Louvain School of Management

# Forecasting macroeconomic variables through the term-structure of interest rates in emerging countries

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# 1 Abstract

This paper assesses whether macroeconomic variables in emerging markets can be forecasted with three components – the level, slope, and curvature – of their national yield curve, as well as the euro area and USA curves. Unlike most papers in the literature who only use the slope, we employ all three factors of the yield curve. We then create three vector autoregression (VAR) models for each country that respectively includes the national, euro and USA curves. Almost all macroeconomic variables in every country can successfully be forecasted with varying horizons and degrees of certainty. All three factors of the curves contain predictive power. The euro and USA curves are particularly effective in neighbouring markets such as Russia or Mexico. Further analysis should be performed with more sophisticated non-linear techniques, and with a rolling time window to see if the forecasting power of the curves varies over time.

# 2 Introduction

In economics, the yield curve or term structure has drawn the attention of researchers for decades. One of its intriguing factors is the term spread, which is the difference between short-term and long-term interest rates. Many researchers have examined its ability to predict economic variables, such as inflation, output, or GDP growth in developed economies. The ability of the yield curve to forecast those variables could be useful for politicians, investors and central bankers who want an inkling of what the economy will look like in the future.

The yield curve is the relationship between the yields (i.e. the rate of return) on government bonds and the remaining maturity of those bonds. For instance, governments can issue bonds with a 3-month, 5-year and 10 year maturity. Under normal economic circumstances, the yields on short-term bonds are lower than those on long-term bonds: the yield curve thus slopes upwards.

In the literature, the consensus is that the yield curve or term structure indeed predicts economic data. But the strength of that predictive ability remains a bone of contention. Most researchers have historically use the spread component of the yield curve only. It varies across countries, timeframes and methodologies. Observers have noticed that after the nineties, the term structure's forecasting power has deteriorated. Chinn and Kucko (2015) have found out that, except for Germany and the UK, the yield curve's predictive ability has been weakening in recent decades. This may be due to output growth being more stable over time in developed countries according to Wheelock and Wohar (2009).

The methodology used for those studies has evolved over time. Prior to the 2010s, researchers mostly relied on linear regressions (Estrella and Hardouvelis (1991) using the spread factor of the yield curve. To forecast economic recessions using the term spread, probit models are often used, and the occurrence of a recession is represented as a binary variable. Yield curve spreads are found to be especially useful for forecasting over a one-year horizon (Estrella and Hardouvelis (1991)

Starting from the 2010s onwards, new forecasting methods have been gradually replacing linear regressions. Some researchers such as Plakandaras et al. (2019) have made use of new machine learning techniques such as the Support Vector Regression model (SVR). Some authors such as Diebold and Li (2006) or

Møller (2014) have split the yield curve into three components using the Nelson-Siegel theoretical framework for yield curve modelling, or an empirical approach that is an approximation of Nelson-Siegel. The three components are the curvature, the spread, and the level. The curvature may have more predictive power than the spread according to Møller (2014). Splitting the yield curve will be the focus of this paper.

The theoretical explanations for this relationship are not widely agreed upon. Long-term interest rates may convey the expectations of investors, according to the expectations theory and the theory of intertemporal consumption. A lack of consensus on what causes this interconnection has led to the curve's predictive power being referred to as a "stylized fact" (Wheelock and Wohar (2009).

A gap in the literature concerning the yield curve is that insights on its predictive power have been centred on the developed world, with few studies on emerging countries. Output growth and recessions can be forecasted for Germany, the UK and the US, but not in all eurozone countries. However, it is hard to infer from the literature the forecasting power of the yield curve in emerging countries. One of the reasons being that according to Mehl (2009), illiquid and shallow debt markets mean that data on such economies were scarce. This "gap" in the literature (the absence of yield curve forecasting power evidence in emerging nations) is the reason why this thesis topic was selected.

This paper therefore makes a unique academic contribution. It is the first of its kind to use the entire term structure of interest rates, and not just the spread, to forecast macroeconomic variables in emerging markets.

We will start this paper by reviewing the literature concerning the forecasting power of the yield curve in different economic areas of the world. Secondly, we will then explain our own forecasting methodology, and why we have chosen vector autoregressive (VAR) models for that purpose. We will calculate the yield curve components (level, spread, and curvature) from government bond data using an empirical approach used by Diebold and Li (2006) and Kumar et al. (2021) among others.

