the Level caused a negative response in the Slope in most studied markets, meaning an upward parallel shift could be followed by a reduction in the Slope, similar to findings from Sowmya & Prasanna (2018). The reduction of the Slope is the response of the central bank hiking its rate and affecting the short rate, as a reaction to higher inflation. Thus, a shock to the POLRATE caused a negative response in the Slope in most studied countries. Accordingly, the short end of the yield curve responds promptly to the monetary policy (Chirinos-Leañez & Pagliacci, 2015). In addition, shocks to the GDP and INF led to a negative response in the Slope, as the short rate rises.

- According to academic literature, the monetary policy has a negative relationship with the stock market, as a hike in the policy rate depresses the equity market (Ioannidis & Kontonikas, 2006; Suhaibu et al., 2017), the EQUITY did not seem to behave accordingly for the second Eigenvectors, the Slope. Equity indices were positively associated with macro variables for yield curves inversions, while for yield curves increase in Slope they were stagnant with no association, reflecting the state of the economy. Accordingly, Laopodis (2013) suggested that the relationship between the monetary policy and the stock market was not consistent, and the dynamics of this relation was different in each monetary regime. Reaffirming our previous statement for the first Eigenvectors that the relation of the EQUITY to other macro variables is dynamic.
- It is worth mentioning that the FX had very low association with the second Eigenvectors, as the monetary policy relationship with foreign exchange rates differ based on the country's currency system (Dilmaghani & Tehranchian, 2015). In addition, Kearns & Manners (2005) stated that monetary policy changes account for only a small part of the observed variability in exchange rates.

Curvature

- The Curvature was a highly Endogenous variable Granger Caused by most variables, similar to findings from Sowmya & Prasanna (2018), and contrary to other academic scholars who did not find the Curvature highly responsive to other macro variables (Djuranovik, 2014; Shareef and Shijin, 2017). The Curvature was found to have a strong predictive power over the economy in five studied markets, similarly Moller (2014) used the Curvature to predict the GDP and suggested that the Curvature had more predictive power than the Slope.
- The Level and Curvature had a leading effect on the EQUITY. Ahmed et al. (2017) proved that interest rates Granger Caused the stock market. Similar to Plihal (2016) findings, we did not find any violation of the weak form of the Efficient Market Hypothesis, with the exception of the EUR, as most macro variables seem to be independent of equity indices, meaning that they seem to already contain all information about macro variables.

EQUITY

- The EQUITY seemed to lead the GDP in most studied markets. Plihal (2016) was able to prove that the stock market is a leading indicator, as it Granger Caused the economy. On other hand, The GDP caused a positive response in the EQUITY, in fact, a growing economy leads to higher income, which in turn increases the investment and spending. Fromentin (2022) found evidence of a Causality from the industrial production to the stock market.
- As we have previously mentioned that the EQUITY is a leading indicator of economic growth, a shock to the EQUITY causes an appreciation of the FX rates of almost all studied markets, consequently, a positive shock to the GDP causes an appreciation of the FX as well in five out of the nine studied markets.
- The EQUITY Granger Caused the INF in four studied markets, similar to Pradhan et al. (2015) who found Causality from both economic growth and the stock market to the inflation, in the short and long run, and Chiang (2023) who found evidence of a negative correlation between the stock market and inflation.
- Academic scholars found out evidence of a relationship between the stock market and inflation, hence, a shock to the EQUITY leads to a negative response in the Slope, caused by the reaction of the short rate to higher inflation expectations (Pradhan et al., 2015; Chiang, 2023). In addition, shocks to the Level and Slope caused a negative response in the EQUITY, as these two yield curve factors react according to higher inflation expectations.
- The relationship of the policy rate to the EQUITY was ambiguous, as one would expect that the hike in the policy rate would cause equity indices to fall, however, a shock to the POLRATE caused a negative response in four studied markets, and a positive one in five markets. One possible explanation could be that the monetary policy is not transmitted effectively to the stock market. Laopodis (2013) concluded that his results suggest that the relationship between the monetary policy and the stock market was dynamic and not consistent.
- The FX shock caused a mixed response in the EQUITY.

FX

- FX rate movements of developed markets, the US, UK and EUR encompassed more info, more Endogenous than the rest of the selected markets.
- The FX was strongly influenced by information coming from the yield curve, i.e., Level, Slope and POLRATE. According to Ahmed et al. (2017) interest rates cause a slight appreciation in the country's exchange rate. Though, Shareef and Shijin (2017) noted that the effect of the Level on the currency exchange rate was not significant. Kearns & Manners (2005) confirmed that changes in the policy rate are rapidly transmitted into the foreign exchange rate. Thus, a shock to the Level caused a negative response in the FX, as it is an indication of inflationary pressures.
- Although, a shock to the INF caused a positive response in the FX, the response was not predominantly high. Dilmaghani & Tehranchian (2015) stated that the country's exchange rate is also affected by other macro variables such as the inflation and GDP.

POLRATE

- The POLRATE of the UK, EUR and SAF are more Endogenous, since movements in the majority of variables in the system led the policy rate, implying that the monetary policy rates of these markets are more effectively set.
- The POLRATE is affected by yield curve factors, such as the Level and Slope, conform to academic literature. Shocks to the Level, GDP and INF caused a positive response in the POLRATE for almost all markets, conform to academic literature.
- The POLRATE was Granger Caused by the EQUITY, and shocks to the EQUITY led to a positive response in the POLRATE, similar to Suhaibu et al. (2017) who found out that the stock markets are affected by their respective monetary policies through interest rates, and in the long term this relation is bidirectional.
- The FX led the POLRATE in four studied markets, as a matter of fact the foreign exchange rates play a dominant role in determining the behavior of the monetary policy (Olamide & Maredza, 2019). Skibinska (2017) stated that central banks react to a weaker exchange rate by hiking their policy rates. On the other hand, shocks to the FX caused a mixed response in the POLRATE, highlighting different: monetary policy mechanisms, and specific reactions to countries' foreign exchange rate shocks.

- It's clear that the POLRATE dynamics were different from a country to another, since in some studied markets the FX had a high explanatory power over the POLRATE, while in others it was the GDP, adding to the fact that in some other countries it was the Level and the Slope that had explanatory power.

GDP

- The Level Granger Caused the GDP in four studied markets, similar to findings by Shareef and Shijin (2017). Hence, shocks to the Level led to a positive response in the GDP in almost all studied markets.
- The FX and INF led the GDP in three studied markets. According to Dilmaghani & Tehranchian (2015) inflation has a negative effect on the country's exchange rate, as an increase in the domestic price level makes local goods relatively more expensive.
- The POLRATE led the GDP in the majority of the studied markets. Amaral et al. (2022) demonstrated that the monetary policy did have a positive impact on economic growth in the short term, and not in the long term.
- Shocks to the INF and POLRATE caused a mixed response in the GDP, however, five out of nine studied markets had a slightly negative impact on the GDP in the long run, since central banks react to higher interest rates by hiking their policy rates, which will increase the borrowing cost and slow down the economy. Amaral et al. (2022) demonstrated that the monetary policy did have a positive impact on economic growth. Contrarily, Hameed (2011) argued that the interest rate has a minor impact on the GDP.
- Shocks to the FX did not cause substantially high responses in the GDP in most of the studied markets, as this relationship converges in the long run more than the short run (Comunale, 2017).

INF

- The GDP Granger Caused the INF in the majority of the studied markets, since as we have previously mentioned economic growth leads inflation, as the economy cannot grow without inflationary pressures, causing the Level and the POLRATE to respond accordingly (Rudebusch & Wu, 2003; Ang and Piazzesi, 2003; Diebold et al., 2006; Djuranovik, 2014; Coroneo et al., 2016; Shareef and Shijin, 2017).

- We found evidence of a one-way direction Fisher effect in two studied markets, where the INF was Granger Caused by the Level (Everaert, 2014; Phiri, 2022). Djuranovik (2014) estimated the correlation between the yield curve Level and the inflation forecasts to be quite high equivalent to +0.65, and Incekara et al. (2012) found evidence supporting the Fisher effect in the long term.
- Shocks to the EQUITY caused mostly positive responses in the INF, as the EQUITY is a leading indicator for economic growth, which will lead eventually to inflationary pressures. Accordingly, Pradhan et al. (2015) found evidence of Causality from the stock market to inflation, in the short and long run.
- Conform to academic literature, positive shocks to the FX caused mostly negative responses in the INF, as a currency exchange rate depreciation is likely to cause inflationary pressures as import prices become more expensive, which leads to higher demand for domestic products locally and internationally, since exports become cheaper, therefore, causing an increase in domestic aggregate demand, causing a demand-pull inflation (Whitten, 2016; Pettinger, 2019; Lowry, 2022).

The Answer to RQ1 is summarized next:

- **RQ1:** What are the most common identifiable trends of yield curves and macro variables behavior in terms of co-movement?

  Answer to RQ1: The yield curve parallel shift or the Level has the most persistent association with the policy rate, the GDP and inflation. These findings are consistent with academic literature, since a growth in the economy leads to higher inflationary pressures that will trigger a rise in the yield curve in the form of a parallel shift (the Level), prompting the central bank to hike its policy rate. The Level has the lowest factor weights standard deviations among yield curve factors, implying less uncertainty and more common yield curves and macro variables co-movements. Mainly, the Level was affected by the yield curve own factors, the Slope and Curvature. On the other hand, the Level and Curvature had a leading effect on the EQUITY. In general, the EQUITY's relationships with other macro variables were dynamic.

Furthermore, movements in the GDP seemed to lead the Level, since a growth in the economy leads to higher income and demand, which causes inflationary pressures that will trigger a rise in the yield curve in the form of a parallel shift (the Level) prompting the central bank to hike its policy rate. Moreover, equity indices seemed to lead the GDP, and the Curvature was found to have a strong predictive power over the economy. We were able to conclude that the GDP was a highly Endogenous variable reacting to most variables in the economy, whether yield curves or macro variables. On the other hand, the Level had the most predictive power, followed by the Slope and the GDP.

Shocks to the Level, GDP, and POLRATE, caused a positive response in the INF, adding to the fact that shocks to the EQUITY caused mostly positive responses in the INF, as the EQUITY is a leading indicator for economic growth, which will lead eventually to inflationary pressures. Additionally, positive shocks to the FX caused mostly negative responses in the INF, as a currency exchange rate depreciation (negative shocks) is likely to cause inflationary pressures (positive response) as import prices become more expensive, which leads to higher demand for domestic products locally and internationally.

4.2 Yield Curves Predictions' Results using ANN Regression Multitask Learning

4.2.1 Forecasting Results

For a comparative purpose, we have used the sum of training and out of sample errors in order to compare between all models. Meaning that if a model performed well in the training data and poorly in the out of sample data, it was penalized since its total error (training + out of sample errors) was high and vice versa. We have presented in table 4.24 the results of the 1m horizon total errors for all models and all studied markets. We have computed to the right-hand side of the table the average of each model total errors. We have removed from the averages of the total errors of models 1.07 and 1.10 Egypt's estimates as they are outliers, due to the currency devaluation event that took place in Egypt causing the yield curve to invert and move unexpectedly to very high levels. As you will be able to conclude that model 1.08 of the three-yield curve latent factors and three yield curve proxies performed best for the 1m horizon as its total errors mean was the lowest at 2.07%. These findings are consistent with our results in section 4.1, where the Level, Slope, and Curvature are mainly affected by the yield curve latent factors, and conform to academic literature (Shareef and Shijin, 2017; Sowmya & Prasanna, 2018). We have computed in the last row of table 4.24, the average of the predictions' total errors for each studied market. Over a 1m horizon, these 13 models fitted best China and South Africa as their total errors' averages for all models were the lowest equivalent to 1.48% and 2.56% respectively. We have sorted out the average of the 1m total errors from the lowest to the highest in table 4.25 in Appendix D. It is clear that the model with yield curve latent factors (PCASD) combined with yields proxies performed better than the Autoregressive model 1.04 for the 1m horizon.

Table 4.24 total errors per model and studied market for the 1m horizon predictions

Model number	Model inputs	BRA	US	MEX	UK	EUR	EGP	SAF	IND	CHI	Model predictions total errors Average
1.01	3 PCASD	12.59%	7.63%	10.72%	8.29%	7.87%	13.01%	4.57%	8.92%	2.43%	**8.45%**
1.02	3 AllPCA	11.37%	6.89%	8.17%	8.80%	8.93%	18.87%	4.22%	7.37%	2.39%	**8.56%**
1.03	3 PCASD & 3 AllPCA	11.69%	8.26%	7.86%	10.32%	7.58%	13.23%	4.35%	6.75%	2.28%	**8.04%**
1.04	7 AR YC	5.49%	1.66%	1.57%	1.41%	1.90%	3.68%	1.58%	2.74%	0.97%	**2.33%**
1.05	3 PCASD & 3 AR YC	3.88%	1.68%	1.66%	1.32%	1.29%	3.84%	1.78%	3.41%	1.09%	**2.22%**
1.06	3 AllPCA & 3 AR YC	11.23%	2.54%	4.80%	4.32%	1.33%	4.49%	1.88%	3.22%	0.82%	**3.85%**
1.07	3 YC Proxies	3.96%	2.58%	1.57%	0.95%	2.42%	25.08%	1.62%	2.71%	1.14%	**2.12%**
1.08	3 PCASD & 3 YC Proxies	3.74%	1.57%	1.51%	1.22%	1.17%	3.43%	1.79%	3.13%	1.10%	[19]**2.07%**
1.09	3 AllPCA & 3 YC Proxies	11.20%	2.00%	2.46%	1.90%	1.16%	3.61%	1.76%	2.83%	1.08%	**3.11%**
1.1	3 MA3m YC	4.88%	3.06%	2.18%	4.20%	6.15%	120.45%	4.39%	8.32%	2.44%	**4.45%**
1.11	3 PCASD & 3 MA3mYC	4.16%	1.81%	1.99%	1.41%	1.35%	4.27%	1.87%	3.02%	1.13%	**2.33%**
1.12	3 AllPCA & 3 MA3mYC	4.11%	1.86%	1.79%	1.40%	1.41%	4.92%	1.86%	3.05%	1.55%	**2.44%**
1.13	3 YC Proxies & 3 MA3m YC	3.97%	1.67%	1.70%	1.19%	1.20%	4.06%	1.63%	3.80%	0.86%	**2.23%**
	Studied market predictions total errors Average	**7.10%**	**3.33%**	**3.69%**	**3.60%**	**3.37%**	**17.15%**	**2.56%**	**4.56%**	**1.48%**	

Source: Authors' own calculations

We have presented in table 4.26 the results of the 3m horizon total errors for all models and all countries. We have removed as well from the averages of models 1.07 and 1.10 the total errors of

[19] Lowest total error for the 1m horizon

Egypt as they are outliers. As you will be able to conclude that model 1.12 of the three AllPCAs and three 3m Moving Averages performed best for the 3m horizon, as its total errors average was the lowest at 3.48%. We have sorted out the average of the 3m total errors from the lowest to the highest in table 4.27 in Appendix D. As it is clear from table 4.27 **that the information contained in macro variables (AllPCA) contributed in the prediction of yield curves for longer horizons**, i.e., 3m, as all models containing AllPCA ranked better in general for this horizon. Our results are consistent with findings from academic literature. For example, Ang and Piazzesi (2003) showed that macro variables explain up to 85% of the forecast variance of yields long term forecast horizons; Diebold et al. (2006) found out strong evidence of the effects of macro variables on future movements in yields; Pooter et al. (2010) found out that adding macroeconomic info improved the forecasting accuracy for yields.

Table 4.26 total errors per model and studied market for the 3m horizon

Model number	Model inputs	BRA	US	MEX	UK	EUR	EGP	SAF	IND	CHI	Model predictions total errors Average
1.01	3 PCASD	12.57%	6.68%	13.67%	9.55%	8.15%	13.19%	4.65%	8.84%	2.40%	**8.86%**
1.02	3 AllPCA	11.16%	6.66%	8.07%	7.53%	9.48%	13.85%	4.44%	7.65%	2.39%	**7.92%**
1.03	3 PCASD & 3 AllPCA	10.35%	9.02%	8.65%	9.24%	9.02%	13.64%	4.48%	7.00%	2.34%	**8.19%**
1.04	7 AR YC	6.39%	2.23%	2.69%	3.01%	3.05%	6.56%	2.53%	3.61%	7.13%	**4.13%**
1.05	3 PCASD & 3 AR YC	6.14%	2.66%	2.71%	1.97%	3.48%	6.99%	2.55%	4.69%	1.67%	**3.65%**
1.06	3 AllPCA & 3 AR YC	6.85%	2.28%	6.74%	3.54%	2.30%	6.93%	2.67%	4.73%	1.63%	**4.18%**
1.07	3 YC Proxies	16.36%	2.16%	2.30%	21.03%	3.30%	44.83%	2.66%	3.08%	1.76%	**6.58%**
1.08	3 PCASD & 3 YC Proxies	6.31%	2.62%	2.56%	2.40%	1.98%	7.50%	2.53%	5.00%	1.62%	**3.61%**
1.09	3 AllPCA & 3 YC Proxies	10.58%	2.69%	2.78%	2.64%	2.16%	7.39%	2.47%	4.18%	1.62%	**4.06%**
1.1	3 MA3m YC	10.11%	2.44%	2.94%	14.38%	5.40%	370.08%	4.44%	8.17%	2.46%	**6.29%**
1.11	3 PCASD & 3 MA3mYC	6.49%	2.43%	2.68%	2.07%	2.05%	7.65%	2.77%	4.47%	1.68%	**3.59%**
1.12	3 AllPCA & 3 MA3mYC	6.22%	2.33%	2.73%	2.05%	2.01%	6.86%	2.65%	4.60%	1.88%	[20]**3.48%**
1.13	3 YC Proxies & 3 MA3m YC	8.60%	2.56%	2.62%	2.19%	1.83%	7.26%	2.51%	4.64%	1.66%	**3.76%**
	Studied market predictions total errors Average	**9.09%**	**3.60%**	**4.70%**	**6.28%**	**4.17%**	**39.44%**	**3.18%**	**5.43%**	**2.33%**	

Source: Authors' own calculations

We have presented in table 4.28 the results of the 6m horizon total errors for all models and all countries. We have removed as well from the averages of models 1.07 and 1.10 the total errors of

[20] Lowest total error for the 3m horizon

Egypt as they are outliers. As you will be able to conclude that model 1.08 performed best as well for the 6m horizon, as its total errors average was the lowest at 4.99%. We have sorted out the average of the 6m total errors from the lowest to the highest in table 4.29 in Appendix D, as it is clear that **the models containing yield curve latent factors (PCASD) and macro variables (AllPCA) performed better than the Autoregressive model 1.04 that performed even worse for longer forecasted horizons**.

Table 4.28 total errors per model and studied market for the 6m horizon

Model number	Model inputs	BRA	US	MEX	UK	EUR	EGP	SAF	IND	CHI	Model predictions total errors Average
1.01	3 PCASD	12.35%	7.61%	8.33%	8.51%	8.75%	13.83%	4.64%	8.91%	2.46%	**8.38%**
1.02	3 AllPCA	11.41%	6.47%	7.55%	7.87%	9.54%	14.26%	4.49%	7.60%	2.45%	**7.96%**
1.03	3 PCASD & 3 AllPCA	13.36%	9.94%	12.55%	9.08%	9.00%	13.75%	4.60%	7.27%	2.35%	**9.10%**
1.04	7 AR YC	13.10%	3.26%	4.21%	3.38%	3.77%	9.29%	3.44%	4.97%	15.08%	**6.72%**
1.05	3 PCASD & 3 AR YC	8.92%	2.88%	4.43%	2.69%	2.75%	11.92%	3.44%	6.10%	2.21%	**5.04%**
1.06	3 AllPCA & 3 AR YC	12.25%	3.34%	3.71%	4.53%	3.30%	11.65%	3.19%	6.08%	2.19%	**5.58%**
1.07	3 YC Proxies	19.52%	3.45%	3.60%	3.89%	7.38%	53.96%	3.18%	3.64%	2.37%	**5.88%**
1.08	3 PCASD & 3 YC Proxies	9.10%	3.58%	4.23%	3.14%	3.20%	10.08%	2.96%	6.48%	2.14%	[21] **4.99%**
1.09	3 AllPCA & 3 YC Proxies	19.50%	8.55%	3.92%	3.61%	3.76%	10.13%	3.19%	5.58%	2.10%	**6.71%**
1.1	3 MA3m YC	16.68%	2.45%	3.84%	6.54%	10.68%	349.75%	4.55%	8.15%	2.49%	**6.92%**
1.11	3 PCASD & 3 MA3mYC	8.76%	3.39%	4.09%	3.06%	2.79%	12.10%	3.28%	5.98%	2.19%	**5.07%**
1.12	3 AllPCA & 3 MA3mYC	8.72%	4.03%	4.04%	3.01%	3.07%	10.69%	3.01%	6.27%	2.27%	**5.01%**
1.13	3 YC Proxies & 3 MA3m YC	9.81%	3.43%	4.05%	3.12%	3.01%	9.02%	3.11%	8.00%	2.10%	**5.07%**
	Studied market predictions total errors Average	**12.58%**	**4.80%**	**5.27%**	**4.80%**	**5.46%**	**40.80%**	**3.62%**	**6.54%**	**3.26%**	

Source: Authors' own calculations

We have presented in table 4.30 in Appendix D the total error combined for all horizons in order to select one model that performed best. As it is clear that model 1.08 performed best as it had the lowest combined total error for all horizons and for all studied markets equivalent to 10.67%. Model 1.08 was a stable model across almost all studied markets, compared to the Autoregressive model 1.04 that performed the best for the US, however, was not stable across the rest of the studied markets.

[21] Lowest total error for the 6m horizon

In order to estimate the accuracy of our results, we have used the coefficient of determination R2 by regressing the target variable (dependent variable) against the predicted variable (independent variable) to measure the proportion of the variation in the target variable that was explained by the variation in the predicted variable. More precisely, we have measured the R2 of each predicted yield curve against its target, and then we have taken the average of these R2 per horizon forecasted and per country as illustrated in table 4.31. Concerning the 1m horizon, we were able to achieve a 91.6% (1m mean R2) prediction accuracy on average for the training data, compared to 80.2% prediction accuracy for the out of sample R2. Our average predictions RMSE for the 1-mth prediction horizon for all markets was equivalent to 0.0207, compared to Nunes et al. (2019) RMSE prediction result of 0.045, and Vela (2013) RMSE of 0.0041 based on Singletask yield curves predictions of Latin American countries. Concerning the 3m horizon, the accuracy of the predictions drops to 80.4% for the training data, compared to 45.4% for the out of sample data. Finally, concerning the 6m horizon, the accuracy of the forecast drops even further to 66.1% for the training data, compared to 31.5% for the out of sample data. Comparatively, Vela (2013) longer-term forecasting horizons were not conclusive, since in some cases his prediction results outperformed parametric models, but in other cases the results did not exceed the random walk.

Table 4.31 training and out of sample prediction accuracy results measured by R2

Training data	**BRA**	**CHI**	**EGP**	**EUR**	**IND**	**MEX**	**SAF**	**UK**	**US**	
Horizon	**Training R2**	**Training R2**	**Training R2**	**Training R2**	**Training R2**	**Training R2**	**Training R2**	**Training R2**	**Training R2**	**Average Prediction Accuracy R2**
1m	89.54%	86.10%	87.08%	98.03%	84.65%	95.72%	87.92%	98.36%	97.04%	**91.60%**
3m	78.24%	58.90%	68.91%	93.17%	70.90%	90.46%	74.25%	94.48%	94.48%	**80.42%**
6m	60.67%	24.49%	45.47%	82.86%	55.19%	84.77%	67.89%	85.95%	88.35%	**66.18%**
Outsample data	**BRA**	**CHI**	**EGP**	**EUR**	**IND**	**MEX**	**SAF**	**UK**	**US**	
Horizon	**Outsample R2**	**Outsample R2**	**Outsample R2**	**Outsample R2**	**Outsample R2**	**Outsample R2**	**Outsample R2**	**Outsample R2**	**Outsample R2**	**Average Prediction Accuracy R2**
1m	90.48%	78.02%	86.91%	73.26%	75.48%	95.64%	55.73%	77.33%	89.01%	**80.21%**
3m	61.76%	57.44%	55.58%	21.40%	25.43%	90.42%	21.76%	20.15%	55.34%	**45.47%**
6m	36.02%	30.91%	38.41%	21.95%	5.69%	81.39%	12.04%	27.82%	29.25%	**31.50%**
Average R2	**BRA**	**CHI**	**EGP**	**EUR**	**IND**	**MEX**	**SAF**	**UK**	**US**	
Horizon	**Average R2**	**Average R2**	**Average R2**	**Average R2**	**Average R2**	**Average R2**	**Average R2**	**Average R2**	**Average R2**	**Average Prediction Accuracy R2**

1m	90.01%	82.06%	86.99%	85.64%	80.06%	95.68%	71.83%	87.85%	93.03%	**85.91%**
3m	70.00%	58.17%	62.25%	57.28%	48.16%	90.44%	48.01%	57.31%	74.91%	**62.95%**
6m	48.34%	27.70%	41.94%	52.41%	30.44%	83.08%	39.97%	56.89%	58.80%	**48.84%**

Source: Authors' own calculations

We have illustrated in Figure 4.5 the prediction accuracy versus the horizon forecasted. As you will be able to conclude that the mean of the prediction accuracy total errors rose linearly with the horizon forecasted from 4% for the 1m horizon to 6.3% for the 6m horizon, as the prediction accuracy R2 for the training data accuracy dropped as well almost linearly from 91% for the 1m horizon to 66% for the 6m horizon. Though, the R2 for the out of sample data dropped significantly non-linearly by 34% from the 1m to the 3m horizon, compared to only a drop of 13.9% from the 3m to the 6m horizon. Therefore, we are able to conclude that the total error (RMSE) along with the R2 on the training data behaved almost linearly with the horizon, however, the deterioration of the prediction accuracy on the out of sample data was non-linear, and significantly higher than the deterioration in the prediction accuracy on the training data.

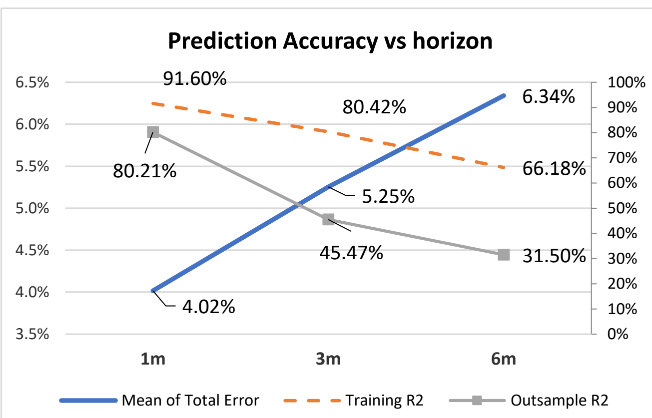
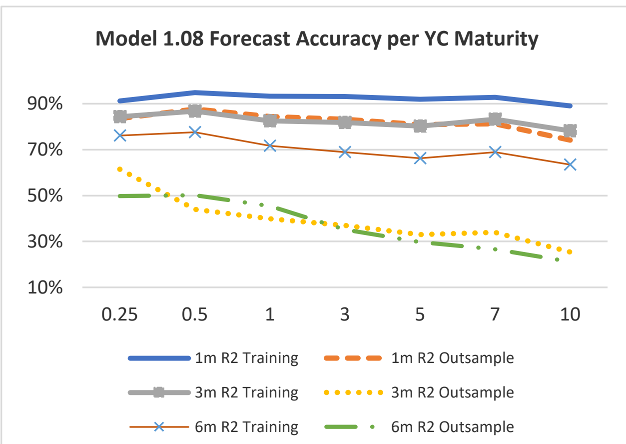


Figure 4.5 Prediction Accuracy vs Horizon
Source: Authors' own calculations

In order to analyze the forecast accuracy per yield curve maturity or tenor, we have illustrated in Figure 4.6 and table 4.32 the average of the forecast R2 for model 1.08 and 1.07 for the nine studied markets per maturity forecasted. As it is clear that the forecast accuracy dropped with the maturity, meaning that the average forecast accuracy R2 for the 3m (0.25) tenor was higher than the 10Y (10) tenor for all horizons, with a more pronounced deviation for the out of sample R2 and for longer horizons. For example, for model 1.08, the 1m horizon out of sample average forecast accuracy R2 for the 3m yield was equivalent to 83%, compared to 74% for the 10Y tenor, a drop of 9% in the accuracy. On the other hand, the 6m horizon out of sample average forecast accuracy R2 for the 3m yield was equivalent to 49%, compared to 21% for the 10Y yield, a drop of 28% in the forecast accuracy. The same was also observed for model 1.07 where the forecast accuracy dropped for longer tenors and was more pronounced for the out of sample data, though, it did not increase with the forecasted horizon. Sambasivan & Das (2017) addressed that matter and used a hybrid model, based on a combination of machine learning and Gaussian processes, in order to the improve the forecasts for medium/longer term yield maturities.



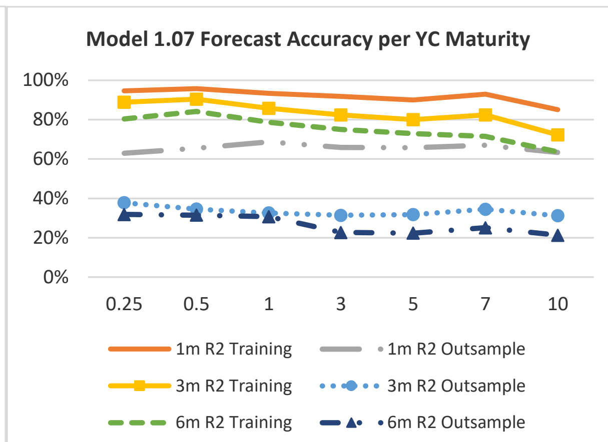


Figure 4.6 Average forecast accuracy vs maturity
Source: Authors' own calculations

Table 4.32 Average forecast accuracy vs maturity

Maturity	0.25 (3m)	0.5 (6m)	1 (1Y)	3 (3Y)	5 (5Y)	7 (7Y)	10 (10Y)	Difference between 0.25-10
Model 1.08 1m R2 Training	91.17 %	94.80%	93.28%	93.07%	91.96%	92.82%	88.98%	2.19%
Model 1.08 1m R2 Outsample	83.51 %	87.67%	84.35%	83.23%	80.82%	81.24%	74.16%	9.36%
Model 1.08 3m R2 Training	84.36 %	86.78%	82.53%	81.76%	80.16%	83.17%	78.20%	6.16%
Model 1.08 3m R2 Outsample	61.48 %	44.01%	39.90%	36.92%	33.02%	33.96%	25.45%	36.03%
Model 1.08 6m R2 Training	76.14 %	77.57%	71.67%	68.89%	66.18%	68.91%	63.39%	12.75%
Model 1.08 6m R2 Outsample	49.75 %	50.09%	45.43%	35.19%	29.79%	26.58%	21.14%	28.62%

Maturity	0.25 (3m)	0.5 (6m)	1 (1Y)	3 (3Y)	5 (5Y)	7 (7Y)	10 (10Y)	Difference between 0.25-10
Model 1.07 1m R2 Training	94.64 %	95.72%	93.36%	91.81%	90.00%	92.96%	85.01%	9.63%
Model 1.07 1m R2 Outsample	62.93 %	65.49%	68.65%	65.86%	65.79%	67.02%	63.35%	-0.42%
Model 1.07 3m R2 Training	88.79 %	90.35%	85.74%	82.32%	79.95%	82.41%	72.21%	16.58%
Model 1.07 3m R2 Outsample	37.84 %	34.56%	32.64%	31.40%	31.78%	34.50%	31.17%	6.67%
Model 1.07 6m R2 Training	80.35 %	84.20%	78.68%	74.96%	72.97%	71.55%	63.69%	16.66%
Model 1.07 6m R2 Outsample	31.84 %	31.50%	30.68%	22.70%	22.34%	25.09%	21.26%	10.58%

Source: Authors' own calculations

4.2.2 Singletask vs Multitask

In order to measure the difference between ANN Singletask and Multitask learning prediction accuracy, we have used model 1.08 and reduced the number of output nodes (O) or predicted yields, and computed the error term and R2 for the training and out of sample data, as illustrated in Figure 4.7. The training error behaved linearly for the three horizons forecasted: the 1m, 3m and 6m. For example, the training error for the 1m horizon was 0.20% with a single output node (1O), rising to 0.74% when the output nodes rose to seven (7O), or when the predicted yield points became seven all at once. In addition, for the three forecasted horizons, the out of sample error behaved non-linearly and deviated from the training error as we added output nodes. On the other hand, the forecast accuracy R2 for the training and out of sample data behaved non-linearly as well. The prediction accuracy, measured by the R2 (training and outsample R2), did not seem to be affected much for the first three output nodes (1O to 3O) or for the model with one to three predicted yields at once, meaning, the Singletask learning accuracy seemed to have almost similar accuracy as Multitask learning for up to three output nodes (3O), or three predicted yields at once. From the fourth to the seventh output node (4O to 7O), the predictions lost accuracy with a falling R2 for both training and out of sample data. For example, for the 3m horizon the training R2 for a single output node (1O) was equivalent to 96.89%, dropping to only 96.61% for three output nodes (3O), compared to a drop to 90% for seven output nodes (7O). The out of sample R2 behaved similarly to the training R2. Contrarily to our findings, Nunes et al. (2019) did not find a clear differentiation between Single and Multitask prediction accuracy. Taking into consideration that Nunes et al. (2019) used only 5O and a 20 days forecasted horizon, thus, our longer forecasted horizons and additional output nodes caused a higher deterioration in the prediction accuracy.

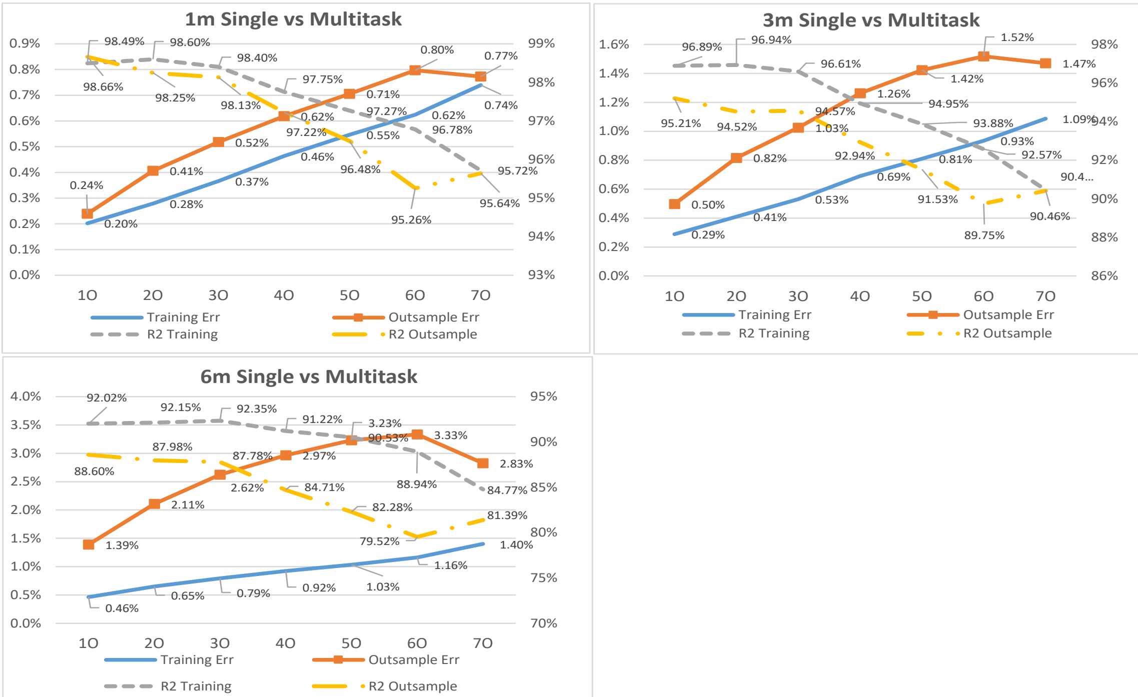


Figure 4.7 Singletask vs Multitask prediction accuracy R2 and training error per output node

Source: Authors' own calculations

4.2.3 Sigmoid Regression Hidden Layer Nodes Sensitivity

Based on the linear regression performed on the sensitivity analysis of the error term, where the independent variables were: the number of hidden nodes (H), the number of forecasted months (F), and the number of output nodes (O); against each dependent variable: training error first, out of sample error second, R2 training third, and finally R2 out of sample, as illustrated in table 4.33.

Table 4.33 Hidden nodes, forecast horizon, and output nodes impact on the error term regression results

	Model 1.04		**Model 1.07**		**Model 1.08**	
Training Error	**R2** 72.06%		**R2** 86.53%		**R2** 89.15%	
	Coefficients	***P-value***	***Coefficients***	***P-value***	***Coefficients***	***P-value***
H	-0.07%	0.33%	-0.07%	0.00%	-0.06%	-0.05%
F	0.11%	0.00%	0.09%	0.00%	0.11%	0.12%
O	0.19%	0.00%	0.14%	0.00%	0.15%	0.16%
Outsample Error	**R2** 86.58%		**R2** 81.01%		**R2** 75.65%	
	Coefficients	***P-value***	***Coefficients***	***P-value***	***Coefficients***	***P-value***

	Model 1.04		Model 1.07		Model 1.08	
H	-0.01%	**[22]55.51%**	0.03%	**[22]36.75%**	0.05%	0.09%
F	0.28%	0.00%	0.29%	0.00%	0.33%	0.34%
O	0.21%	0.00%	0.15%	0.00%	0.14%	0.21%
R2 Training	**R2** 79.05%		**R2** 77.80%		**R2** 85.04%	
	Coefficients	***P-value***	***Coefficients***	***P-value***	***Coefficients***	***P-value***
H	0.91%	0.01%	1.43%	0.00%	1.13%	1.99%
F	-1.51%	0.00%	-1.71%	0.00%	-2.04%	-1.25%
O	-1.90%	0.00%	-1.46%	0.00%	-1.62%	-0.99%
R2 Outsample	**R2** 87.65%		**R2** 80.69%		**R2** 67.14%	
	Coefficients	***P-value***	***Coefficients***	***P-value***	***Coefficients***	***P-value***
H	-0.49%	1.28%	-0.41%	**[22]15.80%**	-0.05%	0.17%
F	-2.46%	0.00%	-2.38%	0.00%	-2.68%	-1.89%
O	-1.75%	0.00%	-1.69%	0.00%	-1.43%	-1.19%

Source: Authors' own calculations

Illustrated in table 4.33 the results of our regressions. As it is clear, the number of hidden nodes (H), the forecast horizon per month (F), and the number of output nodes (O) did seem to have an impact on the training error, as all their P-values were statistically significant. For example, increasing the number of hidden nodes (H) decreased the training error for all three models (by -0.07% for models 1.04 and 1.07), **since increasing H causes the model to overfit the data, hence, we recommend the use of simple hidden layer structures**, which is consistent with academic literature recommendations. In fact, a significant number of nodes leads to inadequate results in the optimization and increases the probability that the parameters converge to a local optimum (Hamzacebi et al., 2009). In light of the above, it is recommended to set up the neural networks based on a simple architecture. Dunis & Morrison (2007) forecasted 10-year gov bond yields based on five hidden nodes. Jahn (2018) used three hidden neurons to predict the GDP of fifteen developed countries. Nunes et al. (2019) used ten hidden units in order to forecast yield curves based on Multitask learning. Chuku et al. (2019) used from three to four hidden nodes to forecast the GDP of African countries.

[22] Not statistically significant

Moreover, increasing the forecasted horizon (F), increased the training error for all three models (by +0.11% for model 1.04 and 1.08). Adding to the fact that the training error rose with the number of output nodes (O) for all three models (by + 0.19% for model 1.04). Comparably, we got similar results from the third regression, when R2 on the training data was the dependent variable, where increasing H improved the forecast accuracy R2 for all three models (by +0.91% for model 1.04), and increasing F decreased the forecast accuracy R2 for all three models (by -1.71% for model 1.07), and finally increasing O decreased the forecast accuracy R2 for all three models as well (by -1.46% for model 1.07). We have concluded that increasing the forecast horizon (F) caused a higher deterioration in the model accuracy R2 for two models (models 1.07 and 1.08), than increasing the output nodes O, as their regression coefficients were more negatively pronounced. Concerning regression two, when the out of sample error was the dependent variable, H was not statically significant for two models (models 1.04 and 1.07) and the coefficient for the third model was almost zero (0.05%), **meaning that H had no impact on the out of sample error or at least its impact might not be linear, hence, we do not recommend using the out of sample error as a selection criteria for the optimum number of hidden nodes**. Contrarily to one academic scholars, Nunes et al. (2019) who used the out of sample error as a selection criterion for the number of hidden nodes. In addition, F and O seemed to have a negative impact on the out of sample error, with a higher magnitude for F. These results from regression two (out of sample error) were similar to the results obtained from regression four (R2 out of sample) for the impact of F and O. Referring to H, it had a negative impact on the out of sample R2 for models 1.04 & 1.08, **meaning that increasing the number of hidden nodes H caused a deterioration in the out of sample accuracy R2**. In addition, the impact of F was higher than O as for the results in regression two.

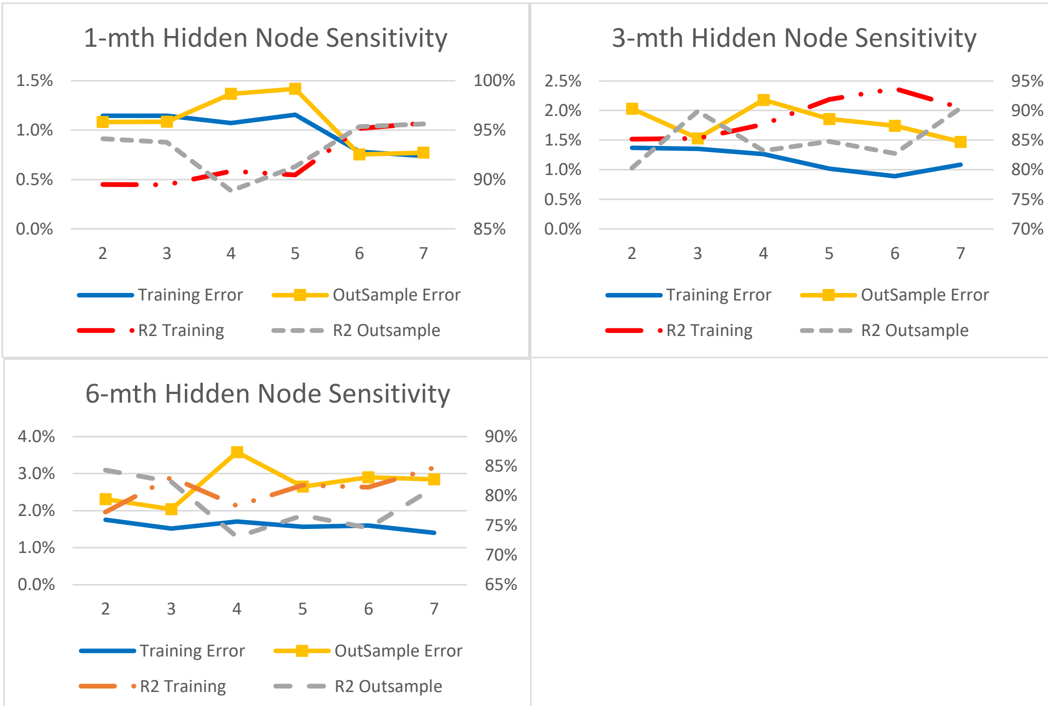


Figure 4.8 the impact of changing the hidden nodes on the error term and prediction accuracy R2

Source: Authors' own calculations

Using the previous hidden nodes sensitivity results, we have defined a model that determines the optimum number of hidden nodes for a Sigmoid Neural Network model. Illustrated in Figure 4.8 an example of hidden node sensitivity for the three horizons forecasted for model 1.08, where we have plotted the training and out of sample errors along with the training and out of sample R2 per hidden node, varying from two to seven hidden nodes. For example, for the 1m horizon the training error did not change significantly from the second till the fifth hidden node, afterwards, the error dropped. In addition, the **out of sample error behavior was highly non-linear** as we have highlighted previously.

In order to facilitate the visualization of the hidden node impact on the error and R2, we have plotted in Figure 4.9 the total error (total error=training error+out of sample error) and average R2 (average R2 was the average of training and out of sample R2). For example, for the 1m horizon the total error dropped and average R2 rose after the fifth hidden node. For the horizon of 1m, the sixth node was the most optimum choice as the total error and average R2 did not change significantly afterwards. For the 3m horizon, the seventh node was the most optimum choice, in addition, the seventh node was the most optimum as well for the 6m horizon.

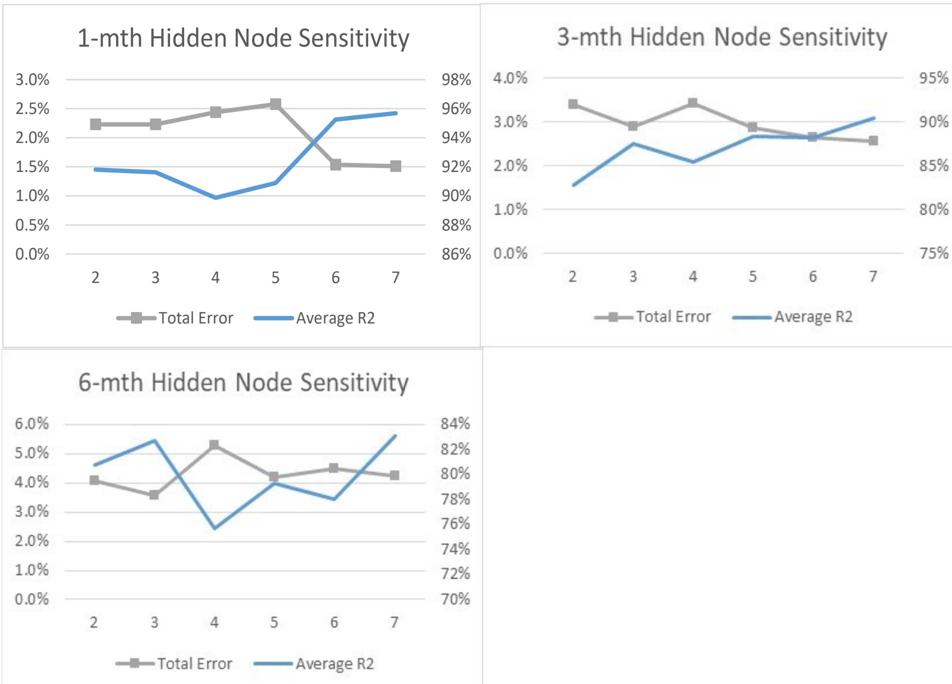


Figure 4.9 the impact of changing the hidden nodes on the total error and average R2
Source: Authors' own calculations

Followingly, after having selected the optimum number of hidden nodes per input nodes, output nodes, and forecast horizon, we have used this data and performed a linear regression where the dependent variable was the optimum number of hidden nodes (H) that we have selected, and the independent variables were: the number of inputs (I), number of output nodes (O), and the forecast horizon per month (F). Table 4.34 shows the regression results, as it is clear that all coefficients were statistically significant (F is significant at the 10% level). The intercept was equivalent to 1.8, meaning that the minimum number of hidden nodes for all models was equivalent to approximately 2. It was interesting to note that the coefficient for the output nodes O, equal to 0.42, was higher than the coefficient for the input nodes I, equal to 0.32. In other words, **the output nodes affected the optimum number of hidden nodes more than the input nodes**, unlike some of the academic literature that defined the appropriate number of hidden nodes as being an average between the input and output nodes, or 2/3 of inputs. In addition, the forecast horizon F had the lowest influence on the optimum number of hidden nodes, as its coefficient was the lowest. For example, a model with 6 inputs, 3 outputs, and a forecast horizon of 1m, would have an optimum number of hidden nodes equal to 5.21, approximately 5 nodes/neurons (1.83 + 6 x 0.32 + 3 x 0.42 + 1 x 0.20 = 5.21).

Table 4.34 Optimum hidden node regression results

Adjusted R2	45.52%	
	Coefficients	***P-value***
Intercept	1.83	3.65%
I	0.32	1.23%
O	0.42	0.09%
F	0.20	6.02%

Source: Authors' own calculations

4.2.4 Independent Variable Contribution Analysis

To the best of our knowledge, the Independent Variable Contribution analysis was not applied before in yield curve prediction, since the majority of academic work focusses on the techniques that provides the highest prediction results, rather than the predictive power of the variables, thus, the application of this method is one of the contributions of this study. Illustrated in table 4.35, the results of our Independent Variable Contribution weights per horizon forecasted for model 1.08. For the first forecast horizon of 1m, the weights were equally distributed among the inputs. We have illustrated in table 4.36 the variance in weights from a horizon to another, first from the 3m weights to the 1m weights, then from the 6m weights to the 1m weights. As illustrated in table 4.36, the weight of Slope on average (for all studied markets) increased by 3.63% from the 1m to the 3m horizon, and increased by 1.8% from the 1m to the 6m horizon. We have attributed the increase in Slope's weight to the considerable yield curve slope changes during the sample period, in fact, the term's spread (term spread = 10yr yield - 3m yield) standard deviation increased with the forecasted horizon. In addition, the weight of the yield curve short term proxy (shortYC) increased on average by 1.66% from the 1m to the 3m horizon, and increased as well by 4.81% from the 1m to the 6m horizon, due to the fact that during the sample period the short end of the yield curve changed with a higher magnitude than the rest of the yield curve. Therefore, **the Independent Variable Contribution cannot be generalized, as they depend on each market/country yield curve behavior**.

Table 4.35 Independent Variable Contribution weights per horizon forecast

Weights forecasted horizon	Level	Slope	Curvature	shortYC	mediumYC	longYC
Weights for the 1m horizon BRA	6.14%	19.78%	18.49%	15.97%	15.60%	24.01%
Weights for the 1m horizon CHI	35.73%	21.80%	4.95%	8.42%	22.65%	6.45%
Weights for the 1m horizon EGP	11.77%	7.69%	13.06%	20.43%	19.35%	27.71%
Weights for the 1m horizon EUR	8.94%	9.45%	11.32%	17.14%	30.55%	22.61%
Weights for the 1m horizon IND	20.90%	10.27%	16.83%	21.94%	10.60%	19.45%
Weights for the 1m horizon MEX	10.46%	11.16%	15.94%	18.89%	25.22%	18.33%
Weights for the 1m horizon SAF	15.98%	6.48%	14.64%	25.31%	15.81%	21.78%
Weights for the 1m horizon UK	9.37%	10.83%	11.93%	16.19%	29.14%	22.55%
Weights for the 1m horizon US	7.32%	16.91%	14.33%	16.32%	26.33%	18.80%
Average of 1m horizon weight for all studied markets	**14.07%**	**12.71%**	**13.50%**	**17.85%**	**21.69%**	**20.19%**
Weights for the 3m horizon BRA	5.93%	25.87%	14.96%	20.39%	14.98%	17.89%
Weights for the 3m horizon CHI	34.22%	23.06%	4.97%	6.73%	24.30%	6.72%
Weights for the 3m horizon EGP	12.47%	11.21%	12.63%	12.18%	15.92%	35.59%
Weights for the 3m horizon EUR	7.87%	6.93%	14.21%	18.19%	32.72%	20.08%
Weights for the 3m horizon IND	18.51%	10.88%	17.50%	36.24%	8.02%	8.84%
Weights for the 3m horizon MEX	4.09%	22.48%	11.34%	22.74%	21.28%	18.07%
Weights for the 3m horizon SAF	15.69%	6.18%	15.06%	32.98%	14.32%	15.77%
Weights for the 3m horizon UK	2.82%	21.02%	13.20%	12.27%	37.35%	13.34%
Weights for the 3m horizon US	3.04%	19.39%	13.20%	13.83%	28.41%	22.14%
Average of 3m horizon weight for all studied markets	**11.63%**	**16.33%**	**13.01%**	**19.51%**	**21.92%**	**17.60%**
Weights for the 6m horizon BRA	7.03%	23.20%	17.39%	20.92%	19.44%	12.03%
Weights for the 6m horizon CHI	33.98%	23.08%	5.14%	7.09%	23.49%	7.22%
Weights for the 6m horizon EGP	12.44%	11.72%	12.71%	11.79%	13.48%	37.87%
Weights for the 6m horizon EUR	8.48%	7.36%	14.61%	21.27%	29.67%	18.60%
Weights for the 6m horizon IND	18.56%	10.86%	17.48%	36.22%	8.03%	8.85%
Weights for the 6m horizon MEX	9.35%	19.45%	11.48%	23.44%	13.48%	22.79%
Weights for the 6m horizon SAF	17.95%	7.12%	18.78%	35.54%	9.75%	10.86%
Weights for the 6m horizon UK	7.40%	10.40%	8.50%	22.23%	29.83%	21.63%
Weights for the 6m horizon US	7.48%	17.39%	15.16%	25.42%	19.47%	15.08%
Average of 6m horizon weight for all studied markets	**13.63%**	**14.51%**	**13.47%**	**22.66%**	**18.52%**	**17.21%**

Source: Authors' own calculations

Table 4.36 Independent Variable Contribution weights change from one horizon to another

	Studied market	Level	Slope	Curvature	shortYC	mediumYC	longYC
Weights for 3m – weights for 1m	**BRA**	-0.21%	6.09%	-3.54%	4.41%	-0.62%	-6.13%
Weights for 3m – weights for 1m	**CHI**	-1.51%	1.26%	0.02%	-1.69%	1.65%	0.27%
Weights for 3m – weights for 1m	**EGP**	0.71%	3.52%	-0.42%	-8.25%	-3.43%	7.87%
Weights for 3m – weights for 1m	**EUR**	-1.07%	-2.53%	2.89%	1.05%	2.17%	-2.53%
Weights for 3m – weights for 1m	**IND**	-2.39%	0.61%	0.67%	14.30%	-2.58%	-10.61%
Weights for 3m – weights for 1m	**MEX**	-6.37%	11.32%	-4.60%	3.85%	-3.94%	-0.26%
Weights for 3m – weights for 1m	**SAF**	-0.29%	-0.30%	0.42%	7.67%	-1.49%	-6.02%
Weights for 3m – weights for 1m	**UK**	-6.55%	10.19%	1.27%	-3.92%	8.22%	-9.21%
Weights for 3m – weights for 1m	**US**	-4.28%	2.48%	-1.13%	-2.49%	2.08%	3.35%
	Average of weights	**-2.44%**	**3.63%**	**-0.49%**	**1.66%**	**0.23%**	**-2.58%**
Weights for 6m – weights for 1m	**BRA**	0.89%	3.42%	-1.11%	4.94%	3.83%	-11.98%
Weights for 6m – weights for 1m	**CHI**	-1.75%	1.28%	0.19%	-1.33%	0.84%	0.77%
Weights for 6m – weights for 1m	**EGP**	0.67%	4.03%	-0.35%	-8.64%	-5.87%	10.16%
Weights for 6m – weights for 1m	**EUR**	-0.46%	-2.09%	3.29%	4.13%	-0.88%	-4.00%
Weights for 6m – weights for 1m	**IND**	-2.33%	0.58%	0.65%	14.28%	-2.57%	-10.60%
Weights for 6m – weights for 1m	**MEX**	-1.11%	8.30%	-4.46%	4.55%	-11.73%	4.46%
Weights for 6m – weights for 1m	**SAF**	1.97%	0.64%	4.14%	10.23%	-6.07%	-10.92%
Weights for 6m – weights for 1m	**UK**	-1.96%	-0.43%	-3.42%	6.04%	0.70%	-0.92%
Weights for 6m – weights for 1m	**US**	0.16%	0.48%	0.83%	9.10%	-6.86%	-3.72%
	Average of weights	**-0.44%**	**1.80%**	**-0.02%**	**4.81%**	**-3.18%**	**-2.97%**

Source: Authors' own calculations

We have illustrated in table 4.37 the YC factors vs YC proxies weights by summing the weights for the three yield curve factors (YC factors=Level+ Slope+ Curvature) and the three yield curve proxies (YC proxies=shortYC+mediumYC+longYC). For example, for the 1m horizon the average of the YC factors and YC proxies weights were 40.27% and 59.73% respectively. These weights changed slightly when the forecasted horizon increased, more precisely, the YC factors average weights increased by 0.70% from the 1m to the 3m horizon, and they increased even further by 1.34% from the 1m to the 6m horizon, as illustrated in table 4.38. **Leading us to the conclusion that YC factors contain some information about future yields.**

Table 4.37 YC factors vs YC proxies weights

Studied market	Weights for 1m		Weights for 3m		Weights for 6m	
	YC factors	YC proxies	YC factors	YC proxies	YC factors	YC proxies
BRA	44.41%	55.59%	46.75%	53.25%	47.62%	52.38%

Studied market	Weights for 1m		Weights for 3m		Weights for 6m	
	YC factors	YC proxies	YC factors	YC proxies	YC factors	YC proxies
CHI	62.48%	37.52%	62.24%	37.76%	62.20%	37.80%
EGP	32.51%	67.49%	36.31%	63.69%	36.86%	63.14%
EUR	29.71%	70.29%	29.01%	70.99%	30.46%	69.54%
IND	48.00%	52.00%	46.89%	53.11%	46.90%	53.10%
MEX	37.56%	62.44%	37.91%	62.09%	40.29%	59.71%
SAF	37.09%	62.91%	36.93%	63.07%	43.85%	56.15%
UK	32.12%	67.88%	37.04%	62.96%	26.31%	73.69%
US	38.55%	61.45%	35.62%	64.38%	40.03%	59.97%
Average of weights	**40.27%**	**59.73%**	**40.97%**	**59.03%**	**41.61%**	**58.39%**

Source: Authors' own calculations

Table 4.38 YC factors vs YC proxies weights changes from one horizon to another

Studied market	Weights for 3m – weights for 1m		Weights for 6m – weights for 1m	
	YC factors	YC proxies	YC factors	YC proxies
BRA	2.34%	-2.34%	3.21%	-0.87%
CHI	-0.24%	0.24%	-0.28%	0.04%
EGP	3.81%	-3.81%	4.35%	-0.55%
EUR	-0.70%	0.70%	0.75%	-1.45%
IND	-1.11%	1.11%	-1.10%	-0.01%
MEX	0.34%	-0.34%	2.72%	-2.38%
SAF	-0.16%	0.16%	6.76%	-6.92%
UK	4.91%	-4.91%	-5.81%	10.73%
US	-2.93%	2.93%	1.48%	-4.41%
Average of weights	**0.70%**	**-0.70%**	**1.34%**	**-1.34%**

Source: Authors' own calculations

4.2.5 K-Fold Cross Validation

In table 4.39, we have illustrated the results of our original prediction accuracy (R2) on the out of sample data, named HoldOut period, compared to the k-fold cross validation (Kfold). The first portion of the table is the HoldOut period prediction accuracy on the out of sample data previously estimated, the second portion of the table is the Kfold prediction accuracy on the out of sample data, and the third and last potion of the table is the variance in the prediction accuracy between both techniques. For example, the average of the out of sample prediction accuracy R2 for the HoldOut 3m horizon was 45%, compared to 63% for the Kfold. It is clear from the last portion of the table that the Kfold improved the out of sample prediction accuracy R2 by 17.6% for the 3m horizon, and by 12.9% for the 6m horizon, though, the 1m accuracy improvement was very minimal. Hence, **the k-fold cross validation improved the accuracy R2 for longer forecast horizons, and it is not necessary to use such a computationally difficult technique for short term horizons forecasts**. Some academic scholars argued that the improvement in results caused by k-fold cross validation is optimistically biased and could lead to misleading results (Puglia & Tucker, 2020).