After fitting the VAR models, we then look at the coefficient estimates and at the results from the Granger causality tests, impulse responses and forecast error variance decompositions. Those elements are explained in the Literature review and give us an idea of the yield curve's forecasting power. Finally, based on those results, we bring the paper to a conclusion.

# 3 Literature review

## 3.1 Forecasting using the entire term structure of the yield curve

Many papers on this subject have shown that a country's yield curve contains predictive power, but most of these studies (particularly older papers written before the 2010s) are focused on the yield curve's ability to predict USA macroeconomic variables. Examples of this are papers by Estrella and Hardouvelis (1991) or Dombrosky and Haubrich (1996). Evidence outside America exists chiefly in other developed countries like Germany or the United Kingdom, with barely any analysis performed with economic data from lesser-developed or emerging countries. In the literature, the most employed technique to forecast macro data consists of performing a linear regression with one component of the yield curve: the term spread or the difference between short- and long-term bonds. This is explained in detail by Wheelock and Wohar (2009). Other factors of the yield curve, such as the level or curvature, are in many cases not included.

In the past few years, however, a handful of papers have shed light on the predictive powers of other components of the yield curve other than the spread. Møller (2014) reckons that another element of the yield curve, the curvature, which is calculated from short-, medium- and long-term yields, is more useful than the spread when forecasting GDP. The level of the curve is also helpful in forecasting output, according to Bordo and Haubrich (2008), because it conveys inflation expectations. The usefulness of the three components (spread, curvature and level) varies among horizons and countries. For example, the curvature is significant in France and Germany at a one-year horizon but not in the UK or the US (Kumar et al. (2021).

## 3.2 Theoretical explanations

Why can the yield curve forecast economic data in developed countries? Explanations for the term structure's predictive power are scarce, but two theories are emphasized in academia. One of them is the expectations theory, the other is the consumer expectation theory.

According to the expectations theory, the long-term interest rate is determined by the average of present and future short-term ones. When analysts forecast lower economic growth, future short-term rates fall, which translates into lower long-term interest rates. This is because during a recession, investors expect central bank to lower short-term rates.

Another case is when excessive inflation must be subdued. In those circumstances, central banks will raise interest rates, as we saw in the first semester of 2022. This has the effect of pushing up the spread, inverting the yield curve, slowing economic growth and driving stock market valuations down. The level rises in tandem with inflation expectations.

The second theory put forward is the theory of intertemporal consumption, first defined by Harvey (1988). When people anticipate economic shocks, they will try to safeguard their income by buying long-term bonds. The price of the latter rises while rates fall, flattening or inverting the yield curve.

All those theories are, however, not universally agreed upon by researchers. For this reason, the predictive power of the curve is often referred to as a "stylized fact", or an empirical fact without a strong theoretical background according to Wheelock and Wohar (2009). Few studies have confirmed the two theories. It is presumed that more studies will be done on this subject to clear things up (see Evgenidis et al. (2020) and De Backer et al. (2019)

What about the curvature and level? Many studies indicate that the curvature reflects short- and medium-term effects of the central bank's monetary policy. For instance, when fiscal conditions begin to tighten, this will be signalled by the curvature factor (Diebold and Li (2006).

On the other hand, the level factor of the yield curve denotes inflation expectations over medium- and long-term horizons, and can be expressed as the long-term interest rate on government bonds.

Finally, the spread reflects business cycles, but it also tends to rise when central banks implement tighter monetary policies (e.g. when the Fed adjusts the Federal funds rate). As we can observe in figure 1, the spread in euro area countries has shifted upwards in the first quarter of 2022 due to soaring inflation across the developed world and the financial tightening that ensued.

Figure 1 shows an illustration of the euro area yield curve, aggregated from the bond data of constituent eurozone countries. The spread has fallen since 2011 due to flattening interest rates in the developed world but has started climbing again from 2020 onwards because of COVID, surging inflation, the war in Ukraine, and the European Central Bank (ECB) raising interest rates. Recession events in 2008, 2011 and 2020 are lightly shaded in grey.