Table 4.39 HoldOut prediction accuracy compared to the K-fold cross validation results on the out of sample data

HoldOut prediction accuracy R2	BRA	CHI	EGP	EUR	IND	MEX	SAF	UK	US	
Horizon	**R2**	**R2**	**R2**	**R2**	**R2**	**R2**	**R2**	**R2**	**R2**	**Average of prediction accuracy per horizon**
1m	90.48%	78.02%	86.91%	73.26%	75.48%	95.64%	55.73%	77.33%	89.01%	**80.21%**
3m	61.76%	57.44%	55.58%	21.40%	25.43%	90.42%	21.76%	20.15%	55.34%	**45.47%**
6m	36.02%	30.91%	38.41%	21.95%	5.69%	81.39%	12.04%	27.82%	29.25%	**31.50%**
Kfold prediction accuracy R2	**BRA**	**CHI**	**EGP**	**EUR**	**IND**	**MEX**	**SAF**	**UK**	**US**	
Horizon	**R2**	**R2**	**R2**	**R2**	**R2**	**R2**	**R2**	**R2**	**R2**	**Average of prediction accuracy per horizon**
1m	94.21%	79.74%	90.08%	78.27%	62.32%	95.86%	59.42%	79.70%	91.73%	**81.26%**
3m	80.67%	59.26%	70.39%	54.32%	51.53%	90.30%	21.15%	59.99%	80.39%	**63.11%**
6m	54.63%	32.94%	50.49%	27.29%	21.38%	84.71%	12.94%	44.42%	71.23%	**44.45%**
Kfold prediction R2-HoldOut prediction R2	**BRA**	**CHI**	**EG**	**EU**	**IND**	**MEX**	**SAF**	**UK**	**US**	
Horizon	**R2**	**R2**	**R2**	**R2**	**R2**	**R2**	**R2**	**R2**	**R2**	**Average of prediction accuracy per horizon**
1m	3.73%	1.72%	3.17%	5.01%	13.17%	0.22%	3.68%	2.37%	2.72%	**1.05%**
3m	18.91%	1.82%	14.81%	32.92%	26.10%	-0.12%	-0.61%	39.84%	25.04%	**17.64%**
6m	18.62%	2.03%	12.08%	5.34%	15.69%	3.32%	0.89%	16.60%	41.98%	**12.95%**

Source: Authors' own calculations

In order to visualize how Kfold affected YC factors weights, previously computed from the Independent Variable Contribution, we have estimated the variance between the weights estimated using the Kfold (KfoldW) and the weight estimated using the original prediction HoldOut (HOW) in table 4.40. As its clear from table 4.40 that the YC factors weights contribution increased based on the Kfold for all horizons. For example, the Kfold increased the YC factors weights contribution by 2.57% for the 1m horizon, compared to an increase as well for the 6m horizon by 4.52%. In addition, we could also deduce that the yield curve factors add to the accuracy of long-term horizons, since their weights contribution increased with the forecasted horizons. Furthermore, the Curvature had forecasting power since its contribution increased constantly for the three horizons. For example, the Curvature increased in weights contribution by 1.64% for the 1m horizon, and by 3.65% for the 6m horizon, as illustrated in table 4.40.

Table 4.40 Variance between Kfold and HoldOut weights

KfoldW - HOW	YC factors	YC proxies	Level	Slope	Curvature	shortYC	mediumYC	longYC
1m	2.57%	-2.57%	-0.66%	1.59%	1.64%	-0.07%	-1.50%	-0.99%
3m	4.66%	-4.66%	1.56%	-0.21%	3.31%	1.00%	-4.62%	-1.04%
6m	4.52%	-4.52%	-0.29%	1.15%	3.65%	-1.86%	-0.79%	-1.87%

Source: Authors' own calculations

4.2.6 Summary of Yield Curves Predictions Findings

All results presented in this section are generalized and they provide the detailed answers to **RQ2-RQ6**, the synopsis of the answers was presented at the end of this section.

Forecasting Results

- The model with the three-yield curve latent factors and three yield curve proxies performed best for the 1m horizon as its total errors average was the lowest. These findings are consistent with our results in section 4.1, where the Level, Slope, and Curvature were mainly affected by the yield curve latent factors, and consistent with academic literature (Shareef and Shijin, 2017; Sowmya & Prasanna, 2018).
- The information contained in macro variables contributed in the prediction of yield curves for longer horizons, i.e., 3m and 6m, as all models containing macro variables ranked better in general for longer term horizons. Our results are consistent with findings from academic literature. For example, Ang and Piazzesi (2003) showed that macro variables explained up to 85% of the forecast variance of yields long term forecast horizons; Diebold et al. (2006) found out strong evidence of the effects of macro variables on future movements in yields; Pooter et al. (2010) found out that adding macroeconomic info improved the forecasting accuracy for yields.
- Concerning the 1m horizon, we were able to achieve an 80.2% prediction accuracy for the out of sample R2 (coefficient of determination), on average for all studied markets. These out of sample prediction results varied on average for all studied markets, from 95% for Mexico, and 90% for Brazil, to a low of 73% for the Euro Area, and 55% for

South Africa. Therefore, the prediction results differ considerably from a studied market to another. Similar to Vela (2013) that stated that his yield curves prediction results were highly dependent on the studied yield curve, as the yield curves of Mexico and the US are the ones where the neural networks forecasting models showed better results. Our average predictions RMSE for the 1-mth prediction horizon for all markets was equivalent to 0.0207, compared to Nunes et al. (2019) RMSE prediction result of 0.045, and Vela (2013) RMSE of 0.0041 based on Singletask yield curves predictions of Latin American countries.

- For the 3m horizon, the out of sample average predictions accuracy R2 for all studied markets dropped to 45.4%, ranging on average from 90% for Mexico, to 20% for the UK. Finally, the out of sample average predictions accuracy dropped even further to 31.5% for the 6m horizon. Hence, the deterioration of the prediction accuracy on the out of sample data was non-linear, and significantly higher than the deterioration in the prediction accuracy on the training data. Vela (2013) longer-term forecasting horizons were not conclusive, since in some cases his prediction results outperformed parametric models, but in other cases the results did not exceed the random walk.
- We have noted that the forecast accuracy dropped with the yields' maturities, meaning that the average forecast accuracy for the 3-month yield was higher than the 10-year yield tenor for all horizons, with a more pronounced deviation for the out of sample R2 and for longer horizons. Sambasivan & Das (2017) addressed that matter and used a hybrid model, based on a combination of machine learning and Gaussian processes, in order to improve the yield curve forecasts for longer term yields' maturities.

<u>Singletask vs Multitask</u>

Singletask learning accuracy seemed to have almost similar accuracy as Multitask learning for up to three output nodes (3O), or three predicted yields at once. From the fourth to the seventh output node (4O to 7O), the predictions lost accuracy, contrarily to our findings, Nunes et al. (2019) did not find a clear differentiation between Single and Multitask prediction accuracy. Taking into consideration that Nunes et al. (2019) used only 5O, and a 20 days forecasting horizon, thus, our longer forecasting horizons and additional output nodes caused a higher deterioration in the prediction accuracy.

Sensitivity Analysis on Out of Sample Error

The results in this section are based on the sensitivity analysis performed on the out of sample error, and its behavior versus the hidden nodes, forecasting horizon and output nodes. This type of analysis was not presented before in academic literature, as it is one of the contributions of this study.

Based on the results of the regression, where Y was the Training Error, and X were: the hidden nodes (H), forecasting horizons (F), and output nodes (O).

- Increasing the number of **H** decreased the training error, thus, increasing **H** leads to overfitting the data, which confirms academic literature recommendations. In fact, a significant number of nodes leads to inadequate results in the optimization and increases the probability that the parameters converge to a local optimum (Hamzacebi et al., 2009). In light of the above, it is recommended to set up the neural networks based on a simple architecture. Dunis & Morrison (2007) forecasted 10-year gov bond yields based on five hidden nodes. Jahn (2018) used three hidden neurons to predict the GDP of fifteen developed countries. Nunes et al. (2019) used ten hidden units in order to forecast yield curves based on Multitask learning. Chuku et al. (2019) used from three to four hidden nodes to forecast the GDP of African countries.
- Increasing **F** and **O** increased the training error, as it is theocratically expected.

Based on the results of the second regression, where Y was the out of sample error, and X were: the hidden nodes (H), forecasting horizon (F), and output nodes (O).

- The number of **H** was not statically significant, meaning that **H** had no impact on the out of sample error, contrary to one academic scholars, Nunes et al. (2019) who used the out of sample error as a selection criterion for the number of hidden nodes. Thus, we do not recommend using the out of sample of error as a selection criterion for the number of hidden nodes.
- **F** and **O** seemed to have a negative impact on the out of sample error.

Optimum Number of Hidden Nodes Model

Using the results of the sensitivity analysis performed on the out of sample error, we have designed a model that computes the optimum number of hidden nodes. The design of this model is one of the contributions of this study, as it was not conducted before in academic literature, as researchers base their selection criterion on trial and error or ad-hoc techniques (Moshiri & Cameron, 2000; Tkacz, 2001; Badea, 2013; Shah & Debnath, 2017; Jahn, 2018; Nunes et al., 2019; Chuku et al., 2019; Castello & Resta, 2022).

Based on the methodology described, we have performed a regression, where Y was the optimum number of hidden nodes, and X were: the input nodes (I), forecasting horizon (F), and output nodes (O). Our objective was to design a model that computes the optimum number of hidden nodes as a function of the number of inputs, forecasted months and output nodes.

- The intercept of the regression was equivalent to 1.8, meaning that the minimum number of hidden nodes for all models was equivalent to approximately 2.
- The coefficient for the **O** =+0.42 was higher than the coefficient for the **I** =+0.32, in other words, the output nodes affected the optimum number of hidden nodes more than the input nodes, unlike some of the academic literature that defined the appropriate number of hidden nodes as being an average between the input and output nodes, or 2/3 of inputs.
- **F** had the lowest influence on the optimum number of hidden nodes.
- As an example on the simplicity of the application of our model, 6 inputs, 3 outputs, and a forecast horizon of 1m, would have an optimum number of hidden nodes equal to 5.21, approximately 5 nodes/neurons ($1.83 + 6 \times 0.32 + 3 \times 0.42 + 1 \times 0.20 = 5.21$).

Independent Variable Contribution

The Independent Variable Contribution is a useful analysis of the relative importance of each variable in the prediction of the dependent variable in a neural network. To the best of our knowledge, this type of analysis was not used before in yield curve prediction, since the majority of academic work focusses on the techniques that provide the highest prediction results, rather than the predictive power of the variables, thus, the application of this method is one of the contributions of this study.

Based on our results, the weight of the Slope on average (for all studied markets) has increased by 3.63% from the 1m to the 3m horizon, and increased by 1.8% from the 1m to the 6m horizon. We have attributed the increase in Slope's weight to the considerable yield curve Slope changes during the sample period. Hence, the Independent Variable Contribution cannot be generalized, as they depend on each country's yield curve behavior and forecasted horizons.

K-Fold Cross Validation

K-fold Cross Validation improved the average out of sample forecast accuracy by 17.6% for the 3m horizon, and by 12.9% for the 6m horizon. In other words, k-fold Cross Validation had a significant impact on longer forecasted horizons, and it is not necessary to use such a computationally difficult technique for short term forecasts. Some academic scholars argued that the improvement in results caused by k-fold Cross Validation is optimistically biased and could lead to misleading results (Puglia & Tucker, 2020).

Answers to RQ2-RQ6 are summarized next:

- **RQ2:** Can ANN Regression Multitask learning be used in forecasting yield curves, in contrast to the Singletask learning currently applied by academic scholars?

  Answer to RQ2: ANN Multitask learning successfully predicted the yield curves of nine studied markets and was able to achieve an 80.2% prediction accuracy for the out of sample data on average, for all studied markets. Though, these prediction results varied drastically from a country to another, for example, the average prediction results varied from 95% for Mexico, to a low of 55% for South Africa. For the 3m horizon, the out of sample average predictions accuracy dropped to 45.4%, ranging on average from 90% for Mexico, to 20% for the UK.

- **RQ3:** How does the number of hidden nodes affect the training and out of sample error?

  Answer to RQ3: Increasing the number of hidden nodes decreased the training error, thus, increasing the number of hidden nodes leads to overfitting the data, which confirms academic literature recommendations. In light of the above, it is recommended to set up the neural networks based on a simple architecture. On the other hand, the number of hidden nodes had no impact on the out of sample error. Thus, we do not recommend using the out of sample of error as a selection criterion for the number of hidden nodes.

- **<u>RQ4:</u>** Can we design a scientific model that computes the optimum number of hidden nodes, rather than relying on the ad-hoc techniques currently applied by academic scholars?

  <u>Answer to RQ4:</u> We have successfully designed a model that computes the optimum number of hidden nodes as a function of the number of inputs, outputs and forecasted horizons. This simple model could be used by academic researchers to compute their optimum number of hidden nodes in an ANN hidden layer. In this model, the coefficient for the output nodes was higher than the coefficient for the input nodes, in other words, the output nodes affected the optimum number of hidden nodes more than the input nodes. Finally, the forecasting horizon had the lowest influence on the optimum number of hidden nodes. An example of our model application, an ANN with 6 inputs, 3 outputs, and a forecast horizon of 1m, would have an optimum number of hidden nodes equal to 5.21, approximately 5 nodes/neurons.

- **<u>RQ5:</u>** Can the Independent Variable Contribution Analysis provide useful insights on the predictive power of the variables?

  <u>Answer to RQ5:</u> The Independent Variable Contribution Analysis provided useful insights on the predictive power of the variables as the weight of the Slope on average has increased for longer term forecasts, due to the considerable yield curve Slope changes during the sample period. Hence, the Independent Variable Contribution cannot be generalized, as they depend on each country's yield curve behavior.

- **<u>RQ6:</u>** Does the k-fold Cross Validation improve the prediction accuracy?

  <u>Answer to RQ6:</u> K-fold Cross Validation improved the average prediction results mainly for longer term horizons. Hence, it is not necessary to use such a computationally difficult technique for short term forecasts.

4.3 Macro Variables Prediction using Three Classifiers: KNN, Sigmoid & Softmax

4.3.1 KNN Classifier Model Results

4.3.1.1 KNN EQUITY Prediction Results

We have illustrated in table 4.41 the EQUITY prediction results for all studied markets and all horizons. For example, we were able to predict 72.34% of the outcomes correctly for the Brazilian equity index for the 3m horizon using model 2.01, and we were able to reach a max prediction accuracy of 74.47% using model 2.04. In general, 74.47% was the highest prediction accuracy for this horizon reached for the Brazilian and Indonesian equity indices. The best EQUITY prediction model on average for this horizon was 2.01 reaching an average accuracy of 64.54%, **leading us to conclude that the yield curve latent factors contained valuable information on the future behavior of equity markets**. Model 2.01 was also the best prediction model for the equity markets for the horizon of 6m as well reaching an average prediction accuracy of 63.96%, leading us to sustain the same finding for the 3m horizon, where the yield curve seemed to be a good predictor for the equity markets for the 6m horizon as well. Noting that the highest prediction accuracy was equivalent to 79.55% for the 6m horizon. These findings are consistent with our results in section 4.1 and academic literature, where the yield curve factors had a leading effect on the EQUITY. According to Ahmed et al. (2017) interest rates Granger Caused the stock market. In addition, Bissoon et al. (2016) proved the negative relation between the interest rate and the stock market in the short and long run. However, for a longer horizon such as the 12m, model 2.04 seemed to outperform other models reaching an average prediction accuracy of 71.64%, meaning that **macro variables added very valuable information on long term horizon equity forecasts**. Noting that the highest prediction accuracy was equivalent to 84.21% for the 12m horizon. Thus, **the yield curve contained information on the shorter-term behavior of equity markets, and in order to improve the accuracy over longer term horizons, i.e., 12m, the inclusion of other macro variables data was necessary**. Similarly, academic scholars found evidence from macro variables effect on the EQUITY, for example, Ahmed et al. (2017) found a Causality relationship from the exchange rate to the stock market, and Fromentin (2022) found evidence of a Causality from the industrial production to the stock market.

Table 4.41 KNN Classifier EQUITY prediction accuracy results for all horizons

Studied market	Horizon	Model 2.01	Model 2.02	Model 2.03	Model 2.04	Predictions Max per studied market	Predictions Average per studied market
BRA	3m	72.34%	68.09%	70.21%	74.47%	**74.47%**	**71.28%**
CHI	3m	65.96%	55.32%	63.83%	70.21%	**70.21%**	**63.83%**
EGP	3m	57.45%	59.57%	61.70%	57.45%	**61.70%**	**59.04%**
EUR	3m	59.57%	55.32%	61.70%	59.57%	**61.70%**	**59.04%**
IND	3m	74.47%	68.09%	65.96%	65.96%	**74.47%**	**68.62%**
MEX	3m	63.83%	63.83%	63.83%	65.96%	**65.96%**	**64.36%**
SAF	3m	55.32%	55.32%	59.57%	55.32%	**59.57%**	**56.38%**
UK	3m	61.70%	59.57%	57.45%	59.57%	**61.70%**	**59.57%**
US	3m	70.21%	65.96%	65.96%	68.09%	**70.21%**	**67.55%**
	Predictions Averages	**64.54%**	**61.23%**	**63.36%**	**64.07%**		
BRA	6m	79.55%	75.00%	77.27%	75.00%	**79.55%**	**76.70%**
CHI	6m	65.96%	55.32%	63.83%	70.21%	**70.21%**	**63.83%**
EGP	6m	57.45%	59.57%	61.70%	57.45%	**61.70%**	**59.04%**
EUR	6m	54.55%	52.27%	56.82%	52.27%	**56.82%**	**53.98%**
IND	6m	70.45%	70.45%	70.45%	70.45%	**70.45%**	**70.45%**
MEX	6m	59.09%	59.09%	56.82%	56.82%	**59.09%**	**57.95%**
SAF	6m	56.82%	50.00%	52.27%	54.55%	**56.82%**	**53.41%**
UK	6m	59.09%	59.09%	56.82%	59.09%	**59.09%**	**58.52%**
US	6m	72.73%	72.73%	72.73%	79.55%	**79.55%**	**74.43%**
	Predictions Averages	**63.96%**	**61.50%**	**63.19%**	**63.93%**		
BRA	12m	84.21%	84.21%	84.21%	84.21%	**84.21%**	**84.21%**
CHI	12m	71.05%	57.89%	60.53%	71.05%	**71.05%**	**65.13%**
EGP	12m	71.05%	71.05%	81.58%	78.95%	**81.58%**	**75.66%**
EUR	12m	55.26%	52.63%	52.63%	55.26%	**55.26%**	**53.95%**
IND	12m	73.68%	73.68%	76.32%	73.68%	**76.32%**	**74.34%**
MEX	12m	68.42%	65.79%	65.79%	71.05%	**71.05%**	**67.76%**
SAF	12m	57.89%	57.89%	60.53%	57.89%	**60.53%**	**58.55%**
UK	12m	65.79%	65.79%	68.42%	71.05%	**71.05%**	**67.76%**
US	12m	81.58%	81.58%	81.58%	81.58%	**81.58%**	**81.58%**
	Predictions Averages	**69.88%**	**67.84%**	**70.18%**	**71.64%**		

Source: Authors' own calculations

Table 4.42 in Appendix E shows the averages of all EQUITY prediction accuracy per model for all studied markets and horizons. If we were to generalize and choose the best performing model for the equity markets, we would choose model 2.04 that yielded the highest prediction accuracy average of 66.55% for all horizons, although, model 2.01 based on the yield curve had a very close prediction accuracy average of 66.13%.

4.3.1.2 KNN FX Prediction Results

We have illustrated in table 4.43 the FX prediction results for all studied markets and all horizons. The best FX prediction model on average for the 3m horizon was model 2.03 of macro variables reaching an average prediction accuracy of 57.45%, though, the yield curve only model 2.01 average prediction results were very close. The maximum FX prediction accuracy for the 3m horizon was equivalent to 68.09%. Model 2.01 of yield curve factors was the best prediction model for the FX 6m horizon reaching an average prediction accuracy of 58.81%, while the maximum prediction accuracy for that horizon was 75%. Similar to the 3m horizon, the 12m horizon macro variables model 2.03 had the highest average prediction accuracy of 64.62%, while the maximum prediction accuracy for that tenor was equivalent to 78.95%. Thus, **macro variables seemed to hold predictive power over the future behavior of FX in each studied market**. Academic scholars also found evidence of the effect of macro variables on the FX, for example, Kearns & Manners (2005) confirmed that changes in the policy rate are rapidly transmitted into the foreign exchange rate, additionally, Dilmaghani & Tehranchian (2015) stated that the country's exchange rate is also affected by other macro variables such as the inflation and GDP.

Table 4.43 KNN Classifier FX prediction accuracy results for all horizons

Studied market	Horizon	Model 2.01	Model 2.02	Model 2.03	Model 2.04	Predictions Max per studied market	Predictions Average per studied market
BRA	3m	65.96%	48.94%	55.32%	65.96%	**65.96%**	**59.04%**
CHI	3m	42.55%	40.43%	46.81%	48.94%	**48.94%**	**44.68%**
EGP	3m	61.70%	57.45%	68.09%	57.45%	**68.09%**	**61.17%**
EUR	3m	53.19%	48.94%	59.57%	61.70%	**61.70%**	**55.85%**
IND	3m	68.09%	57.45%	61.70%	63.83%	**68.09%**	**62.77%**
MEX	3m	44.68%	31.91%	48.94%	40.43%	**48.94%**	**41.49%**
SAF	3m	61.70%	53.19%	61.70%	59.57%	**61.70%**	**59.04%**
UK	3m	63.83%	53.19%	55.32%	57.45%	**63.83%**	**57.45%**
US	3m	53.19%	44.68%	59.57%	44.68%	**59.57%**	**50.53%**
	Predictions Averages	**57.21%**	**48.46%**	**57.45%**	**55.56%**		
BRA	6m	61.36%	40.91%	54.55%	52.27%	**61.36%**	**52.27%**
CHI	6m	42.55%	40.43%	46.81%	48.94%	**48.94%**	**44.68%**

Studied market	Horizon	Model 2.01	Model 2.02	Model 2.03	Model 2.04	Predictions Max per studied market	Predictions Average per studied market
EGP	6m	61.70%	57.45%	68.09%	57.45%	**68.09%**	**61.17%**
EUR	6m	56.82%	45.45%	59.09%	59.09%	**59.09%**	**55.11%**
IND	6m	68.18%	72.73%	72.73%	75.00%	**75.00%**	**72.16%**
MEX	6m	47.73%	22.73%	45.45%	45.45%	**47.73%**	**40.34%**
SAF	6m	63.64%	47.73%	52.27%	61.36%	**63.64%**	**56.25%**
UK	6m	63.64%	40.91%	61.36%	68.18%	**68.18%**	**58.52%**
US	6m	63.64%	38.64%	59.09%	59.09%	**63.64%**	**55.11%**
	Predictions Averages	**58.81%**	**45.22%**	**57.72%**	**58.54%**		
BRA	12m	60.53%	60.53%	63.16%	60.53%	**63.16%**	**61.18%**
CHI	12m	31.58%	39.47%	36.84%	39.47%	**39.47%**	**36.84%**
EGP	12m	73.68%	73.68%	73.68%	73.68%	**73.68%**	**73.68%**
EUR	12m	60.53%	52.63%	63.16%	60.53%	**63.16%**	**59.21%**
IND	12m	73.68%	71.05%	76.32%	78.95%	**78.95%**	**75.00%**
MEX	12m	63.16%	28.95%	76.32%	63.16%	**76.32%**	**57.89%**
SAF	12m	50.00%	47.37%	55.26%	52.63%	**55.26%**	**51.32%**
UK	12m	68.42%	71.05%	73.68%	71.05%	**73.68%**	**71.05%**
US	12m	52.63%	36.84%	63.16%	57.89%	**63.16%**	**52.63%**
	Predictions Averages	**59.36%**	**53.51%**	**64.62%**	**61.99%**		

Source: Authors' own calculations

Table 4.44 in Appendix E shows the averages of all FX prediction accuracy per model for all studied markets and horizons. If we were to generalize and choose the best performing model for the FX, we would choose model 2.03 that yielded the highest prediction accuracy average of 59.93% for all horizons.

4.3.1.3 KNN POLRATE Prediction Results

We have illustrated in table 4.45 the POLRATE prediction results for all studied markets and all horizons. Interpreting the results of the POLRATE were a little bit different than the rest of the macro variables, cause macro variables have two states, whether upwards denoted by the binary value of 1 or downwards by the binary value of 0, which is different from the POLRATE in the sense that the variable can either move upwards, downwards, or remain unchanged. Therefore, for the POLRATE we have predicted whether the variable will move upwards or not. The best POLRATE prediction model on average for the 3m horizon was model 2.01 of yield curve factors reaching an average prediction accuracy of 76.6%. Although, the maximum prediction accuracy was equivalent to 100% for the Euro Area, the result is misleading cause some policy rates decreased to very low levels and did not change afterwards. Similarly, model 2.01 performed best for the 6m horizon as well reaching an average prediction accuracy of 71.49%. Though, for the 12m horizon model 2.04 of yield curve and macro variables had the highest average prediction accuracy level of 69.88%. Leading us to the conclusion that **the yield curve contained predictive power capabilities over the POLRATE for the horizon of 3m and 6m, similar to the equity predictions**. These results are consistent with academic literature, and our findings in section 4.1, where the POLRATE was mainly affected by yield curve factors, such as the Level and Slope, in fact, as we previously mentioned that the Level leads the POLRATE. **For a longer horizon like the 12m, the inclusion of macro variables data was necessary.** On the other hand, academic scholars found out evidence from the effect of macro variables on the POLRATE, such as Suhaibu et al. (2017) who stated that the relation between the stock markets and their respective monetary policies is bidirectional, and Olamide & Maredza (2019) who stated that the foreign exchange rate play a dominant role in determining the behavior of the monetary policy.

Table 4.45 KNN Classifier POLRATE prediction accuracy results for all horizons

Studied market	Horizon	Model 2.01	Model 2.02	Model 2.03	Model 2.04	Predictions Max per studied market	Predictions Average per studied market
BRA	3m	89.36%	93.62%	89.36%	89.36%	**93.62%**	**90.43%**
CHI	3m	100.00%	100.00%	100.00%	100.00%	**100.00%**	**100.00%**
EGP	3m	63.83%	68.09%	70.21%	63.83%	**70.21%**	**66.49%**
EUR	3m	100.00%	100.00%	100.00%	100.00%	**100.00%**	**100.00%**
IND	3m	85.11%	80.85%	87.23%	87.23%	**87.23%**	**85.11%**
MEX	3m	36.17%	38.30%	44.68%	31.91%	**44.68%**	**37.77%**
SAF	3m	72.34%	72.34%	72.34%	72.34%	**72.34%**	**72.34%**
UK	3m	89.36%	87.23%	87.23%	89.36%	**89.36%**	**88.30%**
US	3m	53.19%	42.55%	44.68%	44.68%	**53.19%**	**46.28%**
	Predictions Averages	76.60%	75.89%	77.30%	75.41%		
BRA	6m	86.36%	86.36%	86.36%	86.36%	**86.36%**	**86.36%**
CHI	6m	100.00%	100.00%	100.00%	100.00%	**100.00%**	**100.00%**
EGP	6m	63.83%	68.09%	70.21%	63.83%	**70.21%**	**66.49%**
EUR	6m	100.00%	100.00%	100.00%	100.00%	**100.00%**	**100.00%**
IND	6m	79.55%	79.55%	79.55%	79.55%	**79.55%**	**79.55%**

Studied market	Horizon	Model 2.01	Model 2.02	Model 2.03	Model 2.04	Predictions Max per studied market	Predictions Average per studied market
MEX	6m	34.09%	54.55%	29.55%	34.09%	**54.55%**	**38.07%**
SAF	6m	65.91%	59.09%	65.91%	68.18%	**68.18%**	**64.77%**
UK	6m	79.55%	72.73%	72.73%	75.00%	**79.55%**	**75.00%**
US	6m	34.09%	25.00%	27.27%	34.09%	**34.09%**	**30.11%**
	Predictions Averages	**71.49%**	**71.71%**	**70.18%**	**71.23%**		
BRA	12m	84.21%	68.42%	84.21%	84.21%	**84.21%**	**80.26%**
CHI	12m	100.00%	100.00%	100.00%	100.00%	**100.00%**	**100.00%**
EGP	12m	73.68%	65.79%	63.16%	76.32%	**76.32%**	**69.74%**
EUR	12m	100.00%	100.00%	100.00%	100.00%	**100.00%**	**100.00%**
IND	12m	78.95%	78.95%	78.95%	78.95%	**78.95%**	**78.95%**
MEX	12m	31.58%	34.21%	28.95%	39.47%	**39.47%**	**33.55%**
SAF	12m	63.16%	63.16%	71.05%	68.42%	**71.05%**	**66.45%**
UK	12m	60.53%	57.89%	60.53%	65.79%	**65.79%**	**61.18%**
US	12m	21.05%	0.00%	2.63%	15.79%	**21.05%**	**9.87%**
	Predictions Averages	**68.13%**	**63.16%**	**65.50%**	**69.88%**		

Source: Authors' own calculations

Table 4.46 in Appendix E shows the averages of all policy rates prediction accuracy per model for all studied markets and horizons. If we were to generalize and choose the best performing model for the policy rates, we would choose model 2.04 that yielded the highest prediction accuracy average of 72.18% for all horizons.

4.3.1.4 KNN GDP Prediction Results

We have illustrated in table 4.47 the GDP prediction results for all studied and all horizons. The best GDP prediction model on average for the 3m horizon was model 2.03 of macro variables reaching an average prediction accuracy of 67.14%. The maximum GDP prediction accuracy for the 3m horizon was equivalent to 80.85%, which is consistent with our previous findings in section 4.1, where the EQUITY, FX and INF led the GDP, adding to the fact that academic scholars proved the effect of the stock market, inflation and exchange rate on the country's GDP (Dilmaghani & Tehranchian, 2015; Plihal, 2016; Amaral et al., 2022). For longer term maturities, such as the 6m and 12m, model 2.02 with the Autoregressive inputs outperformed other models reaching an average prediction accuracy of 69.59% and 92.11% respectively. Thus,

the GDP past values seemed to have a dominant effect on the future performance of the GDP. Similarly, Clements & Galvao (2013) improved the prediction RMSE when forecasting output growth and inflation with an Autoregressive model on lightly revised data, and Adedotun & Taiwo (2020) used different types of Autoregressive models in order to predict the GDP.

Table 4.47 KNN Classifier GDP prediction accuracy results for all horizons

Studied market	Horizon	Model 2.01	Model 2.02	Model 2.03	Model 2.04	Predictions Max per studied market	Predictions Average per studied market
BRA	3m	65.96%	72.34%	74.47%	76.60%	**76.60%**	**72.34%**
CHI	3m	76.60%	74.47%	78.72%	80.85%	**80.85%**	**77.66%**
EGP	3m	74.47%	72.34%	78.72%	74.47%	**78.72%**	**75.00%**
EUR	3m	61.70%	48.94%	76.60%	68.09%	**76.60%**	**63.83%**
IND	3m	59.57%	61.70%	51.06%	61.70%	**61.70%**	**58.51%**
MEX	3m	59.57%	65.96%	63.83%	65.96%	**65.96%**	**63.83%**
SAF	3m	59.57%	63.83%	70.21%	59.57%	**70.21%**	**63.30%**
UK	3m	38.30%	70.21%	44.68%	44.68%	**70.21%**	**49.47%**
US	3m	46.81%	51.06%	65.96%	51.06%	**65.96%**	**53.72%**
	Predictions Averages	**60.28%**	**64.54%**	**67.14%**	**64.78%**		
BRA	6m	70.45%	70.45%	72.73%	75.00%	**75.00%**	**72.16%**
CHI	6m	76.60%	74.47%	78.72%	80.85%	**80.85%**	**77.66%**
EGP	6m	74.47%	72.34%	78.72%	74.47%	**78.72%**	**75.00%**
EUR	6m	65.91%	52.27%	61.36%	68.18%	**68.18%**	**61.93%**
IND	6m	47.73%	75.00%	47.73%	45.45%	**75.00%**	**53.98%**
MEX	6m	63.64%	65.91%	65.91%	63.64%	**65.91%**	**64.77%**
SAF	6m	47.73%	75.00%	61.36%	50.00%	**75.00%**	**58.52%**
UK	6m	50.00%	84.09%	52.27%	38.64%	**84.09%**	**56.25%**
US	6m	52.27%	56.82%	52.27%	54.55%	**56.82%**	**53.98%**
	Predictions Averages	**60.98%**	**69.59%**	**63.45%**	**61.20%**		
BRA	12m	60.53%	76.32%	71.05%	71.05%	**76.32%**	**69.74%**
CHI	12m	73.68%	71.05%	71.05%	71.05%	**73.68%**	**71.71%**
EGP	12m	78.95%	84.21%	76.32%	76.32%	**84.21%**	**78.95%**
EUR	12m	71.05%	23.68%	55.26%	63.16%	**71.05%**	**53.29%**
IND	12m	44.74%	86.84%	34.21%	31.58%	**86.84%**	**49.34%**
MEX	12m	63.16%	76.32%	68.42%	71.05%	**76.32%**	**69.74%**
SAF	12m	65.79%	86.84%	63.16%	52.63%	**86.84%**	**67.11%**
UK	12m	50.00%	92.11%	73.68%	39.47%	**92.11%**	**63.82%**
US	12m	52.63%	68.42%	39.47%	44.74%	**68.42%**	**51.32%**
	Predictions Averages	**62.28%**	**73.98%**	**61.40%**	**57.89%**		

Source: Authors' own calculations

Table 4.48 in Appendix E shows the averages of all GDP prediction accuracy per model for all studied markets and horizons. If we were to generalize and choose the best performing model for the GDP, we would choose model 2.02 that yielded the highest prediction accuracy average of 69.37% for all horizons.

4.3.1.5 KNN INF Prediction Results

We have illustrated in table 4.49 the INF prediction results for all studied markets and all horizons. The best **INF prediction model on average for the three forecasted maturities, was model 2.02 with the Autoregressive inputs**, reaching the max prediction accuracy on average of 70.76% for the 12m horizon. Accordingly, Nasr et al. (2015) found evidence that past information on inflation improves the future prediction of inflation, and Lanne & Luoto (2017) stated that both expected and lagged inflation dominate the current inflation level.

Table 4.49 KNN Classifier INF prediction accuracy results for all horizons

Studied market	Horizon	Model 2.01	Model 2.02	Model 2.03	Model 2.04	Predictions Max per studied market	Predictions Average per studied market
BRA	3m	55.32%	65.96%	63.83%	68.09%	**68.09%**	**63.30%**
CHI	3m	55.32%	65.96%	57.45%	57.45%	**65.96%**	**59.04%**
EGP	3m	57.45%	61.70%	65.96%	57.45%	**65.96%**	**60.64%**
EUR	3m	46.81%	61.70%	55.32%	48.94%	**61.70%**	**53.19%**
IND	3m	63.83%	63.83%	63.83%	63.83%	**63.83%**	**63.83%**
MEX	3m	61.70%	59.57%	59.57%	55.32%	**61.70%**	**59.04%**
SAF	3m	61.70%	59.57%	48.94%	53.19%	**61.70%**	**55.85%**
UK	3m	61.70%	72.34%	63.83%	63.83%	**72.34%**	**65.43%**
US	3m	61.70%	68.09%	53.19%	57.45%	**68.09%**	**60.11%**
	Predictions Averages	**58.39%**	**64.30%**	**59.10%**	**58.39%**		
BRA	6m	54.55%	70.45%	56.82%	59.09%	**70.45%**	**60.23%**
CHI	6m	55.32%	65.96%	57.45%	57.45%	**65.96%**	**59.04%**
EGP	6m	57.45%	61.70%	65.96%	57.45%	**65.96%**	**60.64%**
EUR	6m	47.73%	56.82%	43.18%	43.18%	**56.82%**	**47.73%**
IND	6m	43.18%	52.27%	54.55%	63.64%	**63.64%**	**53.41%**
MEX	6m	63.64%	70.45%	63.64%	63.64%	**70.45%**	**65.34%**
SAF	6m	61.36%	61.36%	50.00%	52.27%	**61.36%**	**56.25%**
UK	6m	50.00%	81.82%	63.64%	56.82%	**81.82%**	**63.07%**

Studied market	Horizon	Model 2.01	Model 2.02	Model 2.03	Model 2.04	Predictions Max per studied market	Predictions Average per studied market
US	6m	59.09%	93.18%	52.27%	61.36%	**93.18%**	**66.48%**
	Predictions Averages	**54.70%**	**68.22%**	**56.39%**	**57.21%**		
BRA	12m	47.37%	65.79%	50.00%	47.37%	**65.79%**	**52.63%**
CHI	12m	71.05%	73.68%	65.79%	65.79%	**73.68%**	**69.08%**
EGP	12m	57.89%	63.16%	65.79%	60.53%	**65.79%**	**61.84%**
EUR	12m	31.58%	65.79%	44.74%	39.47%	**65.79%**	**45.39%**
IND	12m	47.37%	55.26%	47.37%	50.00%	**55.26%**	**50.00%**
MEX	12m	57.89%	68.42%	55.26%	60.53%	**68.42%**	**60.53%**
SAF	12m	60.53%	68.42%	65.79%	65.79%	**68.42%**	**65.13%**
UK	12m	52.63%	84.21%	52.63%	44.74%	**84.21%**	**58.55%**
US	12m	81.58%	92.11%	78.95%	84.21%	**92.11%**	**84.21%**
	Predictions Averages	**56.43%**	**70.76%**	**58.48%**	**57.60%**		

Source: Authors' own calculations

Table 4.50 in Appendix E shows the averages of all INF prediction accuracy per model for all studied markets and horizons. Irrespective of the maturity, and similar to the previous section, the best performing model for the INF is the Autoregressive model 2.02 that yielded the highest prediction accuracy average of 67.76%% for all horizons.

4.3.1.6 Weighted KNN vs KNN

To the best of our knowledge, wKNN was not applied before for macro variables predictions, thus, the application of wKNN for macro variables predictions is one of the contributions of this study. We have summarized the wKNN prediction results in tables 4.51 and 4.52, and we have computed the variance in the prediction accuracy between the two techniques per horizon, where we have subtracted the prediction accuracy of the KNN from the wKNN, meaning wKNN minus KNN. For example, the application of wKNN caused a deterioration of the average prediction accuracy by -1.25% for the EQUITY 3m horizon, as illustrated in table 4.52. As you will be able to conclude that in general **wKNN, except for the FX 12m prediction, caused a deterioration in the prediction accuracy of almost all macro variables and horizons.**

Table 4.51 wKNN Classifier average predictions per macro variable and per horizon

Macro variable	3m	6m	12m	Variance from 12m to 3m	Best Prediction Model per Macro variable for the wKNN classifier
EQUITY	62.82%	62.69%	64.51%	**1.70%**	**2.04**
FX	54.61%	55.21%	73.19%	**18.58%**	**2.04**
POLRATE	73.76%	67.93%	62.28%	**-11.48%**	**2.04**
GDP	52.96%	57.66%	67.54%	**14.59%**	**2.04**
INF	58.39%	60.62%	64.33%	**5.94%**	**2.02**

Source: Authors' own calculations

Table 4.52 Variance in prediction between wKNN and KNN (wKNN-KNN)

Macro variable	3m	6m	12m
EQUITY	[23]-1.25%	-1.24%	-7.12%
FX	-2.84%	-2.51%	[24]8.57%
POLRATE	-1.65%	-3.30%	-7.60%
GDP	-11.58%	-11.94%	-6.43%
INF	-5.91%	-7.61%	-6.43%

Source: Authors' own calculations

4.3.1.7 K versus the Prediction Accuracy and the Forecasted Horizon

In this section, we have analyzed the behavior of K versus the maturity and prediction accuracy, and we have drawn important conclusions on the matter. The behavior of K in KNN prediction was not explored previously in academic literature, thus, the results presented in this section is one of this research contributions. Gathering the data for this section was computationally extensive, since it was necessary to gather all the prediction accuracies for all the Ks for the total of n in the data sample (training data), per studied market, and horizon forecasted.

We have plotted in Figure 4.10 the 3m prediction accuracy for the best performing model of the EQUITY, FX and GDP, per K, and studied market. The best performing models for the EQUITY, FX and GDP, were 2.04, 2.03 and 2.02 respectively. It's clear from the three graphs that the behavior of K is erratic, and it was not possible to indicate a pattern, though, we were able to at least state that **K is not a function of the prediction accuracy**, as when K increased,

[23] a negative sign means a deterioration in prediction accuracy cause wKNN prediction results were lower than KNN prediction results
[24] a positive sign means an improvement in prediction accuracy cause wKNN prediction results were higher than KNN prediction results

the prediction accuracy decreased or remained unchanged. For the same prediction model, forecasted horizon and predicted variable, the peak of the prediction accuracy was reached at completely different levels of K for each studied market.

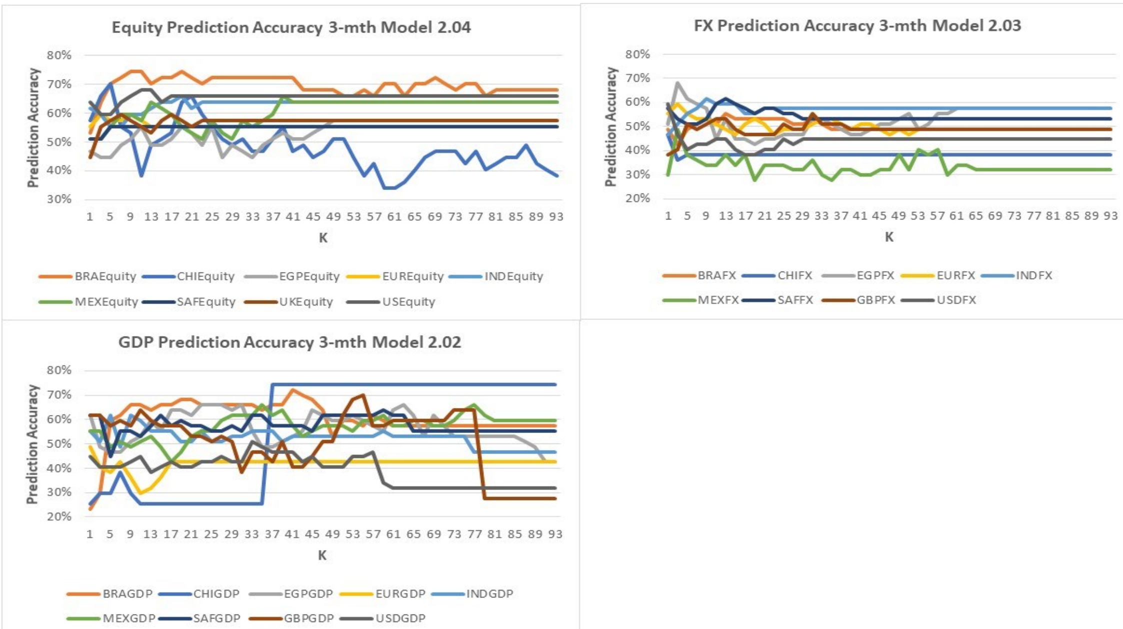


Figure 4.10 the 3m prediction accuracy for the best performing model of the EQUITY, FX and GDP, per K and studied market

Source: Authors' own calculations

In order to remove this erratic behavior, we have averaged the prediction accuracy of the best performing model, per K, per variable, per horizon forecasted, and studied market, as illustrated in Figure 4.11.

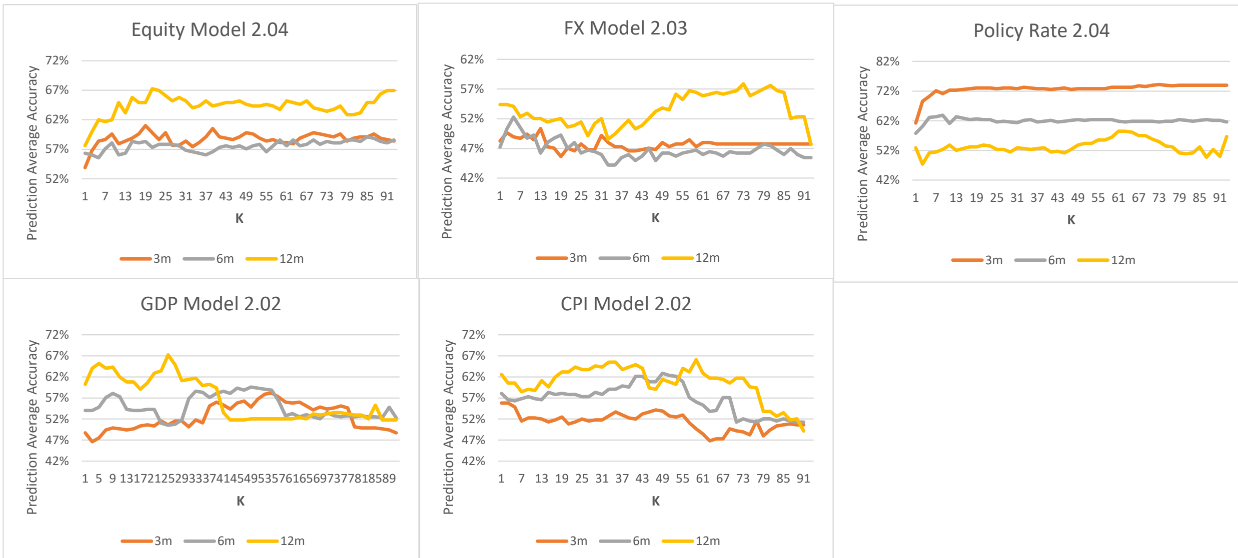


Figure 4.11 Macro variable prediction accuracy per K for the best performing model

Source: Authors' own calculations

After having calculated the average of the prediction accuracy, we have selected in table 4.53 the K at which the maximum average prediction accuracy was realized. For example, the max average prediction accuracy for the 3m EQUITY horizon for all studied markets on average was realized at K=43. In general, you will be able to conclude that **K increased with the maturity/horizon forecasted on average except for the GDP**.

Table 4.53 the K at which the maximum average prediction accuracy is realized

	EQUITY			FX			POLRATE			GDP			INF		
Model	**3m**	**6m**	**12m**	**3m**	**6m**	**12m**	**3m**	**6m**	**12m**	**3m**	**6m**	**12m**	**3m**	**6m**	**12m**
2.01	43	17	91	5	1	89	45	25	61	39	9	1	3	69	91
2.02	83	91	91	17	39	91	1	11	9	55	49	25	1	49	59
2.03	79	27	91	13	5	73	79	47	93	9	7	3	9	37	7
2.04	19	85	21	1	3	51	73	9	61	7	15	11	35	5	87

Source: Authors' own calculations

In Figure 4.12 and table 4.54, we have computed the average K per maturity in general, and as you will be able to conclude that **K rose for longer forecasted horizon**. For example, the average K increased from the 3m to the 12m horizon, from K=31 to K=55.

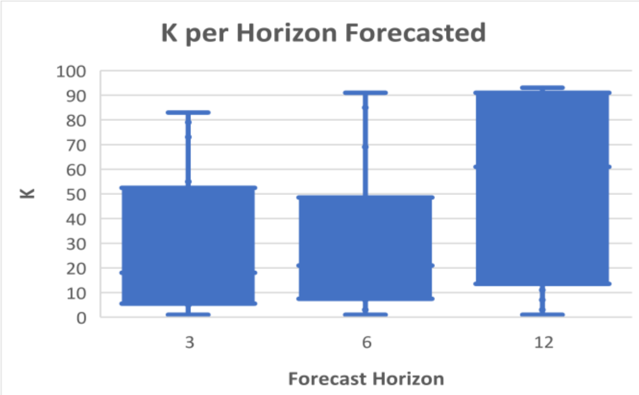


Figure 4.12 K per horizon forecasted

Source: Authors' own calculations

Table 4.54 Average K per horizon forecasted

Horizon	Average K
3m	31
6m	30
12m	55

Source: Authors' own calculations

In table 4.55, we have computed the average K per model in general. The yield curve and macro variables, model 2.04, necessitated less K neighboring points in order to forecast macro variables, compared to the Autoregressive process, model 2.02. Meaning that the yield curve and macro variables laten factors contained valuable information about the future state of the economy. In addition, the yield curve and macro variables on their own (model 2.01 and 2.03) contained separately more information than the Autoregressive process.

Table 4.55 Average K per model

Model	Average K
2.01	39
2.02	45
2.03	39
2.04	32

Source: Authors' own calculations

We have plotted in Figure 4.13, K per average prediction accuracy, where you will be able to conclude that all variables were scattered randomly around the graph, hence, there was **no relationship between K and the average prediction accuracy,** meaning K did not increase nor decrease versus the accuracy.

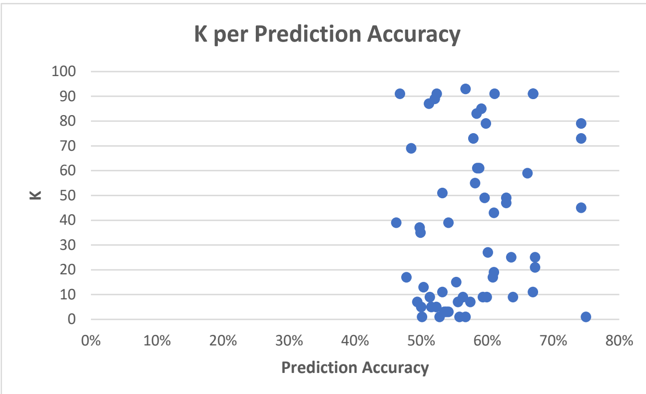


Figure 4.13 K per prediction accuracy

Source: Authors' own calculations

In order to further enhance our analysis, we have performed a linear regression where the X variable was the horizon forecasted, and the Y variable was the average number of K, meaning that we were testing when the forecasted horizon increased by one month, how did this affect the number of K required for the prediction. You will find in table 4.56 the results of our regression, as you will be able to conclude that the results were statistically significant for the FX and INF on a standalone basis. For example, **for every one month predicted ahead we needed K=7.9 and K=5.17 additional neighboring points to predict the FX and INF respectively**. When we performed the same regression on all the data combined, the results were also statistically significant, however, this time we required K=2.9 points for every month predicted ahead.

Table 4.56 Regression of horizon forecasted per month versus K

Variable	EQUITY	FX	POLRATE	GDP	INF	All Data
R Square	6.34%	77.04%	3.07%	16.13%	36.68%	11.36%
Slope	2.11	[25]**7.90**	1.40	-1.90	[26]**5.17**	[25]**2.94**
P-value	42.97%	**0.02%**	58.58%	19.57%	**3.69%**	**0.84%**

Source: Authors' own calculations

[25] Statistically significant at the 1% Level
[26] Statistically significant at the 5% Level

We have performed another regression where the X variable was the number of K, and the Y variable was the prediction accuracy, in order to test whether K affects the prediction accuracy or not. From table 4.57, you will be able to conclude that **K did not affect the prediction accuracy** as all regressions P-values were not statistically significant.

Table 4.57 Regression of K per prediction accuracy

Variable	EQUITY	FX	POLRATE	GDP	INF	All Data
R Square	2.40%	8.27%	1.24%	7.83%	0.05%	3.91%
Slope	0.02%	0.02%	-0.02%	0.06%	0.00%	0.04%
P-value	63.10%	36.49%	73.08%	37.83%	94.68%	12.98%

Source: Authors' own calculations

4.3.2 Sigmoid Classifier Model Results

4.3.2.1 Sigmoid EQUITY Prediction Results

We have illustrated in table 4.58 the EQUITY Sigmoid Classifier prediction results for all studied markets and all horizons. For the 3m horizon, the maximum EQUITY average prediction accuracy of 55.10% was reached using the macro variables model 2.03, which was different than the KNN 3m EQUITY prediction results, whereby the yield curve factors model 2.01 was the best. Similarly, academic scholars found evidence of macro variables effect on the stock market. For example, Fromentin (2022) found evidence of a Causality from the industrial production to the stock market; Laopodis (2013) suggested that the relationship between the monetary policy and the stock market was dynamic; Ahmed et al. (2017) found a Causality relationship from the exchange rate to the stock market. However, for the 6m horizon the yield curve factors model 2.01 and yield curve and macro variables model 2.04 had the highest EQUITY average prediction accuracy of 59.09%. In other words, **the yield curve had predictive information about the longer-term behavior of equity markets**, similarly the yield curve factors model 2.01 was also the best for the 12m horizon. These findings are consistent with our results in section 4.1 and the KNN EQUITY results as well, where the yield curve factors had a leading effect on the EQUITY. Academic references provided in the KNN EQUITY section.