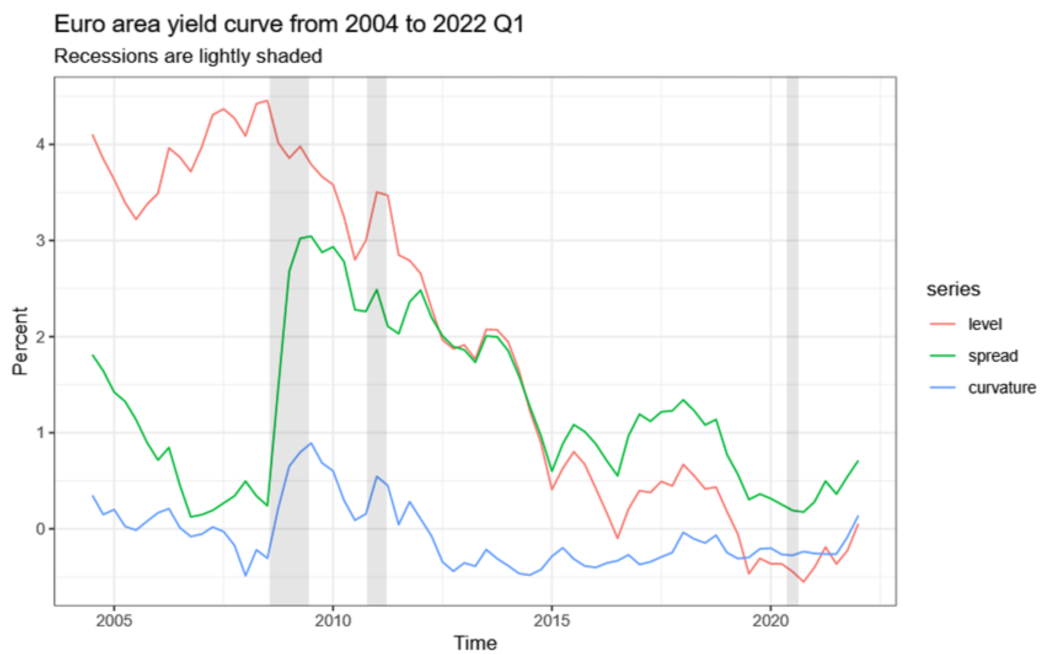


Figure 1: Evolution of the euro yield curve's components over time. Recessions are shaded in grey (in 2008, 2011 and 2020)

## 3.3 Emerging countries

In the literature, the yield curve's predictive power has been found to be significant for a sample of emerging countries. A paper by Mehl (2009) shows that the American and eurozone term structures forecast more information in a sample of 14 emerging economies than the latter's own domestic yield curves. Output, GDP growth and investments can be forecasted with more precision than surveys or other predictors. In his paper, Mehl (2009) performs a linear regression with lagged values for inflation and growth.

An explanation is that financial markets around the world have become more integrated over time. This leads yield curves in richer regions – particularly America and the eurozone – to have an influence on macroeconomic variables in developing ones. It is the result of stronger international financial integration over the past two decades since the end of the Soviet Union in 1991 (Mehl (2009)

As mentioned before, emerging countries have largely been excluded from academic studies involving the yield curve. There are several reasons for this. According to Mehl (2009), at the time of writing, it was due to their shallow bond markets and the ensuing lack of data over their term structures. Today those markets have deepened, and more data is now available for most emerging countries.

But it remains difficult to retrieve timely and free economic data for such countries on the web. For closed or sanctioned economies such as Iran, there is no information over their yield curves available online. Iran, for example, was thus excluded from our analysis. For other emerging nations, GDP growth is only measured annually instead of quarterly. Overall, the lack of available data for certain emerging nations online was a hindrance for this paper.

Nevertheless, we still managed to retrieve data for ten emerging countries, and we will try to give a satisfying answer to the topic of this paper (forecasting emerging countries using the entire term structure). Inspired by Mehl (2009)'s paper on emerging countries, we will work on two hypotheses for this thesis:

$H0$: Emerging economies' macroeconomic data cannot be forecasted by their national, European, and American yield curves.

$H1$: Emerging economies' macroeconomic data can be forecasted by their national, European and American yield curves.