Table 4.58 Sigmoid Classifier EQUITY prediction accuracy results for all horizons

Studied market	Horizon	Model 2.01	Model 2.02	Model 2.03	Model 2.04	Predictions Max per studied market	Predictions Average per studied market
BRA	3m	55.10%	38.30%	61.22%	59.18%	**61.22%**	**53.45%**

Studied market	Horizon	Model 2.01	Model 2.02	Model 2.03	Model 2.04	Predictions Max per studied market	Predictions Average per studied market
CHI	3m	42.86%	42.55%	51.02%	51.02%	**51.02%**	**46.86%**
EGP	3m	48.98%	53.19%	51.02%	48.98%	**53.19%**	**50.54%**
EUR	3m	55.10%	55.32%	51.02%	55.10%	**55.32%**	**54.14%**
IND	3m	55.10%	63.83%	61.22%	63.27%	**63.83%**	**60.86%**
MEX	3m	46.94%	38.30%	48.98%	40.82%	**48.98%**	**43.76%**
SAF	3m	53.06%	55.32%	53.06%	53.06%	**55.32%**	**53.63%**
UK	3m	53.06%	59.57%	55.10%	57.14%	**59.57%**	**56.22%**
US	3m	63.27%	65.96%	63.27%	59.18%	**65.96%**	**62.92%**
	Predictions Averages	**52.61%**	**52.48%**	**55.10%**	**54.20%**		
BRA	6m	70.45%	29.55%	72.73%	59.09%	**72.73%**	**57.95%**
CHI	6m	45.45%	43.18%	43.18%	47.73%	**47.73%**	**44.89%**
EGP	6m	63.64%	31.82%	47.73%	68.18%	**68.18%**	**52.84%**
EUR	6m	59.09%	47.73%	47.73%	61.36%	**61.36%**	**53.98%**
IND	6m	70.45%	22.73%	70.45%	70.45%	**70.45%**	**58.52%**
MEX	6m	45.45%	50.00%	45.45%	43.18%	**50.00%**	**46.02%**
SAF	6m	50.00%	50.00%	50.00%	50.00%	**50.00%**	**50.00%**
UK	6m	54.55%	38.64%	54.55%	59.09%	**59.09%**	**51.70%**
US	6m	72.73%	72.73%	72.73%	72.73%	**72.73%**	**72.73%**
	Predictions Averages	**59.09%**	**42.93%**	**56.06%**	**59.09%**		
BRA	12m	78.95%	44.74%	71.05%	65.79%	**78.95%**	**65.13%**
CHI	12m	60.53%	52.63%	47.37%	52.63%	**60.53%**	**53.29%**
EGP	12m	55.26%	63.16%	50.00%	55.26%	**63.16%**	**55.92%**
EUR	12m	52.63%	52.63%	52.63%	50.00%	**52.63%**	**51.97%**
IND	12m	73.68%	73.68%	73.68%	78.95%	**78.95%**	**75.00%**
MEX	12m	52.63%	50.00%	65.79%	63.16%	**65.79%**	**57.89%**
SAF	12m	57.89%	57.89%	57.89%	57.89%	**57.89%**	**57.89%**
UK	12m	65.79%	34.21%	55.26%	65.79%	**65.79%**	**55.26%**
US	12m	81.58%	81.58%	76.32%	76.32%	**81.58%**	**78.95%**
	Predictions Averages	**64.33%**	**56.73%**	**61.11%**	**62.87%**		

Source: Authors' own calculations

Table 4.59 in Appendix E shows the averages of all EQUITY prediction accuracy per model for all studied markets and horizons. If we were to generalize and choose the best performing model for the equity markets, we would choose both models 2.04 and 2.01 (prediction accuracy averages of 58.72% and 58.68% respectively) that yielded the highest averages for all horizons, meaning that the yield curve factors model, and yield curve and macro variables model, both have valuable information about long term equity markets, a finding that is conform to the KNN average prediction results for the equity markets, and if we were to simplify, the yield curve alone was a good predictor for long term equity markets.

4.3.2.2 Sigmoid FX Prediction Results

We have illustrated in table 4.60 the Sigmoid Classifier FX prediction results for all studied markets and all horizons. Similar to the KNN Classifier, the best Sigmoid FX Classifier prediction model on average for the 3m and 12m horizon was model 2.03 of macro variables. As it seems, **macro variables seemed to hold predictive power over the future long-term behavior of FX in each country, a finding that is similar to the KNN FX result as well**. Academic references provided in the KNN FX section.

Table 4.60 Sigmoid Classifier FX prediction accuracy results for all horizons

Studied market	Horizon	Model 2.01	Model 2.02	Model 2.03	Model 2.04	Predictions Max per studied market	Predictions Average per studied market
BRA	3m	57.14%	48.94%	55.10%	40.82%	**57.14%**	**50.50%**
CHI	3m	40.82%	38.30%	48.98%	40.82%	**48.98%**	**42.23%**
EGP	3m	53.06%	61.70%	44.90%	53.06%	**61.70%**	**53.18%**
EUR	3m	46.94%	48.94%	46.94%	48.98%	**48.98%**	**47.95%**
IND	3m	48.98%	57.45%	48.98%	46.94%	**57.45%**	**50.59%**
MEX	3m	34.69%	31.91%	53.06%	38.78%	**53.06%**	**39.61%**
SAF	3m	57.14%	53.19%	55.10%	53.06%	**57.14%**	**54.62%**
UK	3m	46.94%	53.19%	42.86%	53.06%	**53.19%**	**49.01%**
US	3m	38.78%	44.68%	46.94%	46.94%	**46.94%**	**44.33%**
	Predictions Averages	**47.17%**	**48.70%**	**49.21%**	**46.94%**		
BRA	6m	43.18%	40.91%	40.91%	45.45%	**45.45%**	**42.61%**
CHI	6m	36.36%	34.09%	38.64%	36.36%	**38.64%**	**36.36%**
EGP	6m	68.18%	72.73%	54.55%	63.64%	**72.73%**	**64.77%**
EUR	6m	50.00%	45.45%	50.00%	50.00%	**50.00%**	**48.86%**
IND	6m	65.91%	34.09%	65.91%	72.73%	**72.73%**	**59.66%**
MEX	6m	27.27%	22.73%	56.82%	47.73%	**56.82%**	**38.64%**
SAF	6m	52.27%	47.73%	61.36%	56.82%	**61.36%**	**54.55%**
UK	6m	43.18%	59.09%	36.36%	45.45%	**59.09%**	**46.02%**
US	6m	47.73%	38.64%	40.91%	50.00%	**50.00%**	**44.32%**
	Predictions Averages	**48.23%**	**43.94%**	**49.49%**	**52.02%**		
BRA	12m	42.11%	60.53%	28.95%	42.11%	**60.53%**	**43.42%**
CHI	12m	28.95%	28.95%	31.58%	28.95%	**31.58%**	**29.61%**
EGP	12m	76.32%	73.68%	68.42%	73.68%	**76.32%**	**73.03%**
EUR	12m	55.26%	52.63%	47.37%	36.84%	**55.26%**	**48.03%**

Studied market	Horizon	Model 2.01	Model 2.02	Model 2.03	Model 2.04	Predictions Max per studied market	Predictions Average per studied market
IND	12m	71.05%	73.68%	71.05%	71.05%	**73.68%**	**71.71%**
MEX	12m	52.63%	28.95%	26.32%	36.84%	**52.63%**	**36.18%**
SAF	12m	47.37%	52.63%	57.89%	50.00%	**57.89%**	**51.97%**
UK	12m	26.32%	28.95%	65.79%	44.74%	**65.79%**	**41.45%**
US	12m	39.47%	36.84%	65.79%	34.21%	**65.79%**	**44.08%**
	Predictions Averages	**48.83%**	**48.54%**	**51.46%**	**46.49%**		

Source: Authors' own calculations

Table 4.61 in Appendix E shows the averages of all FX prediction accuracy per model for all studied markets and horizons. If we were to generalize and choose the best performing model for the FX, we would choose model 2.03 that yielded the highest prediction accuracy average of 50.05% for all horizons.

4.3.2.3 Sigmoid POLRATE Prediction Results

The best POLRATE prediction model on average for the 3m horizon was model 2.03 of macro variables, reaching an average prediction accuracy of 73.7%. Model 2.02 performed best for the 6m horizon, reaching an average prediction accuracy of 63.89%. Though, for the 12m horizon model 2.01 of yield curves factors had the highest average prediction accuracy level of 57.31%. Although, these results were somehow different than the KNN POLRATE findings, they were consistent with academic literature, and our findings in section 4.1, where the POLRATE was mainly affected by yield curve factors, such as the Level and Slope, in fact, as we previously mentioned that the Level leads the POLRATE.

Table 4.62 Sigmoid Classifier POLRATE prediction accuracy results for all horizons

Studied market	Horizon	Model 2.01	Model 2.02	Model 2.03	Model 2.04	Predictions Max per studied market	Predictions Average per studied market
BRA	3m	67.35%	76.60%	69.39%	67.35%	**76.60%**	**70.17%**
CHI	3m	100.00%	100.00%	100.00%	100.00%	**100.00%**	**100.00%**
EGP	3m	65.31%	59.57%	69.39%	65.31%	**69.39%**	**64.89%**
EUR	3m	83.67%	100.00%	100.00%	100.00%	**100.00%**	**95.92%**
IND	3m	81.63%	80.85%	83.67%	79.59%	**83.67%**	**81.44%**
MEX	3m	32.65%	31.91%	34.69%	34.69%	**34.69%**	**33.49%**
SAF	3m	63.27%	72.34%	73.47%	71.43%	**73.47%**	**70.13%**
UK	3m	87.76%	87.23%	87.76%	87.76%	**87.76%**	**87.62%**

Studied market	Horizon	Model 2.01	Model 2.02	Model 2.03	Model 2.04	Predictions Max per studied market	Predictions Average per studied market
US	3m	44.90%	42.55%	44.90%	44.90%	**44.90%**	**44.31%**
	Predictions Averages	**69.61%**	**72.34%**	**73.70%**	**72.34%**		
BRA	6m	70.45%	54.55%	68.18%	63.64%	**70.45%**	**64.20%**
CHI	6m	97.73%	100.00%	100.00%	86.36%	**100.00%**	**96.02%**
EGP	6m	56.82%	43.18%	50.00%	54.55%	**56.82%**	**51.14%**
EUR	6m	97.73%	100.00%	95.45%	100.00%	**100.00%**	**98.30%**
IND	6m	79.55%	79.55%	77.27%	75.00%	**79.55%**	**77.84%**
MEX	6m	13.64%	40.91%	11.36%	11.36%	**40.91%**	**19.32%**
SAF	6m	59.09%	59.09%	61.36%	61.36%	**61.36%**	**60.23%**
UK	6m	72.73%	72.73%	72.73%	77.27%	**77.27%**	**73.86%**
US	6m	25.00%	25.00%	25.00%	25.00%	**25.00%**	**25.00%**
	Predictions Averages	**63.64%**	**63.89%**	**62.37%**	**61.62%**		
BRA	12m	76.32%	65.79%	68.42%	60.53%	**76.32%**	**67.76%**
CHI	12m	94.74%	0.00%	81.58%	50.00%	**94.74%**	**56.58%**
EGP	12m	50.00%	65.79%	63.16%	55.26%	**65.79%**	**58.55%**
EUR	12m	92.11%	100.00%	73.68%	97.37%	**100.00%**	**90.79%**
IND	12m	68.42%	76.32%	76.32%	71.05%	**76.32%**	**73.03%**
MEX	12m	10.53%	31.58%	0.00%	0.00%	**31.58%**	**10.53%**
SAF	12m	65.79%	63.16%	63.16%	57.89%	**65.79%**	**62.50%**
UK	12m	57.89%	57.89%	57.89%	57.89%	**57.89%**	**57.89%**
US	12m	0.00%	0.00%	0.00%	0.00%	**0.00%**	**0.00%**
	Predictions Averages	**57.31%**	**51.17%**	**53.80%**	**50.00%**		

Source: Authors' own calculations

Table 4.63 in Appendix E shows the averages of all POLRATE prediction accuracy per model for all studied markets and horizons. If we were to generalize and choose the best performing model for the policy rates, we would choose model 2.03 of macro variables, and model 2.01 of yield curves.

4.3.2.4 Sigmoid GDP Prediction Results

We have illustrated in table 4.64 the GDP prediction results for all studied markets and all horizons. Similar to the KNN findings, the best GDP prediction model on average for the 3m and 12m horizons was model 2.02 with the Autoregressive inputs reaching an average prediction accuracy of 65.01% and 57.31% respectively. Seemingly, **the GDP past values seemed to have**

a dominant effect on the future performance of the GDP, this result is similar to the KNN GDP finding. Academic references provided in the KNN GDP section.

Table 4.64 Sigmoid Classifier GDP prediction accuracy results for all horizons

Studied market	Horizon	Model 2.01	Model 2.02	Model 2.03	Model 2.04	Predictions Max per studied market	Predictions Average per studied market
BRA	3m	65.31%	57.45%	65.31%	73.47%	**73.47%**	**65.38%**
CHI	3m	61.22%	74.47%	53.06%	48.98%	**74.47%**	**59.43%**
EGP	3m	53.06%	55.32%	53.06%	65.31%	**65.31%**	**56.69%**
EUR	3m	36.73%	42.55%	59.18%	75.51%	**75.51%**	**53.50%**
IND	3m	55.10%	53.19%	44.90%	46.94%	**55.10%**	**50.03%**
MEX	3m	53.06%	78.72%	57.14%	46.94%	**78.72%**	**58.97%**
SAF	3m	51.02%	85.11%	59.18%	63.27%	**85.11%**	**64.64%**
UK	3m	36.73%	68.09%	61.22%	42.86%	**68.09%**	**52.23%**
US	3m	34.69%	70.21%	36.73%	34.69%	**70.21%**	**44.08%**
	Predictions Averages	**49.66%**	**65.01%**	**54.42%**	**55.33%**		
BRA	6m	65.91%	61.36%	61.36%	70.45%	**70.45%**	**64.77%**
CHI	6m	77.27%	77.27%	77.27%	61.36%	**77.27%**	**73.30%**
EGP	6m	63.64%	50.00%	65.91%	54.55%	**65.91%**	**58.52%**
EUR	6m	36.36%	40.91%	52.27%	61.36%	**61.36%**	**47.73%**
IND	6m	34.09%	65.91%	54.55%	34.09%	**65.91%**	**47.16%**
MEX	6m	56.82%	34.09%	38.64%	52.27%	**56.82%**	**45.45%**
SAF	6m	45.45%	59.09%	47.73%	43.18%	**59.09%**	**48.86%**
UK	6m	40.91%	75.00%	59.09%	63.64%	**75.00%**	**59.66%**
US	6m	27.27%	43.18%	56.82%	31.82%	**56.82%**	**39.77%**
	Predictions Averages	**49.75%**	**56.31%**	**57.07%**	**52.53%**		
BRA	12m	63.16%	65.79%	63.16%	71.05%	**71.05%**	**65.79%**
CHI	12m	71.05%	71.05%	68.42%	65.79%	**71.05%**	**69.08%**
EGP	12m	47.37%	68.42%	36.84%	47.37%	**68.42%**	**50.00%**
EUR	12m	52.63%	23.68%	42.11%	42.11%	**52.63%**	**40.13%**
IND	12m	26.32%	26.32%	31.58%	28.95%	**31.58%**	**28.29%**
MEX	12m	57.89%	73.68%	60.53%	63.16%	**73.68%**	**63.82%**
SAF	12m	57.89%	52.63%	55.26%	47.37%	**57.89%**	**53.29%**
UK	12m	44.74%	92.11%	42.11%	52.63%	**92.11%**	**57.89%**
US	12m	36.84%	42.11%	34.21%	31.58%	**42.11%**	**36.18%**
	Predictions Averages	**50.88%**	**57.31%**	**48.25%**	**50.00%**		

Source: Authors' own calculations

Table 4.65 in Appendix E shows the averages of all GDP prediction accuracy per model for all studied markets and horizons. If we were to generalize and choose the best performing model for the GDP, we would choose the Autoregressive model 2.02 that yielded the highest prediction accuracy average of 59.54% for all horizons.

4.3.2.5 Sigmoid INF Prediction Results

We have illustrated in table 4.66 the INF prediction results for all studied markets and all horizons. **Similar to the KNN INF finding, the best INF prediction model on average for the three forecasted maturities, was model 2.02 with the Autoregressive inputs**. Academic references provided in the KNN INF section.

Table 4.66 Sigmoid Classifier INF prediction accuracy results for all horizons

Studied market	Horizon	Model 2.01	Model 2.02	Model 2.03	Model 2.04	Predictions Max per studied market	Predictions Average per studied market
BRA	3m	55.10%	53.19%	65.31%	59.18%	**65.31%**	**58.20%**
CHI	3m	53.06%	55.32%	53.06%	51.02%	**55.32%**	**53.12%**
EGP	3m	42.86%	57.45%	48.98%	44.90%	**57.45%**	**48.55%**
EUR	3m	42.86%	40.43%	46.94%	53.06%	**53.06%**	**45.82%**
IND	3m	65.31%	44.68%	44.90%	46.94%	**65.31%**	**50.46%**
MEX	3m	42.86%	53.19%	42.86%	51.02%	**53.19%**	**47.48%**
SAF	3m	38.78%	57.45%	40.82%	40.82%	**57.45%**	**44.46%**
UK	3m	32.65%	63.83%	51.02%	51.02%	**63.83%**	**49.63%**
US	3m	53.06%	72.34%	46.94%	42.86%	**72.34%**	**53.80%**
	Predictions Averages	**47.39%**	**55.32%**	**48.98%**	**48.98%**		
BRA	6m	43.18%	65.91%	52.27%	38.64%	**65.91%**	**50.00%**
CHI	6m	63.64%	63.64%	40.91%	59.09%	**63.64%**	**56.82%**
EGP	6m	40.91%	56.82%	40.91%	52.27%	**56.82%**	**47.73%**
EUR	6m	43.18%	59.09%	27.27%	34.09%	**59.09%**	**40.91%**
IND	6m	50.00%	31.82%	52.27%	50.00%	**52.27%**	**46.02%**
MEX	6m	43.18%	72.73%	47.73%	61.36%	**72.73%**	**56.25%**
SAF	6m	40.91%	52.27%	54.55%	38.64%	**54.55%**	**46.59%**
UK	6m	50.00%	65.91%	52.27%	56.82%	**65.91%**	**56.25%**
US	6m	38.64%	79.55%	29.55%	52.27%	**79.55%**	**50.00%**
	Predictions Averages	**45.96%**	**60.86%**	**44.19%**	**49.24%**		
BRA	12m	39.47%	76.32%	42.11%	39.47%	**76.32%**	**49.34%**
CHI	12m	50.00%	63.16%	52.63%	47.37%	**63.16%**	**53.29%**
EGP	12m	50.00%	65.79%	52.63%	65.79%	**65.79%**	**58.55%**
EUR	12m	50.00%	73.68%	26.32%	52.63%	**73.68%**	**50.66%**
IND	12m	44.74%	47.37%	55.26%	47.37%	**55.26%**	**48.68%**
MEX	12m	44.74%	78.95%	52.63%	60.53%	**78.95%**	**59.21%**
SAF	12m	50.00%	55.26%	52.63%	36.84%	**55.26%**	**48.68%**

Studied market	Horizon	Model 2.01	Model 2.02	Model 2.03	Model 2.04	Predictions Max per studied market	Predictions Average per studied market
UK	12m	31.58%	21.05%	34.21%	55.26%	**55.26%**	**35.53%**
US	12m	44.74%	78.95%	65.79%	47.37%	**78.95%**	**59.21%**
	Predictions Averages	**45.03%**	**62.28%**	**48.25%**	**50.29%**		

Source: Authors' own calculations

Table 4.67 in Appendix E shows the averages of all INF prediction accuracy per model for all studied markets and horizons. Similar to the KNN section, the best performing model for the INF was the Autoregressive model 2.02 that yielded the highest prediction accuracy average of 59.49%% for all horizons.

4.3.2.6 Sigmoid Classifier Hidden Layer Nodes Sensitivity Results

We have conducted a sensitivity analysis on the hidden nodes and measured its impact on the forecasting accuracy, by changing the hidden nodes and re-optimizing model 1.04 (yield curve and macro variables) for the equity predictions, by which creating 48 different scenarios. Illustrated in Figure 4.14, a sample of the training and out of sample error term versus the different hidden nodes. As its clear that the impact of changing the hidden nodes on the out of sample error was highly uncertain, since increasing the hidden nodes did sometimes, increase the error term, decrease the error term, or kept it unchanged. Adding to the fact that the out of sample error behavior was non-linear, hence, the impact of changing the hidden nodes on the error term was highly unpredictable.

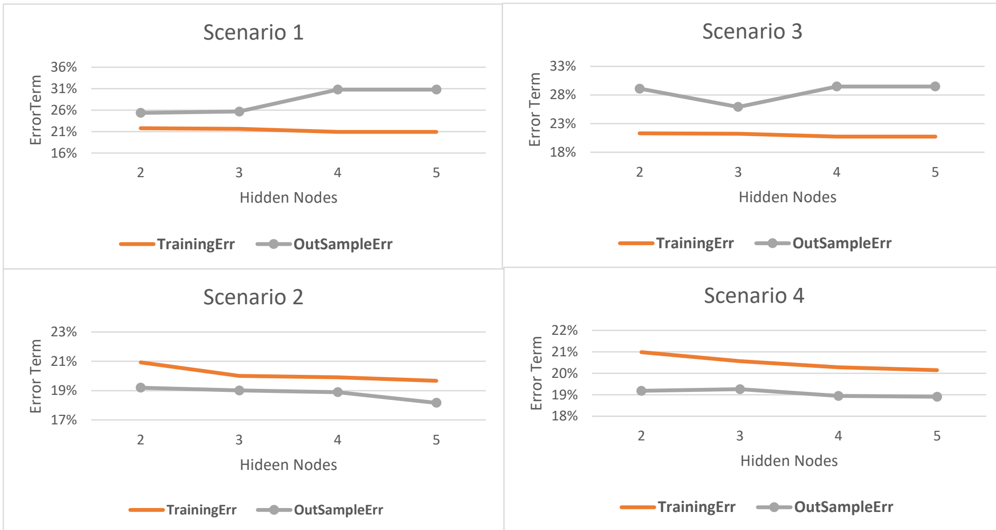


Figure 4.14 Sigmoid Classifier hidden nodes sensitivity versus the error term

Source: Authors' own calculations

In order to test how the inputs, hidden nodes, forecasting horizons affect the error term, we have performed a regression, where Y was the error term, and X were: the number of inputs (I), hidden nodes (H), forecasting months (F), as illustrated in table 4.68. <u>It is clear from table 4.68:</u>

- The number of hidden nodes (H) and forecasted months (F) did affect the training error, as their P-values were statistically significant. In fact, the higher the hidden nodes and forecasted months, the lower the error, as their coefficients had a negative sign, -0.51% and -0.69% respectively, meaning that their relationship was opposite to the training error, meaning an increase in the number of hidden nodes causes a decrease in the training error, and the longer the forecasted months the lower the training error, which actually makes sense since equity predictions improved over the long term.
- Referring to the out of sample error, the forecasted months (F) was the only statistically significant coefficient, thus, the number of hidden nodes impact on the error term was not statistically significant, hence, it was difficult to deduce the relationship between the hidden nodes and out of sample error.
- The total error findings were similar to the out of sample error, as the forecasted months was the only statistically significant coefficient, and the hidden nodes impact on the error term was inconsistent.

Table 4.68 The impact of changing the inputs, hidden nodes and horizon forecasted on the training, out of sample, and total error

	Training Error		**Outsample Error**		**Total Error**	
	Adjusted R2	89.22%	**Adjusted R2**	15.25%	**Adjusted R2**	37.36%
	Coefficients	***P-value***	***Coefficients***	***P-value***	***Coefficients***	***P-value***
I	0.23%	6.39%	-0.03%	97.41%	0.19%	85.42%
H	[27]-0.51%	0.00%	0.04%	96.75%	-0.47%	65.44%
F	[27]-0.69%	0.00%	[27]-1.05%	0.15%	[27]-1.73%	0.00%

Source: Authors' own calculations

In order to design a model that selected the optimum number of hidden nodes according to the number of input nodes and forecasted months ahead, we have performed a regression where the dependent variable was the optimum number of hidden nodes, chosen according to the minimum total error, and the independent variables were: the number of inputs (I), and the forecasted horizon per month (F) (there are no output nodes (O) as it is always 1). Kindly find attached in table 4.69 the regression results, where the only significant coefficient was the forecasted months ahead equivalent to 21.4%, meaning as we forecasted further into the future, we needed to add hidden nodes. More precisely, for every 4-5 forecasted months ahead, we needed to add one additional hidden node (21%*5=1.05).

Table 4.69 Regression results for the optimum hidden node per input and per forecasted horizon for the Sigmoid Classifier

	Adjusted R2	38.74%
	Coefficients	***P-value***
Intercept	1.9	15.97%
I	13.3%	59.76%
F	[28]21.4%	1.64%

Source: Authors' own calculations

[27] Statistically significant at the 1% Level
[28] Statistically significant at the 5% Level

4.3.3 Softmax Classifier Model Results

4.3.3.1 Softmax EQUITY Prediction Results

We have illustrated in table 4.70 the EQUITY Softmax Classifier prediction results for all studied markets and all horizons. The maximum EQUITY average prediction was reached using the macro variables model 2.03 for all three horizons. Although, these results are different than the KNN and Sigmoid EQUITY Classifier findings, the general state of the economy or macro variables were found to have an impact on the EQUITY. For example, Ahmed et al. (2017) found a Causality relationship from the exchange rate to the stock market, and Fromentin (2022) found evidence of a Causality from the industrial production to the stock market.

Table 4.70 Softmax Classifier EQUITY prediction accuracy results for all horizons

Studied market	Horizon	Model 2.01	Model 2.02	Model 2.03	Model 2.04	Predictions Max per studied market	Predictions Average per studied market
BRA	3m	61.70%	38.30%	63.83%	61.70%	**63.83%**	**56.38%**
CHI	3m	31.91%	38.30%	40.43%	44.68%	**44.68%**	**38.83%**
EGP	3m	51.06%	55.32%	48.94%	53.19%	**55.32%**	**52.13%**
EUR	3m	46.81%	51.06%	46.81%	46.81%	**51.06%**	**47.87%**
IND	3m	55.32%	55.32%	53.19%	53.19%	**55.32%**	**54.26%**
MEX	3m	42.55%	19.15%	53.19%	27.66%	**53.19%**	**35.64%**
SAF	3m	46.81%	34.04%	46.81%	46.81%	**46.81%**	**43.62%**
UK	3m	51.06%	46.81%	51.06%	51.06%	**51.06%**	**50.00%**
US	3m	63.83%	34.04%	63.83%	61.70%	**63.83%**	**55.85%**
	Predictions Averages	**50.12%**	**41.37%**	**52.01%**	**49.65%**		
BRA	6m	60.00%	40.91%	62.22%	60.00%	**62.22%**	**55.78%**
CHI	6m	48.89%	45.45%	40.00%	42.22%	**48.89%**	**44.14%**
EGP	6m	62.22%	52.27%	53.33%	51.11%	**62.22%**	**54.73%**
EUR	6m	53.33%	29.55%	55.56%	53.33%	**55.56%**	**47.94%**
IND	6m	62.22%	68.18%	60.00%	60.00%	**68.18%**	**62.60%**
MEX	6m	40.00%	31.82%	60.00%	40.00%	**60.00%**	**42.95%**
SAF	6m	42.22%	31.82%	42.22%	40.00%	**42.22%**	**39.07%**
UK	6m	51.11%	45.45%	55.56%	46.67%	**55.56%**	**49.70%**
US	6m	64.44%	59.09%	60.00%	62.22%	**64.44%**	**61.44%**
	Predictions Averages	**53.83%**	**44.95%**	**54.32%**	**50.62%**		
BRA	12m	64.10%	34.21%	74.36%	76.92%	**76.92%**	**62.40%**
CHI	12m	43.59%	47.37%	38.46%	35.90%	**47.37%**	**41.33%**
EGP	12m	56.41%	39.47%	53.85%	56.41%	**56.41%**	**51.54%**
EUR	12m	53.85%	42.11%	56.41%	58.97%	**58.97%**	**52.83%**
IND	12m	69.23%	52.63%	69.23%	69.23%	**69.23%**	**65.08%**
MEX	12m	58.97%	65.79%	69.23%	53.85%	**69.23%**	**61.96%**

Studied market	Horizon	Model 2.01	Model 2.02	Model 2.03	Model 2.04	Predictions Max per studied market	Predictions Average per studied market
SAF	12m	51.28%	50.00%	51.28%	51.28%	**51.28%**	**50.96%**
UK	12m	58.97%	28.95%	61.54%	56.41%	**61.54%**	**51.47%**
US	12m	79.49%	18.42%	79.49%	79.49%	**79.49%**	**64.22%**
	Predictions Averages	**59.54%**	**42.11%**	**61.54%**	**59.83%**		

Source: Authors' own calculations

Table 4.71 in Appendix E shows the averages of all EQUITY prediction accuracy per model for all studied markets and horizons. If we were to generalize and choose the best performing model for the equity markets, we would choose model 2.03 that yielded the highest prediction accuracy average for all horizons. However, the yield curve only model 2.01 had valuable information about long term equity markets, a finding that's similar to the KNN and Sigmoid average prediction results for the equity markets, hence, **the yield curve alone was a good predictor for long term equity markets**. Academic references provided in the KNN EQUITY section.

4.3.3.2 Softmax FX Prediction Results

We have illustrated in table 4.72 the Softmax FX prediction results for all studied markets and all horizons. The best Softmax FX prediction model on average for the 3m was the yield curve only model 2.01, however, for the 6m and 12m horizons, the macro variables model 2.03 yielded higher prediction results. Thus, **macro variables seemed to hold predictive power over the future long-term behavior of FX in each studied market, a finding consistent with the KNN and Sigmoid Classifiers results**. Academic references provided in the KNN FX section.