## 3.4 Vector autoregression models

The main challenge of this paper was to choose a methodology that was appropriate for time series forecasting. For reasons specified at the end of this section, vector autoregression (VAR) models form a simple and useful method to assess the link between macroeconomic variables and yield curve components.

A vector autoregression (VAR) is a time series model where the variable $y$ at time $t$ is defined by lagged values of itself and past values of other variables, plus an error term $e$. The constant is $c$. A VAR model may have $n$ time series variables with $n$ equations, and is referred to as VAR($p$) where $p$ is the number of lags.

An example of a single variable VAR(1) model with $p$ lags is equivalent to:

$$y_t = c + A_1 y_{t-1} + A_2 y_{t-2} + ... \ + A_p y_{t-p} + e_t$$

where $y_t \dots y_{t-p}$ is a series of time series variables, $t$ is the time period, $c$ is a constant, $A_1 \dots A_p$ is a series of coefficients, and $e$ is the error term.

A VAR($p$) model with three time series variables $y_1$, $y_2$, and $y_3$ is equivalent to:

$$\begin{aligned} y_{t,1} =& c_1 + A_{11} y_{t-1,1} + \dots \ + A_{1p} y_{t-p,1} + B_{11} y_{t-1,2} + \dots \ + B_{1p} y_{t-p,2} \\ &+ C_{11} y_{t-1,3} + \dots \ + C_{1p} y_{t-p,3} + e_{t,1} \end{aligned} \tag{1}$$

$$\begin{aligned} y_{t,2} =& c_2 + A_{21} y_{t-1,1} + \dots \ + A_{2p} y_{t-p,1} + B_{21} y_{t-1,2} + \dots \ + B_{2p} y_{t-p,2} \\ &+ C_{21} y_{t-1,3} + \dots \ + C_{2p} y_{t-p,3} + e_{t,2} \end{aligned} \tag{2}$$

$$\begin{aligned} y_{t,3} =& c_3 + A_{31} y_{t-1,1} + \dots \ + A_{3p} y_{t-p,1} + B_{31} y_{t-1,2} + \dots \ + B_{3p} y_{t-p,2} \\ &+ C_{31} y_{t-1,3} + \dots \ + C_{3p} y_{t-p,3} + e_{t,3} \end{aligned} \tag{3}$$

In this set of equations, $A$¸$B$ and $C$ are three $p \times 3$ matrices of coefficients.

With matrices, a VAR model can be summarized as:

$$Y = BZ + U$$

where $Y$ is a matrix of time series variables, $B$ is a matrix of coefficients, $Z$ is a matrix of past values of $Y$, and $U$ is a matrix containing error terms.

Stock and Watson (2001) claims that VAR is an excellent tool to forecast macroeconomic variables, as it captures co-movements between them. But their usefulness and interpretation are largely determined by economic theory, especially when it comes to interpreting correlation and causation between variables.

The co-movements and VAR's forecasting power can be seen in the VAR model equations. In addition to the constants and error terms, all time series variables are described by past values of itself and other time series variables.

Since the term structure of interest rates is influenced by macroeconomic variables, such as inflation, VAR models also have the advantage of incorporating those co-movements. For instance, a country's GDP growth can influence its credit rating – an estimation of its ability to pay back debt as determined by credit agencies – which then affects its national term spread (Uribe and Yue (2006).

The coefficients of VAR models themselves are rarely reported. Instead, researchers draw on Granger causality tests, impulse responses and forecast error variance decompositions (FEVD) to assess the forecasting performance of a model. Impulse responses show how one variable reacts to a sudden exogeneous shock – for example an increase of 1% – in another variable, and FEVDs depict the contribution of exogeneous shocks to the forecast error of a variable, in effect showing how time series variables in a VAR model affect each other. Nevertheless, we will still report the coefficient estimates of our VAR models in this paper.

## 3.5 Central banks' monetary policy

GDP, inflation, and CPI are not the only variables to exert an influence on yield curves. Central banks' monetary policies also affect the interest rate on government bonds. The ramifications of rising US interest rates in emerging market economies (EME) have been well documented in the literature. When the Federal Reserve in the US increases interest rates by tweaking the Federal Funds Rate, they drive up Treasury bond yields. Therefore, this leads to capital outflows from emerging countries as the world's largest economy becomes more attractive for investors. It adds to the debt burden for heavily indebted nations (Hoek et al. (2021). It would be thus interesting to see if changes in the Federal Funds Rate have an effect on the forecasting performance of the yield curves.