Table 4.72 Softmax Classifier FX prediction accuracy results for all horizons

Studied market	Horizon	Model 2.01	Model 2.02	Model 2.03	Model 2.04	Predictions Max per studied market	Predictions Average per studied market
BRA	3m	38.30%	40.43%	44.68%	40.43%	**44.68%**	**40.96%**
CHI	3m	40.43%	40.43%	29.79%	31.91%	**40.43%**	**35.64%**
EGP	3m	44.68%	31.91%	31.91%	31.91%	**44.68%**	**35.11%**
EUR	3m	40.43%	40.43%	40.43%	36.17%	**40.43%**	**39.36%**
IND	3m	53.19%	36.17%	53.19%	53.19%	**53.19%**	**48.94%**
MEX	3m	31.91%	31.91%	53.19%	27.66%	**53.19%**	**36.17%**
SAF	3m	55.32%	46.81%	44.68%	53.19%	**55.32%**	**50.00%**
UK	3m	42.55%	44.68%	44.68%	42.55%	**44.68%**	**43.62%**
US	3m	42.55%	44.68%	40.43%	40.43%	**44.68%**	**42.02%**

Studied market	Horizon	Model 2.01	Model 2.02	Model 2.03	Model 2.04	Predictions Max per studied market	Predictions Average per studied market
	Predictions Averages	43.26%	39.72%	42.55%	39.72%		
BRA	6m	42.22%	36.36%	48.89%	46.67%	**48.89%**	**43.54%**
CHI	6m	35.56%	63.64%	33.33%	33.33%	**63.64%**	**41.46%**
EGP	6m	64.44%	18.18%	48.89%	55.56%	**64.44%**	**46.77%**
EUR	6m	42.22%	43.18%	42.22%	40.00%	**43.18%**	**41.91%**
IND	6m	57.78%	31.82%	53.33%	53.33%	**57.78%**	**49.07%**
MEX	6m	20.00%	40.91%	53.33%	20.00%	**53.33%**	**33.56%**
SAF	6m	51.11%	47.73%	53.33%	53.33%	**53.33%**	**51.38%**
UK	6m	35.56%	36.36%	42.22%	37.78%	**42.22%**	**37.98%**
US	6m	35.56%	52.27%	42.22%	42.22%	**52.27%**	**43.07%**
	Predictions Averages	42.72%	41.16%	46.42%	42.47%		
BRA	12m	30.77%	36.84%	41.03%	43.59%	**43.59%**	**38.06%**
CHI	12m	28.21%	65.79%	28.21%	30.77%	**65.79%**	**38.24%**
EGP	12m	69.23%	73.68%	79.49%	74.36%	**79.49%**	**74.19%**
EUR	12m	33.33%	47.37%	46.15%	28.21%	**47.37%**	**38.77%**
IND	12m	66.67%	65.79%	64.10%	64.10%	**66.67%**	**65.17%**
MEX	12m	48.72%	26.32%	64.10%	41.03%	**64.10%**	**45.04%**
SAF	12m	43.59%	44.74%	41.03%	43.59%	**44.74%**	**43.24%**
UK	12m	64.10%	26.32%	38.46%	33.33%	**64.10%**	**40.55%**
US	12m	38.46%	34.21%	38.46%	38.46%	**38.46%**	**37.40%**
	Predictions Averages	47.01%	46.78%	49.00%	44.16%		

Source: Authors' own calculations

Table 4.73 in Appendix E shows the averages of all FX prediction accuracy per model for all studied markets and horizons. If we were to generalize and choose the best performing model for the FX, we would choose model 2.03 that yielded the highest prediction accuracy average of 45.99% for all horizons.

4.3.3.3 Softmax POLRATE Prediction Results

The best POLRATE prediction model on average for the 3m and 6m horizons was model 2.03 of macro variables, however, for longer term horizons such as the 12m, the yield curve model performed best, findings confirmed by the Sigmoid Classifier as well (noting that we have removed from the averages the outliers highlighted in yellow). In other words, the **POLRATE seemed to be affected by macro variables, however, in the long term, the yield curve had**

more effect on the POLRATE, findings consistent with the KNN and Sigmoid Classifiers results. Academic references provided in the KNN POLRATE section.

Table 4.74 Softmax Classifier POLRATE prediction accuracy results for all horizons

Studied market	Horizon	Model 2.01	Model 2.02	Model 2.03	Model 2.04	Predictions Max per studied market	Predictions Average per studied market
BRA	3m	46.81%	31.91%	53.19%	53.19%	**53.19%**	**46.28%**
CHI	3m	80.85%	80.85%	68.09%	70.21%	**80.85%**	**75.00%**
EGP	3m	53.19%	29.79%	48.94%	53.19%	**53.19%**	**46.28%**
EUR	3m	80.85%	93.62%	80.85%	82.98%	**93.62%**	**84.57%**
IND	3m	44.68%	42.55%	59.57%	42.55%	**59.57%**	**47.34%**
MEX	3m	38.30%	31.91%	59.57%	38.30%	**59.57%**	**42.02%**
SAF	3m	59.57%	59.57%	59.57%	59.57%	**59.57%**	**59.57%**
UK	3m	80.85%	80.85%	80.85%	80.85%	**80.85%**	**80.85%**
US	3m	44.68%	42.55%	42.55%	44.68%	**44.68%**	**43.62%**
	Predictions Averages	**58.87%**	**54.85%**	**61.47%**	**58.39%**		
BRA	6m	53.33%	52.27%	60.00%	60.00%	**60.00%**	**56.40%**
CHI	6m	66.67%	79.55%	64.44%	64.44%	**79.55%**	**68.78%**
EGP	6m	46.67%	40.91%	46.67%	44.44%	**46.67%**	**44.67%**
EUR	6m	11.11%	13.64%	26.67%	31.11%	**31.11%**	**20.63%**
IND	6m	51.11%	45.45%	66.67%	55.56%	**66.67%**	**54.70%**
MEX	6m	24.44%	43.18%	66.67%	22.22%	**66.67%**	**39.13%**
SAF	6m	46.67%	45.45%	44.44%	46.67%	**46.67%**	**45.81%**
UK	6m	62.22%	59.09%	60.00%	57.78%	**62.22%**	**59.77%**
US	6m	28.89%	25.00%	26.67%	28.89%	**28.89%**	**27.36%**
	Predictions Averages	**43.46%**	**44.95%**	**51.36%**	**45.68%**		
BRA	12m	66.67%	55.26%	64.10%	64.10%	**66.67%**	**62.53%**
CHI	12m	15.38%	76.32%	43.59%	53.85%	**76.32%**	**57.92%**
EGP	12m	71.79%	57.89%	56.41%	58.97%	**71.79%**	**61.27%**
EUR	12m	30.77%	31.58%	23.08%	25.64%	**31.58%**	**27.77%**
IND	12m	76.92%	52.63%	58.97%	61.54%	**76.92%**	**62.52%**
MEX	12m	15.38%	13.16%	58.97%	15.38%	**58.97%**	**58.97%**
SAF	12m	46.15%	57.89%	53.85%	48.72%	**57.89%**	**51.65%**
UK	12m	30.77%	26.32%	28.21%	23.08%	**30.77%**	**27.09%**
US	12m	0.00%	0.00%	0.00%	2.56%	**2.56%**	**0.64%**
	Predictions Averages	**53.85%**	**51.13%**	**48.40%**	**47.99%**		

Source: Authors' own calculations

Table 4.75 in Appendix E shows the averages of all POLRATE prediction accuracy per model for all studied markets and horizons, as you will be able to confirm the previous findings, both macro variables and yield curves separately had predictive powers over the POLRATE.

4.3.3.4 Softmax GDP Prediction Results

We have illustrated in table 4.76 the GDP prediction results for all studied markets and all horizons. **Similar to the KNN and Sigmoid findings, the best Softmax model for the GDP predictions on average was model 2.02 with the Autoregressive inputs**. Seemingly, **the GDP past values seemed to have a dominant effect on the future performance of the GDP**. Academic references provided in the KNN GDP section.

Table 4.76 Softmax Classifier GDP prediction accuracy results for all horizons

Studied market	Horizon	Model 2.01	Model 2.02	Model 2.03	Model 2.04	Predictions Max per studied market	Predictions Average per studied market
BRA	3m	55.32%	46.81%	68.09%	68.09%	**68.09%**	**65.38%**
CHI	3m	23.40%	70.21%	14.89%	14.89%	**70.21%**	**59.43%**
EGP	3m	38.30%	55.32%	42.55%	46.81%	**55.32%**	**56.69%**
EUR	3m	29.79%	42.55%	44.68%	42.55%	**44.68%**	**53.50%**
IND	3m	25.53%	38.30%	25.53%	23.40%	**38.30%**	**50.03%**
MEX	3m	44.68%	70.21%	25.53%	36.17%	**70.21%**	**58.97%**
SAF	3m	40.43%	70.21%	51.06%	53.19%	**70.21%**	**64.64%**
UK	3m	25.53%	53.19%	40.43%	36.17%	**53.19%**	**52.23%**
US	3m	38.30%	44.68%	53.19%	53.19%	**53.19%**	**44.08%**
	Predictions Averages	**35.70%**	**54.61%**	**40.66%**	**41.61%**		
BRA	6m	53.33%	61.36%	75.56%	64.44%	**75.56%**	**64.77%**
CHI	6m	46.67%	45.45%	46.67%	46.67%	**46.67%**	**73.30%**
EGP	6m	44.44%	38.64%	35.56%	37.78%	**44.44%**	**58.52%**
EUR	6m	24.44%	29.55%	33.33%	33.33%	**33.33%**	**47.73%**
IND	6m	17.78%	38.64%	22.22%	15.56%	**38.64%**	**47.16%**
MEX	6m	51.11%	56.82%	22.22%	42.22%	**56.82%**	**45.45%**
SAF	6m	37.78%	56.82%	37.78%	35.56%	**56.82%**	**48.86%**
UK	6m	37.78%	52.27%	53.33%	51.11%	**53.33%**	**59.66%**
US	6m	48.89%	36.36%	57.78%	66.67%	**66.67%**	**39.77%**
	Predictions Averages	**40.25%**	**46.21%**	**42.72%**	**43.70%**		
BRA	12m	53.85%	65.79%	69.23%	69.23%	**69.23%**	**65.79%**
CHI	12m	56.41%	55.26%	53.85%	48.72%	**56.41%**	**69.08%**
EGP	12m	58.97%	68.42%	35.90%	33.33%	**68.42%**	**50.00%**
EUR	12m	23.08%	23.68%	30.77%	33.33%	**33.33%**	**40.13%**
IND	12m	17.95%	52.63%	23.08%	17.95%	**52.63%**	**28.29%**
MEX	12m	53.85%	63.16%	23.08%	53.85%	**63.16%**	**63.82%**

Studied market	Horizon	Model 2.01	Model 2.02	Model 2.03	Model 2.04	Predictions Max per studied market	Predictions Average per studied market
SAF	12m	53.85%	60.53%	46.15%	56.41%	**60.53%**	**53.29%**
UK	12m	38.46%	81.58%	46.15%	48.72%	**81.58%**	**57.89%**
US	12m	46.15%	36.84%	41.03%	51.28%	**51.28%**	**36.18%**
	Predictions Averages	**48.08%**	**56.43%**	**41.03%**	**49.36%**		

Source: Authors' own calculations

Table 4.77 in Appendix E shows the averages of all GDP prediction accuracy per model for all studied markets and horizons. If we were to generalize and choose the best performing model for the GDP, we would choose model 2.02 with the Autoregressive inputs that yielded the highest prediction accuracy average of 52.42% for all horizons.

4.3.3.5 Softmax Classifier INF Prediction Results

We have illustrated in table 4.78 the INF prediction results for all studied markets and all horizons. **Similar to the KNN and Sigmoid findings, the best Softmax model for the INF predictions on average, for the three forecasted maturities, was model 2.02 with the Autoregressive inputs**. Academic references provided in the KNN INF section.

Table 4.78 Softmax Classifier INF prediction accuracy results for all horizons

Studied market	Horizon	Model 2.01	Model 2.02	Model 2.03	Model 2.04	Predictions Max per studied market	Predictions Average per studied market
BRA	3m	46.81%	70.21%	53.19%	51.06%	**70.21%**	**55.32%**
CHI	3m	46.81%	46.81%	29.79%	29.79%	**46.81%**	**38.30%**
EGP	3m	36.17%	48.94%	55.32%	46.81%	**55.32%**	**46.81%**
EUR	3m	36.17%	55.32%	46.81%	44.68%	**55.32%**	**45.74%**
IND	3m	51.06%	31.91%	40.43%	40.43%	**51.06%**	**40.96%**
MEX	3m	53.19%	55.32%	40.43%	48.94%	**55.32%**	**49.47%**
SAF	3m	40.43%	42.55%	31.91%	34.04%	**42.55%**	**37.23%**
UK	3m	31.91%	59.57%	40.43%	38.30%	**59.57%**	**42.55%**
US	3m	31.91%	55.32%	27.66%	29.79%	**55.32%**	**36.17%**
	Predictions Averages	**41.61%**	**51.77%**	**40.66%**	**40.43%**		
BRA	6m	48.89%	68.18%	53.33%	46.67%	**68.18%**	**54.27%**
CHI	6m	51.11%	52.27%	35.56%	42.22%	**52.27%**	**45.29%**
EGP	6m	44.44%	50.00%	51.11%	35.56%	**51.11%**	**45.28%**
EUR	6m	37.78%	45.45%	51.11%	51.11%	**51.11%**	**46.36%**
IND	6m	28.89%	34.09%	42.22%	46.67%	**46.67%**	**37.97%**
MEX	6m	53.33%	52.27%	42.22%	44.44%	**53.33%**	**48.07%**
SAF	6m	44.44%	45.45%	44.44%	44.44%	**45.45%**	**44.70%**

Studied market	Horizon	Model 2.01	Model 2.02	Model 2.03	Model 2.04	Predictions Max per studied market	Predictions Average per studied market
UK	6m	24.44%	65.91%	28.89%	31.11%	**65.91%**	**37.59%**
US	6m	33.33%	77.27%	37.78%	35.56%	**77.27%**	**45.98%**
	Predictions Averages	**40.74%**	**54.55%**	**42.96%**	**41.98%**		
BRA	12m	41.03%	71.05%	43.59%	46.15%	**71.05%**	**50.46%**
CHI	12m	53.85%	63.16%	48.72%	48.72%	**63.16%**	**53.61%**
EGP	12m	41.03%	68.42%	43.59%	51.28%	**68.42%**	**51.08%**
EUR	12m	17.95%	71.05%	41.03%	43.59%	**71.05%**	**51.89%**
IND	12m	30.77%	42.11%	38.46%	51.28%	**51.28%**	**40.65%**
MEX	12m	46.15%	76.32%	38.46%	41.03%	**76.32%**	**50.49%**
SAF	12m	43.59%	63.16%	51.28%	53.85%	**63.16%**	**52.97%**
UK	12m	38.46%	89.47%	35.90%	28.21%	**89.47%**	**48.01%**
US	12m	61.54%	81.58%	53.85%	46.15%	**81.58%**	**60.78%**
	Predictions Averages	**44.55%**	**69.59%**	**43.87%**	**45.58%**		

Source: Authors' own calculations

Table 4.79 in Appendix E shows the averages of all INF prediction accuracy averages per model for all studied markets and horizons. Similar to the KNN and Sigmoid sections, the best performing model for the INF was model 2.02 with the Autoregressive inputs that yielded the highest prediction accuracy average of 58.64%% for all horizons.

4.3.4 Summary of Macro Variables Predictions

The findings summarized in this section provide the detailed answers to **RQ7-RQ9**, the synopsis of the answers was presented at the end of this section. Based on the previous descriptive results, we have generalized and summarized the behaviors of the variables, and their predictive powers, based on the confirmed findings of the three Classifiers. Hence, the results presented in this section, are not specific to a model or country. From this perspective, we concluded that:

- Weighted KNN caused a deterioration in the prediction accuracy of almost all macro variables and horizons, compared to the equally weighted KNN results.
- There was no relationship between the average number of K and the average prediction accuracy, meaning K did not increase nor decrease versus the prediction accuracy. On the other hand, there was a positive relationship between the average number of K and the horizon forecasted, meaning that K increased with the horizon forecasted on average. For

example, for every one month predicted ahead, we needed K=7.9 and K=5.17 additional neighboring points in order to predict the FX and INF respectively.

- The yield curve on its own had valuable information and predictive power over equity markets in the long-term. Conform to our findings in section 4.1, the Level and Curvature had a leading effect on the EQUITY. According to Ahmed et al. (2017) interest rates Granger Caused the stock market. In addition, Bissoon et al. (2016) proved the negative relationship between the interest rate and the stock market both in the short and long run.
- Macro variables seemed to hold predictive power over the future long-term behavior of the FX in our studied markets. Kearns & Manners (2005) confirmed that changes in the policy rates are rapidly transmitted into the foreign exchange rate. Adding to the fact that Dilmaghani & Tehranchian (2015) stated that the country's exchange rate is also affected by other macro variables such as the inflation and GDP. On the other hand, based on our findings in section 4.1, macro variables affected the FX. For example, a shock to the EQUITY caused an appreciation of the country's exchange rate in almost all studied markets, consequently, a positive shock to the GDP caused an appreciation of the exchange rate.
- The POLRATE seemed to be affected by macro variables in the short term, however, in the long term the yield curve had more predictive power over the POLRATE. These findings are consistent with our results in section 4.1, and conform to findings in academic literature, where economic growth leads to a positive response in the Level, POLRATE and INF. Additionally, a shock to the Level, GDP and INF caused a positive response in the POLRATE for almost all our studied markets. We have proved as well, in section 4.1, that the POLRATE is affected by the yield curve factors. On the other hand, academic scholars found out that the stock markets and the foreign exchange rates are affected by their respective monetary policies (Suhaibu et al., 2017; Olamide & Maredza, 2019).
- The INF and GDP seemed to be dominated by their own past values, the Classifiers with the Autoregressive inputs, exploiting both: the non-linear capabilities of the Classifiers, and the predictive power of the Autoregressive models. Tkacz (2001) found out, when forecasting the GDP, that the linear Autoregressive model performed as well as the non-linear neural network model for the 3-mth horizon, although, for the 1-year horizon the

non-linear neural network model captured the non-linear behavior of variables, and its performance was superior to the linear Autoregressive model. Nasr et al. (2015) found evidence that past information on the inflation improves the future prediction of the variable, and Lanne & Luoto (2017) stated that both expected and lagged inflation dominated the current inflation level. On the other hand, Clements & Galvao (2013) improved the prediction RMSE when forecasting output growth and inflation with an Autoregressive model on lightly revised data, and Adedotun & Taiwo (2020) used different types of Autoregressive models in order to predict the GDP. Additionally, Maccarrone et al. (2021) found out that the KNN Classifier model captured the self-predictive ability of the US GDP and performed better than traditional linear models.

In order to generalize, we have measured in table 4.80 the best performing model predictions averages per macro variable and per horizon, for the KNN, Sigmoid, and Softmax Classifiers, in addition to the variance from the 12m to the 3m horizon prediction accuracies. <u>You will able to conclude that:</u>

- In general, macro variables prediction accuracy improved over longer-term horizons, consistent with findings in academic literature (Tkacz, 2001; Chirinos-Leañez & Pagliacci, 2015; Boeck & Feldkircher, 2021; Maccarrone et al., 2021).
- For example, as illustrated in table 4.80, the Softmax Classifier EQUITY predictions improved on average by 9.5% from the 3m to the 12m horizon, compared to a similar improvement as well using the Sigmoid Classifier equivalent to 8.6%, hence, long term predictions of equity markets were more accurate. Comparatively, academic scholars provided evidence of the superior performance of machine learning Classifiers, and hybrid machine learning techniques based on Classifiers over traditional techniques in order to predict the stock market (Ballings et al., 2015; Ogundunmade & Adepoju, 2022). Based on a hybrid technique, Fanita & Rustam (2018) predicted the stock market and reached a Classification accuracy of 80%, compared to our highest Classification accuracy of: 71.6% on average for all studied markets, and 84.2% for a single country namely Brazil.

- Similar to the EQUITY predictions, the INF improved greatly over long-term horizon forecasts, for example, the Softmax Classifier INF predictions improved on average by 17% from the 3m to the 12m horizon, compared to a similar improvement as well using the Sigmoid and KNN Classifiers. Rodríguez-Vargas (2020) used different machine learning techniques in order to forecast the inflation rate, and the author was able to reach a maximum KNN prediction classification accuracy of 64%, and a maximum of 71% prediction classification accuracy based on the Random Forest. Comparatively, based on our results we have reached a maximum prediction classification accuracy on average for all studied markets of 70% for our KNN Classifier, and a maximum KNN prediction classification accuracy of 84% for the US on a standalone.
- The POLRATE average predictions deteriorated with the horizon forecast, meaning that policy rates' shorter-term predictions were more accurate than the longer-term, for all three Classifiers. Although, academic work on the prediction of the monetary policy rate is scarce, our findings are supported by academic literature that have differentiated between monetary policy predictability in the short and long term. In fact, researchers focused mainly on the notion of short-term predictability, based on market surveys and polls published by financial markets preceding monetary policy meetings about their expectations on the upcoming decision (Bell, 2005; Blattner et al., 2008). This short-term predictability of the monetary policy rate, by financial markets, have improved over time (Swanson, 2006; Blattner et al., 2008). On the other hand, measuring the central bank's longer-term predictability is more difficult to evaluate, as it is assessed through the understanding of the central bank's objectives, and some proxies such as long-term inflation expectations (Bell, 2005; Blattner et al., 2008). Lastly, Wilhelmsen and Zaghini (2005) noted that central banks' predictability differs from a market to another, for example, the Euro Area's monetary policy rate is the most predictable, followed by the United States and Australia. According to our research findings from section 4.1, the POLRATE of the UK, EUR and SAF were more Endogenous, since movements in the majority of variables in the system led their policy rates, implying that they are more effectively set. In addition, based on our prediction classification accuracies from section 4.3, the policy rates of the central banks of the Euro Area, China and Brazil were the

most predictable, while the policy rates of Mexico and the US had the worst prediction classification accuracy.

- The best long-term predictions accuracy for the horizon of 12m were achieved by first the EQUITY ranging from 61% to 70%, and second by the INF ranging from 62% to 70%, for all three Classifiers. On the other hand, the best short-term predictions accuracy for the horizon of 3m was achieved by the POLRATE ranging from 61% to 75% for all three Classifiers. Finally, the FX rate was the most challenging variable as its average prediction accuracies, amongst all three Classifiers, was the worst for all horizons forecasted averaging for all tenors around 51%. These findings are consistent with the results in section 4.1, where the FX movements had a low association with the rest of the macro variables for the first and second Eigenvectors performed on the yield curves and macro variables. On the topic of FX forecasting, academic scholars have preferred the use of hybrid machine learning techniques that outperformed traditional ANN models (Ince & Trafalis, 2006; Reham et al., 2014; Shen et al., 2015; Islam & Hossain, 2021). Although, researchers mainly focused on short-term horizons forecasts, such as 30 minutes ahead, daily, and weekly (Ince & Trafalis, 2006; Shen et al., 2015; Bal & Demir, 2017; Islam & Hossain, 2021), others such as Reham et al. (2014) forecasted long-term horizons up to 1000 days ahead, realizing prediction accuracies from 14% to 99%. Taking into consideration that prediction accuracy levels reported in academic literature are based on the best performing model, not an average as presented in this study, our FX maximum prediction classification accuracy was: 68% for the 3-mth horizon, 75% for the 6-mth horizon, and 78% for the 1-year horizon. In addition, FX prediction accuracies are highly dependent on the country studied, more than other macro variables. Although, for FX predictions, hybrid machine learning techniques offered an adequate alternative to traditional ANN Regression and Classifier models, it would have been interesting if academic scholars generalized and tested these models on a variety of different currencies, from different geographical regions.

Table 4.80 Prediction averages per macro variable and per horizon, for the KNN, Sigmoid and Softmax Classifiers

Softmax Prediction Averages	3m	6m	12m	Variance 12m-3m	Best Model
EQUITY	52.01%	54.32%	61.54%	9.53%	2.03
FX	42.55%	46.42%	49.00%	6.45%	2.03
POLRATE	61.47%	51.36%	48.40%	-13.07%	2.03
GDP	54.61%	46.21%	56.43%	1.82%	2.02
INF	51.77%	54.55%	69.59%	17.82%	2.02
Sigmoid Prediction Averages	**3m**	**6m**	**12m**	**Variance 12m-3m**	**Best Model**
EQUITY	54.20%	59.09%	62.87%	8.67%	2.04
FX	49.21%	49.49%	51.46%	2.26%	2.03
POLRATE	69.61%	63.64%	57.31%	-12.30%	2.01
GDP	65.01%	56.31%	57.31%	-7.70%	2.02
INF	55.32%	60.86%	62.28%	6.96%	2.02
KNN Prediction Averages	**3m**	**6m**	**12m**	**Variance 12m-3m**	**Best Model**
EQUITY	64.07%	63.93%	71.64%	7.57%	2.04
FX	57.45%	57.72%	64.62%	7.17%	2.03
POLRATE	75.41%	71.23%	69.88%	-5.53%	2.04
GDP	64.54%	69.59%	73.98%	9.44%	2.02
INF	64.30%	68.22%	70.76%	6.46%	2.02

Source: Authors' own calculations

Answers to RQ7-RQ9 are summarized next:

- **RQ7:** Does the application of Weighted KNN improve the prediction results, compared to the equally weighted KNN?

  Answer to RQ7: Weighted KNN caused a deterioration in the prediction accuracy of almost all macro variables and horizons, compared to the equally weighted KNN results.

- **RQ8:** How does K of KNN behave in terms of the prediction accuracy and forecasted horizon?

  Answer to RQ8: There was no relationship between the average number of K and the average prediction accuracy. On the other hand, there was a positive relationship between the average number of K and the horizon forecasted, meaning that K increased with the maturity/horizon forecasted on average.

- **RQ9:** What are the most common identifiable trends of yield curves and macro variables behavior in terms of predictive power?

<u>Answer to RQ9:</u> The yield curve on its own had valuable information and predictive power over equity markets in the long-term. In addition, macro variables seemed to hold predictive power over the future long-term behavior of the FX in our studied markets. Additionally, the POLRATE seemed to be affected by macro variables in the short term, however, in the long term the yield curve had more predictive power over the POLRATE. Finally, the INF and GDP seemed to be dominated by their own past values, the Classifiers with the Autoregressive inputs, exploiting both: the non-linear capabilities of the Classifiers, and the predictive power of the Autoregressive models.

In general, macro variables prediction accuracy improved over longer-term horizons, except for the POLRATE predictions that deteriorated with the horizon forecast, meaning that policy rates shorter-term predictions were more accurate than longer-term. The best long-term predictions accuracy was achieved by first the EQUITY, and second the INF, for all three Classifiers. On the other hand, the best short-term predictions accuracy was achieved by the POLRATE. Finally, the FX rate was the most challenging variable, as its average predictions amongst all three Classifiers was the worst for all horizons forecasted.

5 Conclusion

5.1 Introduction

Our aim was to identify common trends in yield curves and macro variables behaviors from two perspectives: the perspective of interaction between the variables, and the perspective of predictive power of the variables. Studying the yield curves and macro variables from different geographical regions ensures that results are not specific to a particular country or region. Initially, we have analyzed the interaction/co-movement between the yield curves and macro variables by use of the three VAR structural analysis reports: Granger Causality, Impulse Response Function, and Variance Decomposition. Afterwards, we have predicted yield curves based on ANN Regression Multitask learning, and lastly, we have predicted our five macro variables based on three different ANN Classifiers, in order to generalize and present results that are not specific to a country, nor region, nor model.