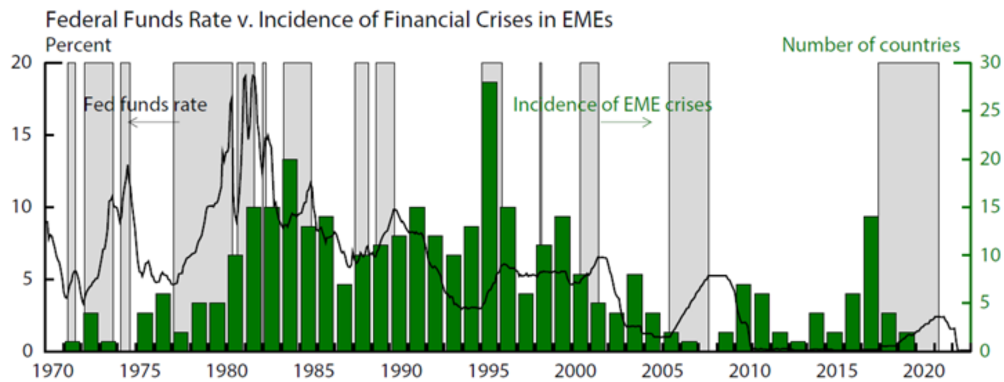


Figure 2: Correlation between adjustments in the Federal Reserve's Funds Rate and financial crises in emerging countries (Hoek et al. (2021)

## 3.6 Recessions

There is a consensus in the literature about the spread component of the yield curve being a reliable indicator of looming recessions in the developed world. In normal times, it curves upwards – reflecting the liquidation preference theory whereby investors prefer holding safer, short-term liquid assets.

But on some occasions, it may flatten or invert. This is the case when long-term yields fall below short-term ones. Researchers in the literature have described it as a potent harbinger of recessions. In the late 90s however, there were no inversion of the yield curve despite the emergence of a recessionary event. Many articles have attempted to explain why such an inversion by announcing a "structural break" such as Wheelock and Wohar (2009).

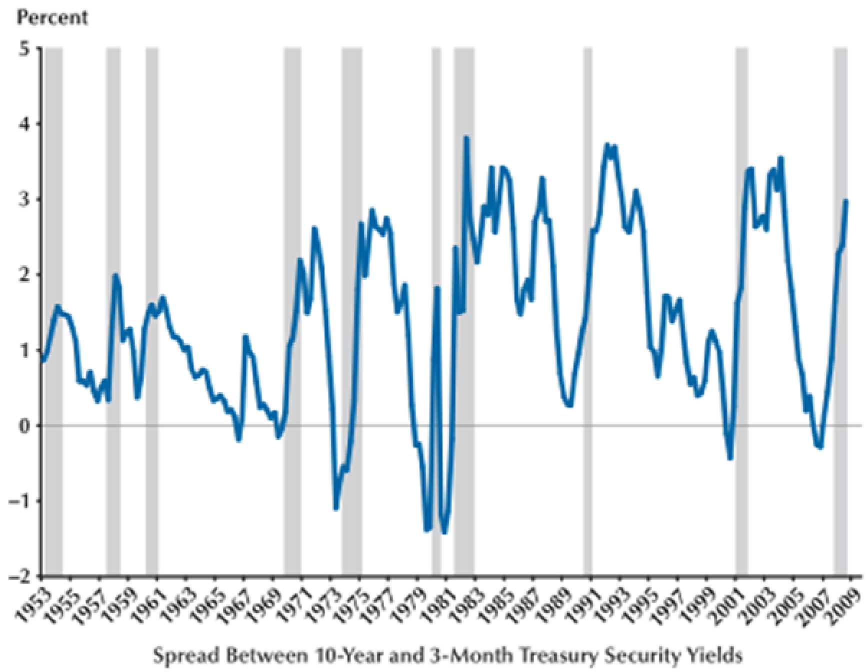


Figure 3: America's yield curve spread over time, with recession events in grey (Wheelock and Wohar (2009)

Researchers mainly deal with developed countries. For Germany and the UK, recessions before 1990s were always marked by a downward-trending yield curve the year before as shown by Wheelock and Wohar (2009). Apart from 1989, every recession in the US was preceded by a negative spread, as shown by figure 3.