We have contributed to academic literature in several aspects. Firstly, on the topic of yield curves and macro variables interaction, our analysis was based on common trends, not country nor region specific. Additionally, we have included an analysis of the Eigenvectors performed on the yield curves and macro variables, and we have identified plausible different scenarios of variables co-dependencies. Lastly, we have included a new variable ordering mechanism for the Cholesky Decomposition based on the predictive power of variables, measured from the Granger Causality. On the topic of yield curves predictions, we have filled in the gap in academic literature on the use of Multitask learning for yield curves predictions, since most of the techniques used in academic literature on the topic of ANN prediction are mainly based on Singletask learning. Furthermore, we have designed a scientific model that computes the optimum number of ANN Sigmoid hidden nodes, using the number of inputs/output nodes, and forecasted months, taking into consideration that academic researchers mainly use ad-hoc or trial and error techniques as their selection criteria for the optimum number of ANN hidden nodes. The application of this model is simple and could be used by academic researchers. We have applied as well the Independent Variable Contribution analysis in order to measure the predictive power of the variables. To the best of our knowledge, the Independent Variable Contribution was not applied before in yield curve prediction, since most academic work on that topic focus on the description of the techniques applied, rather than measuring the predictive power of the variables. On the topic of macro variables prediction using three Classifiers, we were not focused on selecting the Classifier with the highest prediction accuracy, as most academic scholars do, rather, we have contributed to academic literature by presenting results that are based on common identifiable prediction patterns, and not model specific. In other words, our analysis was focused on the predictive power of the variables, and we were able to identify how certain variables have a significant impact on the future outcome of other variables. We have filled in the gap in academic literature on the topic of monetary policy rate prediction, since academic work on that topic is scarce. Adding to the fact, we have provided a behavioral analysis on K of KNN versus the horizon forecast and prediction accuracy, and this type of analysis was not provided before in academic literature on the topic of KNN. Lastly, we have applied a Weighted KNN approach, and compared its precition results to the equally weighted KNN. To the best of our knowledge the Weighted KNN approcah was not applied before for macro variables predictions.

5.2 Summary of Findings

We found evidence that the GDP and INF were positively associated with the Level or yield curve parallel shifts, since a growth in the economy leads to higher inflationary pressures that will trigger a rise in the yield curve in the form of a parallel shift (the Level), prompting the central bank to hike its policy rate. FX rate movements were not aligned with the movements in other macro variables, implying that FX rates are greatly affected by events that are specific to each country. On the other hand, equity indices were positively associated with macro variables for yield curves upward parallel shifts, during economic expansions, though, they were negatively associated with macro variables for yield curves downward parallel shifts, caused by the dynamic and non-consistent relation between the monetary policy and the stock market.

The GDP led the Level, since a growth in the economy leads to higher inflationary pressures that will trigger a rise in the yield curve in the form of a parallel shift (the Level). Thus, shocks to the GDP and INF mainly caused positive responses in the Level. For policy makers, it is crucial to set the level of acceptable target inflation appropriately, as economic growth will not take place without inflation, since these two variables are highly associated. We did not find any violation of the weak form of the Efficient Market Hypothesis, with the exception of the Euro Area, as most macro variables seem to be independent of equity indices. Since an appreciation in the FX rate of the country is due to a higher demand in the country's currency, shocks to the FX caused a positive response in the Level in most studied markets. In fact, FX rate movements of developed markets, US, UK and EUR encompassed more info, more Endogenous, than the rest of the selected markets, and the FX was strongly influenced by information coming from the yield curve, i.e., Level, Slope, and the POLRATE. Although, a shock to the INF caused a positive response in the FX, the response was not predominantly high. For policy makers, it is clear that the reaction of the FX to the rest of macro variables will mostly be uncertain, as it reacts to specific movements related to each country, adding to the fact that the level of economic development affects the behavior of the FX in general.

Equity indices seemed to lead the GDP, as the EQUITY is a leading indicator for economic growth. On other hand, the GDP caused a positive response in the EQUITY, since a growing economy leads to higher income and investment, hence, a shock to the EQUITY causes an appreciation of the country's exchange rate. Consequently, a positive shock to the GDP causes an appreciation of the currency exchange rate. Since the EQUITY Granger Caused the inflation, shocks to the EQUITY led to a negative response in the Slope, caused by the reaction of the short rate to higher inflation expectations. Finally, shocks to the Level and Slope caused a negative response in the EQUITY, as these two yield curve factors react according to higher inflation expectations. For market participants and investors, the stock market seemed to react effectively to the economy, as a matter of fact it is a leading indicator for the economy.

Yield curve factors, such as the Level and Slope, mainly affected the POLRATE, thus, shocks to the Level, GDP and INF caused a positive response in the POLRATE. On the other hand, the FX led the POLRATE, since foreign exchange rates play a dominant role in determining the behavior of the monetary policy, adding to fact that the POLRATE led the GDP. In fact, the POLRATE dynamics were different from a country to another, since in some studied markets the FX had a high explanatory power over the POLRATE, while in others it was the GDP, adding to the fact that in some other countries it was the Level and the Slope that had explanatory powers.

For policy makers, it's important to access the response of their policy rates to macro variables properly, and the opposite as well, prior to any rate hikes or cuts. Lastly, shocks to the FX did not cause substantially high responses in the GDP on most of the studied markets, as this relationship converges in the long run more than the short run. Therefore, policy makers need to be aware that a currency depreciation does not necessarily lead to economic growth, since the relationship between the FX and the GDP is ambiguous.

We found evidence of a one-way direction Fisher Effect in two studied markets, where the INF was Granger Caused by the Level. Shocks to the EQUITY caused mostly positive responses in the INF, as the EQUITY is a leading indicator for economic growth, which will lead eventually to inflationary pressures. Conform to academic literature, positive shocks to the FX caused mostly negative responses in the INF, as a currency exchange rate depreciation is likely to cause inflationary pressures.

Based on the ANN yield curves forecasting results, the model with the three-yield curve latent factors and three yield curve proxies performed best for the 1m horizon, as its total errors average was the lowest. These findings are consistent with our results in section 4.1, the Level, Slope, and Curvature were mainly affected by the yield curve latent factors, and conform to findings in academic literature. The information contained in macro variables contributed to the prediction of yield curves for longer horizons, i.e., 3m and 6m, as all models containing macro variables ranked better in general for longer term horizons forecasts, similar to findings in academic literature. Concerning the 1m horizon, we were able to achieve an 80.2% prediction accuracy on the out of sample data on average for all studied markets. These out of sample prediction results varied on average for all studied markets, from 95% for Mexico, and 90% for Brazil, to a low of 73% for the Euro Area, and 55% for South Africa. For the 3m horizon, the out of sample average predictions accuracy for all studied markets dropped to 45.4%, ranging on average from 90% for Mexico, to 20% for the UK. Finally, the out of sample average predictions accuracy dropped even further to 31.5% for the 6m horizon. Hence, the deterioration of the prediction accuracy on the out of sample data was non-linear and significantly higher than the deterioration in the prediction accuracy on the training data. We recommend to researchers the use of Multitask learning for academic studies on highly correlated variables, as their optimization time is less than Singletask learning, and they are able to use the correlation factors between the target variables more effectively, since their hidden nodes are shared by all targets. In addition, we recommend to researchers the testing of their prediction models on data from different geographical regions, since the prediction results are highly dependent on the selected country.

Singletask learning accuracy seemed to have almost similar accuracy as Multitask learning for up to three output nodes, or three predicted yields at once. From the fourth to the seventh output node, the predictions lost accuracy. Based on the sensitivity analysis performed on the out of sample error, we found out that increasing the number of hidden nodes decreased the training error, thus, increasing the hidden nodes leads to overfitting the data. Hence, we recommend to researchers the use of a simple neural network architecture. In addition, increasing the horizon forecast and output nodes increased the training error, as it is theocratically expected. On the other hand, the number of hidden nodes had no impact on the out of sample error. Thus, we do not recommend to researchers the use of the out of sample error as a selection criterion for the number of hidden nodes. Finally, the horizon forecast and number of output nodes had a negative impact on the out of sample error. Based on the model that we have designed that computes the optimum number of hidden nodes as a function of: input nodes (I), forecasting horizon (F), and output nodes (O), we found out that the output nodes had a higher coefficient than the input nodes, implying that the output nodes affected the optimum number of hidden nodes more than the input nodes. Finally, the forecasted horizon had the lowest influence on the optimum number of hidden nodes. In light of the above, academic scholars will be able to use the simple model that we have designed in order to compute their optimum number of hidden nodes.

Based on the Independent Variable Contribution analysis, the weight of the Slope on average (for all studied markets) increased for longer horizons. We have attributed the increase in Slope weight to the considerable yield curve Slope changes during the sample period. Hence, the Independent Variable Contribution cannot be generalized, as they depend on each country's yield curve behavior and forecasted horizon. Additionally, k-fold Cross Validation improved the average out of sample forecast accuracy for longer terms horizons more than shorter terms, hence, we do not recommend to researchers the use of such a computationally difficult technique for short term forecasts.

The application of the Weighted KNN caused a deterioration in the prediction accuracy of almost all macro variables and horizons, compared to the equally weighted KNN results. Additionally, there was no relationship between the average number of K and the average prediction accuracy, meaning that K did not increase nor decrease versus the prediction accuracy. On the other hand, there was a positive relationship between the average number of K and the horizon forecasted, meaning that K increased with the horizon forecasted on average.

The yield curve on its own had predictive powers over long term equity markets. Conform to our findings in section 4.1, the Level and Curvature had a leading effect on the EQUITY. Furthermore, macro variables seemed to hold predictive powers over the future long-term behavior of the FX, implying that the FX is influenced by macro variables such as the INF, GDP and POLRATE. Findings supported by academic literature, and consistent with our findings in section 4.1. The POLRATE seemed to be affected by macro variables in the short term, however, in the long term the yield curve had more predictive powers on the POLRATE, findings confirmed by our results from section 4.1, and conform to findings in academic literature. The INF and GDP seemed to be dominated by their own past values, the Classifiers with the Autoregressive inputs. Policy makers and market participants needs to be aware that the inflation and the GDP undergo cycles, and their reactions are not immediate.

Although, macro variables prediction accuracy improved over longer-term horizons, such as the EQUITY and INF, which is consistent with findings in academic literature, the POLRATE average prediction accuracy deteriorated with longer horizon forecasts, meaning that shorter-term predictions of the policy rate were more accurate than longer-term. Hence, for market participants it’s crucial to understand that the process of determining the policy rate is a dynamic process that is altered and modified according to the behavior of other variables. On the other hand, the best long-term average predictions accuracy for the horizon of 12m were achieved by first the EQUITY ranging from 61% to 70%, and second by the INF ranging from 62% to 70%. On the other hand, the best short-term average predictions accuracy for the horizon of 3m was achieved by the POLRATE ranging from 61% to 75%. Finally, the FX rate was the most unpredictable value as its average predictions, amongst all three Classifiers, was the worst for all forecasted horizons averaging for all tenors and all Classifiers around 51%, implying that FX prediction accuracies are highly dependent on the country studied, more than other macro variables.

5.3 Limitations of the Study

Since our objective was to identify common trends in yield curves and macro variables behaviors based on different geographical regions to ensure that results are not specific to a particular country or region, we were limited to studying two markets per geographical region. Hence, increasing the studied markets per geographical region, could have affected the results, or not, taking into consideration that we have identified a lot of noise in the data, meaning that a lot of variability in the variables was attributed to specific factors, i.e., related to the studied market specifically. On the other hand, yield curves and macro variables predictions were studied using a non-linear approach based on neural networks, though, the interaction between yield curves and macro variables was studied using a linear approach, since currently there are no neural network approach available for that purpose, thus, findings on the interaction section of this study were based only on the linear behavior of variables.

5.4 Suggestions for Future Research

ANN are very powerful models due to their non-linear twist and flexibility of their architecture, hence, could be applied in many different domains, and we believe that these models will be tapped even further in the future by academic scholars, bankers, policy makers and investors. We believe that the topic of interaction between yield curves and macro variables could be further developed by designing a dynamic machine learning ANN approach that would capture the non-linear co-movement behavior of the variables. In addition, it would be very interesting to follow up this research with further studies on the use of Multitask learning for the prediction of highly correlated variables, such as the GDP and INF. Furthermore, the selection criteria for the optimum number of hidden nodes needs to be explored further in a separate academic study dedicated solely for that topic. Lastly, a comparative analysis between the prediction accuracy of ANN Regression and Classifier for macro variables predictions could also be an interesting framework for academic scholars to pursue in the future.

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Appendices

Appendix A: Yield Curves and Macro Variables Data Sources and Analysis

Yield curves correlation matrices

EGP

Correlation	3m	6m	1Y	3Y	5Y	7Y	10Y
3m	1	0.8791	0.8130	0.6948	0.6816	0.4666	0.3806
6m	0.8791	1	0.8344	0.7167	0.6967	0.4739	0.5132
1Y	0.8130	0.8344	1	0.8172	0.8180	0.7200	0.6758
3Y	0.6948	0.7167	0.8172	1	0.9961	0.7198	0.6739
5Y	0.6816	0.6967	0.8180	0.9961	1	0.7292	0.6805
7Y	0.4666	0.4739	0.7200	0.7198	0.7292	1	0.7102
10Y	0.3806	0.5132	0.6758	0.6739	0.6805	0.7102	1

BRA

Correlation	3m	6m	1Y	3Y	5Y	7Y	10Y
3m	1	0.8357	0.6889	0.4761	0.3862	0.3907	0.3510
6m	0.8357	1	0.8215	0.7234	0.6282	0.6523	0.5896
1Y	0.6889	0.8215	1	0.7707	0.7060	0.7011	0.6212
3Y	0.4761	0.7234	0.7707	1	0.9513	0.9335	0.9069
5Y	0.3862	0.6282	0.7060	0.9513	1	0.9646	0.9495
7Y	0.3907	0.6523	0.7011	0.9335	0.9646	1	0.9564
10Y	0.3510	0.5896	0.6212	0.9069	0.9495	0.9564	1

IND

Correlation	3m	6m	1Y	3Y	5Y	10Y
3m	1	0.7935	-0.0023	0.4657	0.5405	0.5112
6m	0.7935	1	0.4023	0.7690	0.7549	0.7424
1Y	-0.0023	0.4023	1	0.7544	0.7332	0.7150
3Y	0.4657	0.7690	0.7544	1	0.8998	0.9097
5Y	0.5405	0.7549	0.7332	0.8998	1	0.9192
10Y	0.5112	0.7424	0.7150	0.9097	0.9192	1

SAF

Correlation	3m	6m	1Y	3Y	5Y	10Y
3m	1	0.9992	0.9345	0.6203	0.6251	0.5971
6m	0.9992	1	0.9465	0.6316	0.6425	0.6155
1Y	0.9345	0.9465	1	0.7314	0.7453	0.7142
3Y	0.6203	0.6316	0.7314	1	0.9213	0.8707
5Y	0.6251	0.6425	0.7453	0.9213	1	0.9360
10Y	0.5971	0.6155	0.7142	0.8707	0.9360	1

CHI

Correlation	T-Bonds 1Y	T-Bonds 3Y	T-Bonds 5Y	T-Bonds 7Y	T-Bonds 10Y
T-Bonds 1YR	1	0.7117	0.5472	0.4622	0.4342
T-Bonds 3YR	0.7117	1	0.8075	0.6813	0.5809
T-Bonds 5YR	0.5472	0.8075	1	0.8445	0.7337
T-Bonds 7YR	0.4622	0.6813	0.8445	1	0.7999
T-Bonds 10YR	0.4342	0.5809	0.7337	0.7999	1

MEX

Correlation	3m	6m	1Y	3Y	5Y	7Y	10Y
3m	1	0.917	0.755	0.543	0.442	0.457	0.379
6m	0.917	1	0.856	0.635	0.555	0.543	0.486
1Y	0.755	0.856	1	0.695	0.599	0.573	0.521
3Y	0.543	0.635	0.695	1	0.856	0.848	0.792
5Y	0.442	0.555	0.599	0.856	1	0.893	0.897
7Y	0.457	0.543	0.573	0.848	0.893	1	0.946
10Y	0.379	0.486	0.521	0.792	0.897	0.946	1

UK

Correlation	3m	6m	1Y	3Y	5Y	7Y	10Y
3m	1	0.9493	0.7565	0.5087	0.4452	0.3746	0.3228
6m	0.9493	1	0.8047	0.5644	0.4980	0.4284	0.3666
1Y	0.7565	0.8047	1	0.7457	0.6470	0.5650	0.4740
3Y	0.5087	0.5644	0.7457	1	0.9418	0.8354	0.7240
5Y	0.4452	0.4980	0.6470	0.9418	1	0.9570	0.8814
7Y	0.3746	0.4284	0.5650	0.8354	0.9570	1	0.9629
10Y	0.3228	0.3666	0.4740	0.7240	0.8814	0.9629	1

EUR

Correlation	3m	6m	1Y	3Y	5Y	7Y	10Y
3m	1	0.9535	0.8887	0.6458	0.5063	0.4057	0.3419
6m	0.9535	1	0.9394	0.7074	0.5642	0.4457	0.3630
1Y	0.8887	0.9394	1	0.8554	0.7075	0.5819	0.4737
3Y	0.6458	0.7074	0.8554	1	0.9398	0.8527	0.7542
5Y	0.5063	0.5642	0.7075	0.9398	1	0.9646	0.8968
7Y	0.4057	0.4457	0.5819	0.8527	0.9646	1	0.9719
10Y	0.3419	0.3630	0.4737	0.7542	0.8968	0.9719	1

US

Correlation	3m	6m	1Y	3Y	5Y	7Y	10Y
3m	1	0.8995	0.4944	0.5367	0.4051	0.3157	0.2585
6m	0.8995	1	0.7248	0.6553	0.5251	0.4366	0.3772
1Y	0.4944	0.7248	1	0.6451	0.5188	0.4454	0.3900
3Y	0.5367	0.6553	0.6451	1	0.9296	0.8278	0.7606
5Y	0.4051	0.5251	0.5188	0.9296	1	0.9611	0.9111
7Y	0.3157	0.4366	0.4454	0.8278	0.9611	1	0.9718
10Y	0.2585	0.3772	0.3900	0.7606	0.9111	0.9718	1

Source: Authors' own calculations

Yield curves annual volatilities

Yield curve Annual Volatilities	3m	6m	1Y	3Y	5Y	7Y	10Y	Slope
EGP	2.08%	2.13%	2.04%	1.68%	1.73%	1.85%	1.63%	**-0.04%**
BRA	1.31%	1.93%	1.77%	2.25%	2.47%	2.44%	2.31%	**0.09%**
MEX	0.78%	0.83%	0.91%	1.06%	1.15%	1.12%	1.13%	**0.04%**
UK	0.69%	0.69%	0.73%	0.71%	0.74%	0.79%	0.79%	**0.01%**
EUR	0.62%	0.60%	0.63%	0.66%	0.70%	0.69%	0.68%	**0.01%**
US	0.69%	0.65%	0.68%	0.77%	0.84%	0.91%	0.84%	**0.02%**
CHI	NA	NA	0.91%	0.75%	0.72%	0.64%	0.60%	**-0.03%**
IND	2.30%	2.68%	2.60%	2.67%	2.68%	NA	2.54%	**0.01%**
SAF	0.93%	0.94%	1.13%	1.22%	1.39%	NA	1.32%	**0.04%**

Source: Authors' own calculations

Table 3.1 Correlation estimates of the 3m yield to the rest of the yield curve tenors per studied market

3m yield correlation to the rest of Yield curve	*EGP*	*BRA*	*MEX*	*UK*	*EUR*	*US*	*IND*	*SAF*
3m yield	1	1	1	1	1	1	1	1
6m yield	[29]0.8791	0.8357	0.917	0.9493	0.9535	0.8995	0.7935	0.9992
1Y yield	[30]0.8130	0.6889	0.755	0.7565	0.8887	0.4944	-0.0023	0.9345
3Y yield	0.6948	0.4761	0.543	0.5087	0.6458	0.5367	0.4657	0.6203
5Y yield	0.6816	0.3862	0.442	0.4452	0.5063	0.4051	0.5405	0.6251
7Y yield	0.4666	0.3907	0.457	0.3746	0.4057	0.3157	NA	NA
10Y yield	0.3806	0.3510	0.379	0.3228	0.3419	0.2585	0.5112	0.5971
[31]Linear Slope	**-0.0575**	**-0.0587**	**-0.0594**	**-0.0678**	**-0.0704**	**-0.0648**	**-0.0147**	**-0.0438**

Source: Authors' own calculations

Table 3.2 Yield curves annualized volatilities for all countries

Yield curves annual volatilities	**3m yield**	**6m yield**	**1Y yield**	**3Y yield**	**5Y yield**	**7Y yield**	**10Y yield**	**Slope**
EGP	2.08%	2.13%	2.04%	1.68%	1.73%	1.85%	1.63%	[32]-0.04%
BRA	1.31%	1.93%	1.77%	2.25%	2.47%	2.44%	2.31%	0.09%
MEX	0.78%	0.83%	0.91%	1.06%	1.15%	1.12%	1.13%	0.04%
UK	0.69%	0.69%	0.73%	0.71%	0.74%	0.79%	0.79%	0.01%
EUR	0.62%	0.60%	0.63%	0.66%	0.70%	0.69%	0.68%	0.01%
US	0.69%	0.65%	0.68%	0.77%	0.84%	0.91%	0.84%	0.02%
CHI	NA	NA	0.91%	0.75%	0.72%	0.64%	0.60%	-0.03%
IND	2.30%	2.68%	2.60%	2.67%	2.68%	NA	2.54%	0.01%
SAF	0.93%	0.94%	1.13%	1.22%	1.39%	NA	1.32%	0.04%

Source: Authors' own calculations

Table 3.3 Equity indices descriptive statistics

	US	**UK**	**EUR**	**MEX**	**BRA**	**EGP**	**SAF**	**IND**	**CHI**
[33]Return Average	0.55%	0.11%	0.42%	0.52%	0.60%	0.50%	0.64%	1.02%	0.80%
[34]Sigma of Returns	3.98%	3.85%	5.29%	4.68%	6.42%	9.37%	4.45%	5.93%	9.20%
Average/Sigma	13.73%	2.86%	8.01%	11.02%	9.29%	5.39%	14.46%	17.21%	8.71%
[35]Total Positive Returns	275.8%	241.1%	343.5%	315.5%	435.8%	583.2%	318.7%	407.8%	586.6%

[29] The correlation of the EGP 3m and 6m yield is 0.8791
[30] The correlation of the EGP 3m and 6m yield is 0.8130
[31] The Slope of the correlation estimates of the 3m yield to the rest of the Yield curve tenors
[32] Slope of the Yield curve annualized volatility curve
[33] Average of Returns
[34] Sigma is the standard deviation of returns
[35] The summation of all positive returns

	US	UK	EUR	MEX	BRA	EGP	SAF	IND	CHI
[36]Total Negative Returns	-191.1%	-224.0%	-277.8%	-235.7%	-343.4%	-505.0%	-219.0%	-249.5%	-462.5%
[37]% Positive Returns	65.2%	54.8%	58.1%	56.1%	56.1%	58.1%	57.4%	65.8%	58.7%
[38]% Negative Returns	34.8%	45.2%	41.9%	43.9%	43.9%	41.9%	42.6%	34.2%	41.3%
[39]Skewness of Returns	-0.88	-0.58	-0.78	-0.67	-0.55	-0.45	-0.39	-1.85	-0.48
[40]Excess Kurtosis of Returns	1.81	0.80	2.18	2.00	1.79	2.37	1.40	11.45	1.30
[41]Max of Returns	9.12%	8.11%	15.50%	10.95%	15.67%	**31.17%**	12.10%	18.34%	24.63%
[42]Min of Returns	-15.15%	-13.95%	-21.31%	-19.67%	-28.50%	**-40.33%**	-16.14%	-37.72%	-29.91%

Source: Authors' own calculations

Table 3.4 FX descriptive statistics

	US	UK	EUR	MEX	BRA	EGP	SAF	IND	CHI
Return Average	0.11%	-0.17%	-0.04%	-0.37%	-0.36%	-0.72%	-0.53%	-0.28%	0.12%
Sigma of Returns	2.51%	2.68%	2.95%	3.44%	4.64%	**5.99%**	4.72%	2.73%	0.86%
Total Positive Returns	151.7%	141.9%	162.4%	161.7%	236.8%	46.4%	243.2%	117.2%	54.1%
Total Negative Returns	-135.0%	-168.9%	-168.8%	-219.0%	-292.1%	-157.6%	-326.0%	-161.0%	-36.0%
% Positive Returns	48.4%	47.1%	50.3%	47.1%	48.4%	43.2%	45.2%	43.2%	62.6%
% Negative Returns	51.6%	52.9%	49.7%	52.9%	51.6%	56.8%	54.8%	56.8%	37.4%
Skewness of Returns	0.59	-0.56	-0.38	-0.93	-0.47	-9.78	-0.34	-0.52	-0.36
Excess Kurtosis of Returns	2.03	2.03	1.70	2.90	1.40	113.11	0.56	5.73	3.57
Max of Returns	10.22%	9.05%	9.62%	7.37%	11.69%	17.11%	12.03%	9.66%	3.47%
Min of Returns	-7.91%	-10.23%	-10.21%	-15.73%	-16.73%	**-69.25%**	-16.51%	-13.78%	-3.19%

Source: Authors' own calculations

Table 3.5 GDP descriptive statistics

	US	UK	EUR	MEX	BRA	EGP	SAF	IND	CHI
Variable Average	1.72%	1.19%	0.94%	1.47%	1.63%	**4.05%**	1.98%	**5.66%**	**8.91%**
Return Average	0.00%	-0.01%	-0.01%	-0.03%	-0.02%	0.00%	-0.02%	0.01%	-0.04%
Sigma of Returns	0.30%	0.31%	0.29%	0.61%	0.59%	0.66%	0.31%	0.26%	0.30%
Total Positive Returns	16.2%	14.6%	13.6%	31.1%	30.7%	29.4%	16.0%	13.0%	11.9%
Total Negative Returns	-16.4%	-15.8%	-14.6%	-35.5%	-33.2%	-29.7%	-19.0%	-12.2%	-18.1%

36 The summation of all negative returns
37 Percent of the positive returns to the total returns
38 Percent of the negative returns to the total returns
39 The skewness of returns
40 The excess kurtosis of returns
41 The maximum of monthly returns
42 The minimum of monthly returns

	US	UK	EUR	MEX	BRA	EGP	SAF	IND	CHI
% Positive Returns	52.3%	51.0%	51.0%	46.5%	51.0%	56.8%	44.5%	45.8%	38.7%
% Negative Returns	47.7%	49.0%	49.0%	53.5%	49.0%	43.2%	55.5%	54.2%	61.3%
Skewness of Returns	0.41	0.05	**-0.56**	0.55	0.20	**-1.34**	0.45	0.33	0.13
Excess Kurtosis of Returns	3.20	3.54	5.85	3.01	3.75	8.91	2.06	2.46	2.00
Max of Returns	1.17%	1.02%	0.97%	**2.26%**	2.23%	2.11%	1.17%	0.88%	0.86%
Min of Returns	-0.97%	-1.06%	-1.24%	-2.02%	-2.25%	**-3.32%**	-0.83%	-0.73%	-0.84%

Source: Authors' own calculations

Table 3.6 INF descriptive statistics

	US	UK	EUR	MEX	BRA	EGP	SAF	IND	CHI
[43]Variable Average	1.94%	2.38%	**1.75%**	4.16%	5.59%	**12.78%**	5.97%	5.90%	2.66%
Return Average	-0.01%	0.00%	0.00%	0.00%	-0.01%	0.06%	0.00%	-0.08%	0.00%
Sigma of Returns	0.48%	0.30%	0.25%	0.33%	0.34%	1.83%	0.49%	0.92%	0.59%
Total Positive Returns	24.8%	17.9%	14.2%	19.6%	18.5%	107.2%	28.0%	30.8%	33.8%
Total Negative Returns	-26.7%	-17.8%	-14.8%	-19.0%	-19.9%	-97.2%	-27.3%	-44.0%	-33.1%
% Positive Returns	45.8%	40.6%	43.9%	50.3%	52.9%	52.9%	45.8%	45.8%	48.4%
% Negative Returns	54.2%	59.4%	56.1%	49.7%	47.1%	47.1%	54.2%	54.2%	51.6%
Skewness of Returns	-0.79	-0.01	-0.26	-0.02	0.19	0.18	-0.37	**-4.58**	-0.62
Excess Kurtosis of Returns	6.92	0.61	0.80	2.46	2.61	1.73	2.22	41.31	2.67
Max of Returns	2.00%	1.00%	0.60%	1.36%	1.53%	6.77%	1.40%	2.57%	1.60%
Min of Returns	-2.60%	-1.00%	-0.90%	-1.22%	-0.97%	-4.80%	-2.10%	-8.26%	-2.60%

Source: Authors' own calculations

Table 3.7 Central banks' policy rates descriptive statistics

	US	UK	EUR	MEX	BRA	EGP	SAF	IND	CHI
[44]Number of POLRATE Changes	19	**17**	24	32	**67**	31	28	**53**	25
[45]Number of POLRATE Hikes	11	7	9	20	28	17	17	18	13
[46]Number of POLRATE Cuts	8	10	15	12	39	14	11	35	12
[47]Sum of POLRATE Hikes	2.75%	1.75%	2.25%	**6.50%**	13.25%	**15.25%**	**7.25%**	5.50%	3.14%
[48]Sum of POLRATE Cuts	-5.00%	-5.50%	-4.75%	-5.50%	**-23.25%**	-8.75%	**-7.50%**	**-11.00%**	-4.37%
[49]Average of POLRATE Hikes	0.25%	0.25%	0.25%	0.33%	0.47%	0.90%	0.43%	0.31%	0.24%