Such relationship varies among regions, timeframes and methodologies. The eurozone yield curve, for example, did not predict the 2011 recession in Europe. Estrella and Mishkin (1996) have found out that the spread performs best in longer horizons. In the short-term, it is surpassed by other indicators.

Certain articles in the literature offer a theoretical explanation. It has been suggested that the yield curve does not forecast but causes recessions. Wheelock and Wohar (2009) argue that, faced with a negative yield curve, banks may anticipate a dark economic outlook and tighten their lending conditions in response. Stringent financial conditions would in turn stall the economy and provoke a recession. In short, it would constitute a short-fulfilling prophecy.

An inverted yield curve also saps banks' profitability who earn cash by performing maturity transformation. It would make them reluctant to lend and drive them towards investing in riskier assets. In that case, the banking sector would be vulnerable to economic shocks and aggravate recessions (De Backer et al. (2019).

But as with most papers on the subject, the yield curve's predicting power is predicated on the term spread's performance alone – not the level or curvature. Since this paper does not focus on recessions, it would be interesting for another study to gauge all three components' power to predict recessions in the developing world.

# 4 Methodology and data collection

For each emerging country listed in section 4.1, we will build three VAR models. Each one will include all macro variables and the three components of the three yield curves. The first model will contain the national yield curve, and the second and third one will have those from the eurozone and USA. The point of having three separate models is to precisely assess the forecasting ability of the national, eurozone and USA term structures in isolation from each other.

## 4.1 Selecting emerging markets

For this paper, we picked the ten largest emerging markets based on the size of their economy measured by GDP in 2021. This sample resembles that of Mehl (2009), and is representative of the developing world as a whole. Besides, it was easier to find data online for big emerging countries than smaller ones.

The following emerging markets were selected:

- Brazil
- China
- India
- Indonesia
- Malaysia
- Mexico
- Poland
- Russia
- South Africa
- Turkey

The following countries were deliberately excluded: Iran, Saudi Arabia, South Korea, and Taiwan. The reason is that the latter two are now considered developed markets by the World Bank, and the rest had no available macro or yield curve data available online.

## 4.2 Collecting yield curve data

To assess whether yield curves can forecast macro data, we collected monthly yield curve data in the form of three-month, five-year and ten-year national government bond yields for all ten countries mentioned in section 4.1, as well as the euro area and USA curves. The monthly data of the 12 yield curves were collected from investing.com, a financial website on which free data is available. Table 1 summarizes Brazil's yield curve data.

| **Brazil yield curve** | **1-year bond yield (%)** | **5-year bond yield (%)** | **10-year bond yield (%)** |
|---|---|---|---|
| Min | 2.658 | 5.652 | 6.71 |
| Median | 9.706 | 11.176 | 11.439 |
| Mean | 9.343 | 10.717 | 11.048 |
| Max | 15.552 | 16.127 | 16.065 |

Table 1: Statistical summary data (minimum, median, mean and maximum values) for the Brazilian yield curve with 1-year, 5-year and 10-year government bonds

### 4.2.1 Calculating the yield curve factors

Using the same empirical methodology as by Diebold and Li (2006), Kumar et al. (2021), and Møller (2014), we then use the yield curve data illustrated in table 1 to split the curve into three components: the spread, the level, and the curvature.

Those calculations are based on an empirical approach to calculating those components, which gives us approximately the same results as the Nelson-Siegel model, a theoretical framework used to model the entire yield curve. For more detailed explanations on the Nelson-Siegel model, please see Diebold and Li (2006).

For the yield curve of a certain country or region $i$ with long-, medium-, and short-term government bonds at time $t$, the long-term rate will be the variable

$l_{it}$, the medium-term rate $m_{it}$, and the short-term rate $s_{it}$. This empirical method gives us the following calculations:

$$spread_{it} = l_{it} - s_{it} \tag{4}$$

$$level_{it} = l_{it} \tag{5}$$

$$curvature_{it} = 2m_{it} - s_{it} - l_{it} \tag{6}$$

$s_{it}$ is the 3-month or 1-year bond yield (depending on the country), $m_{it}$ is the 5-year yield and $l_{it}$ is the 10-year yield at time $t$. Those values for the yield curve $i$ are expressed in percentages (%).