[43] The average of the variable itself
[44] Number of times the central bank changed during the sample period
[45] Number of times the central bank increased rates
[46] Number of times the central bank decreased rates
[47] The total of all central bank hikes
[48] The total of all central bank Cut
[49] The average of all central bank hikes

	US	UK	EUR	MEX	BRA	EGP	SAF	IND	CHI
[50]Average of POLRATE Cuts	-0.63%	-0.55%	-0.32%	-0.46%	-0.60%	-0.63%	-0.68%	-0.31%	-0.36%
[51]Max of POLRATE single Hike	0.25%	0.25%	0.25%	0.50%	0.75%	3.00%	0.50%	0.50%	0.27%
[52]Min of POLRATE single Cut	-1.25%	-1.50%	-0.75%	-0.75%	-1.50%	-1.00%	-2.00%	-0.50%	-1.08%

Source: Authors' own calculations

Table 3.8 Yield curves Slopes per studied market

	[53]Slope Average	[54]Slope Sigma	[55]Slope Max	[56]Slope Min	[57]% Above 0%	[58]% Above 0.10%	[59]% Below -0.10%
US	0.18%	0.12%	0.42%	-0.08%	90.38%	78.85%	0.00%
UK	0.15%	0.13%	0.41%	-0.09%	82.05%	66.03%	0.00%
EUR	0.14%	0.09%	0.33%	-0.03%	98.72%	66.03%	0.00%
MEX	0.16%	0.13%	0.40%	-0.05%	88.46%	62.82%	0.00%
BRA	0.10%	0.20%	0.60%	-0.31%	71.79%	51.28%	16.67%
EGP	0.16%	0.19%	0.42%	-0.36%	82.05%	73.72%	15.38%
SAF	0.13%	0.08%	0.29%	-0.05%	93.59%	66.67%	0.00%
IND	0.21%	0.08%	0.51%	0.02%	100.00%	94.87%	0.00%
CHI	0.10%	0.06%	0.25%	0.01%	100.00%	41.03%	0.00%

Source: Authors' own calculations

[50] The average of all central bank cuts
[51] The maximum of central bank singles hikes
[52] The maximum of central bank singles cuts
[53] Yield curve Slopes average during the sample period
[54] Yield curve Slopes standard deviation during the sample period
[55] Maximum of Yield curve Slopes
[56] Minimum of Yield curve Slopes
[57] Threshold of above 0% for Yield curves Slopes
[58] Threshold of above 0.10% for Yield curves Slopes
[59] Threshold of below -0.10% for Yield curves Slopes

Yield curves Eigenvectors/values

Eigenvectors	USW1	UKW1	EURW1	MEXW1	BRAW1	EGPW1	SAFW1	INDW1	CHIW1
EQUITY	-0.16	0.11	0.22	0.17	0.22	0.01	0.03	0.33	0.15
FX	0.05	0.22	0.19	0.20	0.20	0.11	0.22	0.29	0.05
POLRATE	-0.22	0.27	0.15	-0.22	-0.16	-0.19	-0.11	-0.16	0.24
GDP	-0.14	0.15	0.12	-0.13	-0.01	0.03	0.00	-0.04	0.25
INF	-0.15	0.10	0.15	-0.05	-0.16	-0.05	-0.10	-0.09	0.16
3m	-0.29	0.33	0.33	-0.32	-0.26	-0.36	-0.39	-0.25	
6m	-0.34	0.34	0.35	-0.35	-0.34	-0.37	-0.40	-0.36	
1Y	-0.33	0.36	0.32	-0.35	-0.34	-0.40	-0.41	-0.31	0.35
3Y	-0.40	0.36	0.39	-0.37	-0.38	-0.39	-0.37	-0.40	0.42
5Y	-0.39	0.36	0.38	-0.36	-0.37	-0.39	-0.40	-0.40	0.44
7Y	-0.37	0.34	0.35	-0.36	-0.38	-0.33			0.42
10Y	-0.35	0.31	0.32	-0.34	-0.37	-0.31	-0.39	-0.40	0.40
Eigenvalues	5.24	5.78	5.65	5.75	5.99	5.43	5.06	5.47	4.20
%	43.64%	48.18%	47.06%	47.88%	49.91%	45.27%	45.99%	49.69%	41.98%
Cum %	**43.64%**	**48.18%**	**47.06%**	**47.88%**	**49.91%**	**45.27%**	**45.99%**	**49.69%**	**41.98%**

Source: Authors' own calculations

Eigenvectors	USW2	UKW2	EURW2	MEXW2	BRAW2	EGPW2	SAFW2	INDW2	CHIW2
EQUITY	-0.12	-0.03	0.04	0.20	0.32	0.34	-0.35	-0.05	0.37
FX	0.17	0.08	-0.06	0.29	0.37	-0.61	0.00	-0.03	-0.23
POLRATE	0.47	-0.41	0.47	0.48	0.42	0.45	0.67	0.45	0.39
GDP	0.16	-0.36	0.41	0.26	0.18	0.18	0.13	0.04	0.44
INF	-0.09	-0.13	0.27	0.11	0.20	0.29	0.45	0.59	0.54
3m	0.38	-0.36	0.29	0.37	0.47	0.19	0.14	-0.49	
6m	0.36	-0.32	0.26	0.31	0.30	0.10	0.14	-0.31	
1Y	0.29	-0.13	0.17	0.22	0.24	-0.01	0.08	0.32	-0.02
3Y	-0.12	0.23	-0.14	-0.13	-0.10	-0.16	-0.24	0.02	-0.12
5Y	-0.28	0.32	-0.27	-0.26	-0.20	-0.17	-0.22	-0.03	-0.22
7Y	-0.34	0.36	-0.35	-0.28	-0.20	-0.19			-0.24
10Y	-0.37	0.38	-0.37	-0.34	-0.23	-0.23	-0.24	-0.04	-0.21
Eigen Values	1.91	1.99	1.86	1.96	1.73	1.82	1.43	1.38	1.21
%	15.93%	16.60%	15.47%	16.30%	14.41%	15.14%	13.00%	12.51%	12.07%
Cum %	**59.57%**	**64.78%**	**62.53%**	**64.18%**	**64.32%**	**60.41%**	**58.98%**	**62.20%**	**54.05%**

Source: Authors' own calculations

Eigenvectors	USW3	UKW3	EURW3	MEXW3	BRAW3	EGPW3	SAFW3	INDW3	CHIW3
EQUITY	-0.54	-0.75	0.23	0.69	0.43	0.58	0.64	-0.15	-0.69
FX	0.60	-0.21	0.35	0.54	0.41	0.07	0.30	-0.35	-0.15
POLRATE	-0.14	0.10	-0.28	-0.23	-0.41	-0.16	0.19	-0.33	0.33
GDP	-0.40	-0.05	-0.36	0.09	0.48	0.67	0.67	-0.68	-0.27

INF	-0.29	0.60	-0.49	0.05	-0.29	-0.13	0.04	-0.24	0.30
3m	0.05	-0.03	0.28	-0.04	-0.15	-0.20	0.01	-0.33	
6m	0.06	-0.02	0.29	-0.02	0.04	-0.15	0.02	-0.23	
1Y	0.08	-0.01	0.25	0.02	0.15	-0.01	0.06	0.23	0.34
3Y	0.15	0.02	-0.02	0.23	0.19	0.08	0.06	0.02	0.18
5Y	0.15	0.05	-0.15	0.18	0.18	0.09	0.04	0.00	-0.01
7Y	0.13	0.08	-0.23	0.21	0.17	0.22			-0.10
10Y	0.07	0.06	-0.27	0.17	0.14	0.20	-0.02	0.11	-0.25
Eigenvalues	1.52	1.06	1.23	1.18	1.41	1.29	1.22	1.13	1.07
%	12.63%	8.85%	10.27%	9.80%	11.72%	10.72%	11.12%	10.30%	10.70%
Cum %	**72.20%**	**73.63%**	**72.80%**	**73.98%**	**76.04%**	**71.13%**	**70.10%**	**72.50%**	**64.75%**

Source: Authors' own calculations

Macro variables Eigenvectors

Eigenvectors	**USW1**	**UKW1**	**EURW1**	**MEXW1**	**BRAW1**	**EGPW1**	**SAFW1**	**INDW1**	**CHIW1**
EQUITY	0.53	0.30	0.32	0.61	0.66	0.67	0.41	0.59	0.47
FX	-0.45	0.45	0.23	0.58	0.61	0.37	0.48	0.54	-0.08
POLRATE	0.36	0.57	0.54	-0.46	-0.36	-0.43	-0.59	-0.48	0.49
GDP	0.49	0.54	0.53	-0.26	0.08	0.48	-0.18	-0.02	0.55
INF	0.40	0.30	0.53	-0.03	-0.23	0.08	-0.47	-0.36	0.47
Eigenvalues	1.98	1.90	1.91	1.75	1.85	1.53	1.57	2.01	1.78
%	39.66%	38.00%	38.17%	34.90%	36.91%	30.68%	31.45%	40.10%	35.51%
Eigenvectors	**USW2**	**UKW2**	**EURW2**	**MEXW2**	**BRAW2**	**EGPW2**	**SAFW2**	**INDW2**	**CHIW2**
EQUITY	-0.44	-0.71	-0.61	0.32	0.13	0.00	0.56	0.30	-0.34
FX	0.57	-0.29	-0.69	0.37	0.27	0.27	0.38	0.43	0.75
POLRATE	0.23	0.17	0.25	0.50	0.42	-0.21	0.28	0.42	0.42
GDP	0.47	0.12	0.22	0.70	0.58	-0.51	0.61	0.50	-0.23
INF	0.45	0.61	0.20	-0.15	0.63	0.79	0.29	0.54	0.31
Eigenvalues	1.16	1.12	1.29	1.32	1.32	1.11	1.32	1.21	1.25
%	23.20%	22.43%	25.85%	26.40%	26.35%	22.18%	26.31%	24.14%	24.94%
Eigenvectors	**USDW3**	**GBPW3**	**EURW3**	**MEXW3**	**BRAW3**	**EGPW3**	**SAFW3**	**INDW3**	**CHIW3**
EQUITY	-0.11	0.02	-0.49	0.06	0.15	-0.06	0.03	0.21	-0.58
FX	-0.23	0.62	0.46	0.13	0.31	0.67	0.42	0.17	-0.45
POLRATE	-0.79	-0.23	0.11	0.18	0.56	0.71	0.03	0.16	-0.16
GDP	0.02	-0.56	-0.53	-0.01	-0.74	0.19	-0.61	-0.85	0.00
INF	0.56	0.49	0.51	0.97	0.14	0.08	0.67	0.42	0.66
Eigenvalues	0.92	0.84	0.73	1.01	0.86	0.97	0.87	0.94	0.75
%	18.36%	16.81%	14.66%	20.11%	17.18%	19.42%	17.37%	18.79%	15.08%

Source: Authors' own calculations

Appendix B: Yield Curves and Macro Variables Results

Table 4.13 Leading variables Granger Causality per studied markets counted

Variables\Studied Market	US	UK	EUR	MEX	BRA	EGP	SAF	IND	CHI	Total
Level	**5**	**4**	3	**4**	**5**	2	2	1	1	**27**
Slope	**4**	**4**	**6**	1	3	3	1	0	1	**23**
Curvature	1	2	3	1	**4**	2	1	1	2	17
EQUITY	1	**4**	2	0	1	1	2	**4**	2	17
FX	1	2	3	2	2	3	2	2	0	17
POLRATE	**4**	2	3	0	2	2	2	2	1	18
GDP	1	1	**5**	2	2	2	2	2	3	**20**
INF	1	1	2	0	2	1	3	1	0	11
Total	18	**20**	**27**	10	**21**	16	15	13	10	

Source: Authors' own calculations

Table 4.15 Sorted Endogenous variables per studied market

Variables\Countries	US	UK	EUR	MEX	BRA	EGP	SAF	IND	CHI	Total
Level	2	1	3	1	2	**5**	0	2	0	16
Slope	1	0	1	0	**5**	0	**4**	2	0	13
Curvature	**6**	**4**	**5**	1	2	**6**	1	0	1	**26**
EQUITY	0	0	4	2	1	2	1	2	0	12
FX	3	3	4	1	2	0	0	3	0	16
POLRATE	2	**5**	4	2	2	1	**5**	0	3	**24**
GDP	**4**	**4**	4	2	**7**	2	2	1	3	**29**
INF	0	3	2	1	0	0	2	3	3	14
Total	18	**20**	**27**	10	**21**	16	15	13	10	

Source: Authors' own calculations

Appendix C: Yield Curve Prediction Data Methodology

Table 3.10 Hidden nodes against error regression hypothetical example

Dependent Variable Y=	Independent Variables X=		
Training Error	[60]H	[61]F	[62]O
0.33%	2	1	2
0.79%	3	1	2

Table 3.11 Optimum hidden node regression hypothetical example

Dependent Variable Y=	Independent Variable X=		
H	[63]I	O	F
6	2	7	1
5	2	7	3
5	2	7	6

[60] Number of hidden nodes
[61] Number of forecasting months
[62] Number of output nodes
[63] Number of input nodes

Appendix D: Yield Curve Prediction Results

Table 4.25 total errors for the 1m horizon predictions sorted from the lowest to highest

Model number	Model inputs	Model predictions total errors Average
1.08	3 PCASD & 3 YC Proxies	**2.07%**
1.07	3 YC Proxies	2.12%
1.05	3 PCASD & 3 AR YC	2.22%
1.13	3 YC Proxies & 3 MA3m YC	2.23%
1.04	7 AR YC	2.33%
1.11	3 PCASD & 3 MA3mYC	2.33%
1.12	3 AllPCA & 3 MA3mYC	2.44%
1.09	3 AllPCA & 3 YC Proxies	3.11%
1.06	3 AllPCA & 3 AR YC	3.85%
1.1	3 MA3m YC	4.45%
1.03	3 PCASD & 3 AllPCA	8.04%
1.01	3 PCASD	8.45%
1.02	3 AllPCA	8.56%

Source: Authors' own calculations

Table 4.27 total errors for the 3m horizon sorted from the lowest to highest

Model number	Model inputs	Model predictions total errors Average
1.12	3 AllPCA & 3 MA3mYC	**3.48%**
1.11	3 PCASD & 3 MA3mYC	3.59%
1.08	3 PCASD & 3 YC Proxies	3.61%
1.05	3 PCASD & 3 AR YC	3.65%
1.13	3 YC Proxies & 3 MA3m YC	3.76%
1.09	3 AllPCA & 3 YC Proxies	4.06%
1.04	7 AR YC	4.13%
1.06	3 AllPCA & 3 AR YC	4.18%
1.1	3 MA3m YC	6.29%
1.07	3 YC Proxies	6.58%
1.02	3 AllPCA	7.92%
1.03	3 PCASD & 3 AllPCA	8.19%
1.01	3 PCASD	8.86%

Source: Authors' own calculations

Table 4.29 total errors for the 6m horizon sorted from the lowest to highest

Model number	Model inputs	Model predictions total errors Average
1.08	3 PCASD & 3 YC Proxies	**4.99%**
1.12	3 AllPCA & 3 MA3mYC	5.01%
1.05	3 PCASD & 3 AR YC	5.04%

Model number	Model inputs	Model predictions total errors Average
1.11	3 PCASD & 3 MA3mYC	5.07%
1.13	3 YC Proxies & 3 MA3m YC	5.07%
1.06	3 AllPCA & 3 AR YC	5.58%
1.07	3 YC Proxies	5.88%
1.09	3 AllPCA & 3 YC Proxies	6.71%
1.04	7 AR YC	6.72%
1.1	3 MA3m YC	6.92%
1.02	3 AllPCA	7.96%
1.01	3 PCASD	8.38%
1.03	3 PCASD & 3 AllPCA	9.10%

Source: Authors' own calculations

Table 4.30 combined total errors per model and country for all horizons forecasted

Model number	**Model inputs**	**BRA**	**US**	**MEX**	**UK**	**EU**	**EG**	**SAF**	**IND**	**CHI**	**Model predictions combined total errors Average**
1.01	3 PCASD	37.51%	21.93%	32.72%	26.35%	24.76%	40.03%	13.86%	26.66%	7.29%	**25.68%**
1.02	3 AllPCA	33.94%	20.03%	23.79%	24.21%	27.95%	46.97%	13.15%	22.61%	7.22%	**24.43%**
1.03	3 PCASD & 3 AllPCA	35.40%	27.22%	29.07%	28.63%	25.60%	40.62%	13.43%	21.02%	6.97%	**25.33%**
1.04	7 AR YC	24.98%	7.15%	8.47%	7.81%	8.73%	19.53%	7.55%	11.32%	23.18%	**13.19%**
1.05	3 PCASD & 3 AR YC	18.94%	7.23%	8.80%	5.98%	7.52%	22.75%	7.76%	14.20%	4.97%	**10.91%**
1.06	3 AllPCA & 3 AR YC	30.33%	8.16%	15.25%	12.39%	6.93%	23.07%	7.74%	14.03%	4.64%	**13.61%**
1.07	3 YC Proxies	39.83%	8.20%	7.46%	25.87%	13.10%	123.88%	7.46%	9.43%	5.26%	**14.58%**
1.08	3 PCASD & 3 YC Proxies	19.14%	7.76%	8.30%	6.76%	6.36%	21.00%	7.28%	14.61%	4.85%	**10.67%**
1.09	3 AllPCA & 3 YC Proxies	41.28%	13.24%	9.15%	8.15%	7.07%	21.13%	7.42%	12.59%	4.80%	**13.87%**
1.1	3 MA3m YC	31.68%	7.95%	8.96%	25.11%	22.23%	840.28%	13.38%	24.63%	7.39%	**17.67%**
1.11	3 PCASD & 3 MA3mYC	19.41%	7.63%	8.75%	6.55%	6.19%	24.02%	7.92%	13.47%	5.00%	**10.99%**
1.12	3 AllPCA & 3 MA3mYC	19.05%	8.21%	8.57%	6.46%	6.49%	22.47%	7.52%	13.92%	5.70%	**10.93%**
1.13	3 YC Proxies & 3 MA3m YC	22.38%	7.66%	8.37%	6.51%	6.04%	20.35%	7.25%	16.44%	4.62%	**11.07%**
	Studied market predictions combined total errors Average	**28.76%**	**11.72%**	**13.67%**	**14.68%**	**13.00%**	**97.39%**	**9.36%**	**16.53%**	**7.07%**	

Source: Authors' own calculations

Appendix E: Macro Variables Prediction Results

Table 4.42 KNN Classifier EQUITY predictions accuracy averages per model for all studied markets and horizons

Horizon	Model 2.01	Model 2.02	Model 2.03	Model 2.04	Predictions Max per horizon	Predictions Average per horizon
3m	64.54%	61.23%	63.36%	64.07%	**64.54%**	**63.30%**
6m	63.96%	61.50%	63.19%	63.93%	**63.96%**	**63.15%**
12m	69.88%	67.84%	70.18%	71.64%	**71.64%**	**69.88%**
Predictions Average per model for all horizons	**66.13%**	**63.52%**	**65.57%**	**66.55%**	**66.55%**	

Source: Authors' own calculations

Table 4.44 KNN Classifier FX predictions accuracy averages per model for all studied markets and horizons

Horizon	Model 2.01	Model 2.02	Model 2.03	Model 2.04	Predictions Max per horizon	Predictions Average per horizon
3m	57.21%	48.46%	57.45%	55.56%	**57.45%**	**54.67%**
6m	58.81%	45.22%	57.72%	58.54%	**58.81%**	**55.07%**
12m	59.36%	53.51%	64.62%	61.99%	**64.62%**	**59.87%**
Predictions Average per model for all horizons	**58.46%**	**49.06%**	**59.93%**	**58.69%**	**59.93%**	

Source: Authors' own calculations

Table 4.46 KNN Classifier POLRATE predictions accuracy averages per model for all studied markets and horizons

Horizon	Model 2.01	Model 2.02	Model 2.03	Model 2.04	Predictions Max per horizon	Predictions Average per horizon
3m	76.60%	75.89%	77.30%	75.41%	**77.30%**	**76.30%**
6m	71.49%	71.71%	70.18%	71.23%	**71.71%**	**71.15%**
12m	68.13%	63.16%	65.50%	69.88%	**69.88%**	**66.67%**
Predictions Average per model for all horizons	**72.07%**	**70.25%**	**70.99%**	**72.18%**	**72.18%**	

Source: Authors' own calculations

Table 4.48 KNN Classifier GDP predictions accuracy averages per model for all studied markets and horizons

Horizon	Model 2.01	Model 2.02	Model 2.03	Model 2.04	Predictions Max per horizon	Predictions Average per horizon
3m	60.28%	64.54%	67.14%	64.78%	**67.14%**	**64.18%**
6m	60.98%	69.59%	63.45%	61.20%	**69.59%**	**63.81%**
12m	62.28%	73.98%	61.40%	57.89%	**73.98%**	**63.89%**
Predictions Average per model for all horizons	**61.18%**	**69.37%**	**64.00%**	**61.29%**	**69.37%**	

Source: Authors' own calculations

Table 4.50 KNN Classifier INF predictions accuracy averages per model for all studied markets and horizons

Horizon	Model 2.01	Model 2.02	Model 2.03	Model 2.04	Predictions Max per horizon	Predictions Average per horizon
3m	58.39%	64.30%	59.10%	58.39%	**64.30%**	**60.05%**
6m	54.70%	68.22%	56.39%	57.21%	**68.22%**	**59.13%**
12m	56.43%	70.76%	58.48%	57.60%	**70.76%**	**60.82%**
Predictions Average per model for all horizons	**56.51%**	**67.76%**	**57.99%**	**57.74%**	**67.76%**	

Source: Authors' own calculations

Table 4.59 Sigmoid Classifier EQUITY predictions accuracy averages per model for all studied markets and horizons

Horizon	Model 2.01	Model 2.02	Model 2.03	Model 2.04	Predictions Max per horizon	Predictions Average per horizon
3m	52.61%	52.48%	55.10%	54.20%	**55.10%**	**53.60%**
6m	59.09%	42.93%	56.06%	59.09%	**59.09%**	**54.29%**
12m	64.33%	56.73%	61.11%	62.87%	**64.33%**	**61.26%**
Predictions Average per model for all horizons	**58.68%**	**50.71%**	**57.42%**	**58.72%**		

Source: Authors' own calculations

Table 4.61 Sigmoid Classifier FX predictions accuracy averages per model for all studied markets and horizons

Horizon	Model 2.01	Model 2.02	Model 2.03	Model 2.04	Predictions Max per horizon	Predictions Average per horizon
3m	47.17%	48.70%	49.21%	46.94%	**49.21%**	**48.00%**
6m	48.23%	43.94%	49.49%	52.02%	**52.02%**	**48.42%**
12m	48.83%	48.54%	51.46%	46.49%	**51.46%**	**48.83%**
Predictions Average per model for all horizons	**48.08%**	**47.06%**	**50.05%**	**48.48%**		

Source: Authors' own calculations

Table 4.63 Sigmoid Classifier POLRATE predictions accuracy averages per model for all studied markets and horizons

Horizon	Model 2.01	Model 2.02	Model 2.03	Model 2.04	Predictions Max per horizon	Predictions Average per horizon
3m	69.61%	72.34%	73.70%	72.34%	**73.70%**	**72.00%**
6m	63.64%	63.89%	62.37%	61.62%	**63.89%**	**62.88%**
12m	57.31%	51.17%	53.80%	50.00%	**57.31%**	**53.07%**
Predictions Average per model for all horizons	**63.52%**	**62.47%**	**63.29%**	**61.32%**		

Source: Authors' own calculations

Table 4.65 Sigmoid GDP predictions accuracy averages per model for all studied markets and horizons

Horizon	Model 2.01	Model 2.02	Model 2.03	Model 2.04	Predictions Max per horizon	Predictions Average per horizon
3m	49.66%	65.01%	54.42%	55.33%	**65.01%**	**56.11%**

Horizon	Model 2.01	Model 2.02	Model 2.03	Model 2.04	Predictions Max per horizon	Predictions Average per horizon
6m	49.75%	56.31%	57.07%	52.53%	**57.07%**	**53.91%**
12m	50.88%	57.31%	48.25%	50.00%	**57.31%**	**51.61%**
Predictions Average per model for all horizons	50.09%	**59.54%**	**53.25%**	**52.62%**		

Source: Authors' own calculations

Table 4.67 Sigmoid INF predictions accuracy averages per model for all studied markets and horizons

Horizon	Model 2.01	Model 2.02	Model 2.03	Model 2.04	Predictions Max per horizon	Predictions Average per horizon
3m	47.39%	55.32%	48.98%	48.98%	**55.32%**	**50.17%**
6m	45.96%	60.86%	44.19%	49.24%	**60.86%**	**50.06%**
12m	45.03%	62.28%	48.25%	50.29%	**62.28%**	**51.46%**
Predictions Average per model for all horizons	46.13%	**59.49%**	**47.14%**	**49.50%**		

Source: Authors' own calculations

Table 4.71 Softmax Classifier EQUITY predictions accuracy averages per model for all studied markets and horizons

Horizon	Model 2.01	Model 2.02	Model 2.03	Model 2.04	Predictions Max per horizon	Predictions Average per horizon
3m	50.12%	41.37%	52.01%	49.65%	**52.01%**	**48.29%**
6m	53.83%	44.95%	54.32%	50.62%	**54.32%**	**50.93%**
12m	59.54%	42.11%	61.54%	59.83%	**61.54%**	**55.75%**
Predictions Average per model for all horizons	**54.50%**	**42.81%**	**55.96%**	**53.36%**		

Source: Authors' own calculations

Table 4.73 Softmax Classifier FX predictions accuracy averages per model for all studied markets and horizons

Horizon	Model 2.01	Model 2.02	Model 2.03	Model 2.04	Predictions Max per horizon	Predictions Average per horizon
3m	43.26%	39.72%	42.55%	39.72%	**43.26%**	**41.31%**
6m	42.72%	41.16%	46.42%	42.47%	**46.42%**	**43.19%**
12m	47.01%	46.78%	49.00%	44.16%	**49.00%**	**46.74%**
Predictions Average per model for all horizons	**44.33%**	**42.55%**	**45.99%**	**42.11%**		

Source: Authors' own calculations

Table 4.75 Softmax Classifier POLRATE predictions accuracy averages per model for all studied markets and horizons

Horizon	Model 2.01	Model 2.02	Model 2.03	Model 2.04	Predictions Max per horizon	Predictions Average per horizon
3m	69.61%	72.34%	73.70%	72.34%	**73.70%**	**72.00%**
6m	63.64%	63.89%	62.37%	61.62%	**63.89%**	**62.88%**

Horizon	Model 2.01	Model 2.02	Model 2.03	Model 2.04	Predictions Max per horizon	Predictions Average per horizon
12m	57.31%	51.17%	53.80%	50.00%	**57.31%**	**53.07%**
Predictions Average per model for all horizons	**63.52%**	**62.47%**	**63.29%**	**61.32%**		

Source: Authors' own calculations

Table 4.77 Softmax GDP predictions accuracy averages per model for all studied markets and horizons

Horizon	Model 2.01	Model 2.02	Model 2.03	Model 2.04	Predictions Max per horizon	Predictions Average per horizon
3m	35.70%	54.61%	40.66%	41.61%	**54.61%**	**43.14%**
6m	40.25%	46.21%	42.72%	43.70%	**46.21%**	**43.22%**
12m	48.08%	56.43%	41.03%	49.36%	**56.43%**	**48.72%**
Predictions Average per model for all horizons	41.34%	**52.42%**	**41.47%**	**44.89%**		

Source: Authors' own calculations

Table 4.79 Softmax INF predictions accuracy averages per model for all studied markets and horizons

Horizon	Model 2.01	Model 2.02	Model 2.03	Model 2.04	Predictions Max per horizon	Predictions Average per horizon
3m	41.61%	51.77%	40.66%	40.43%	**51.77%**	**43.62%**
6m	40.74%	54.55%	42.96%	41.98%	**54.55%**	**45.06%**
12m	44.55%	69.59%	43.87%	45.58%	**69.59%**	**50.90%**
Predictions Average per model for all horizons	**42.30%**	**58.64%**	**42.50%**	**42.66%**		

Source: Authors' own calculations