The results of those calculations and the transformation of the monthly yield curve data into quarterly data are summarized in table 2. All the figures are in percentage (%).

| **Brazil yield curve** | **Level (%)** | **Spread (%)** | **Curvature (%)** |
|---|---|---|---|
| Min | 6.71 | -1.4267 | -2.5467 |
| Median | 11.439 | 1.9115 | 1.12717 |
| Mean | 11.048 | 1.7055 | 1.04269 |
| Max | 16.065 | 4.628 | 7.14267 |

Table 2: Summary of the Brazilian yield curve after calculating the level, spread, and curvature from government bond yields

We are then able to incorporate the spread, level and curvature time-series variables in our VAR($p$) models in section 4.4.

## 4.3 Collecting macroeconomic data

We then collected the following quarterly macroeconomic variables listed below. Choosing the quarter-on-quarter growth of those variables allows us to avoid seasonality-related issues.

- Real gross domestic product (GDP) growth quarter-on-quarter (QoQ) (%), for all countries. Unlike nominal GDP, real GDP is annual economic output adjusted for inflation.

- Customer price index (CPI) growth QoQ (%), for all countries except Malaysia. A CPI measures the price of a weighted basket of goods and services that is regularly consumed by an average household. For example, food and transportation services are included in the CPI. Inflation, which is a rise in the CPI, is an important macroeconomic indicator and it was therefore included in our analysis.
- Exchange rate growth QoQ (%), for all countries except for China, Poland, Mexico, Russia, and Turkey. The exchange rate represents the quantity of national money required to purchase one dollar or one unit of a weighted basket of currencies (which includes the dollar, euro, yen, and other reserve currencies). In addition to GDP and CPI, it is also an important macroeconomic indicator.
- Unemployment rate (%), only available for Poland, Mexico, and Russia.

The variables were selected based on their availability online, their timeliness (whether they go far back enough in time), and the number of observations. They were mainly retrieved from the Federal Reserve of St. Louis FRED database, available online.

Table 3 lists and summarizes the macroeconomic variables used in the analysis.

| Variable | Unit | Description |
|---|---|---|
| Real gross domestic product (GDP) | Percentage | Quarter-on-quarter growth of real GDP, which is the national economic output adjusted for inflation. |
| Consumer price index (CPI) | Percentage | Quarter-on-quarter growth of a weighted basket of goods and services |
| Exchange rate | Percentage | Quarter-on-quarter growth of the national currency's exchange rate to either USD or to a weighted currency basket, depending on the country |
| Unemployment rate | Percentage | Quarter-on-quarter growth of the unemployment rate |

Table 3: Description of macroeconomic variables

Before performing our analysis, we must check whether our variables are stationary or not using the Augmented Dickey-Fuller (ADF) test. The test checks whether there is a unit root or stochastic trend in a certain time series, any of which could be distorting our results. None of them were found to have a unit root, therefore no modifications nor dummy variables had to be implemented in the VAR models.

### 4.3.1 Overview of macroeconomic data

Table 4 displays a statistical summary of every macroeconomic variable quarter-on-quarter growth. All of our variables were found to be stationary. Certain countries such as Russia and Turkey show higher CPI growth values due to episodes of high inflation in the 2010s.

| Country | Economic variable | Min (%) | Median (%) | Mean (%) | Max (%) |
|---|---|---|---|---|---|
| Brazil | GDP | -10.641 | 1.421 | 1.207 | 12.240 |
| | CPI | 2.136 | 5.594 | 5.742 | 10.488 |
| | Exchange rate | -23.827 | 9.643 | 10.136 | 55.878 |
| China | GDP | -5.490 | 11.301 | 12.593 | 23.932 |
| | CPI | -1.531 | 2.106 | 2.433 | 8.097 |
| India | GDP | -24.428 | 7.372 | 6.646 | 20.130 |
| | CPI | 1.458 | 6.523 | 7.099 | 15.315 |
| | Exchange rate | -12.736 | 2.646 | 3.364 | 25.320 |
| Indonesia | GDP | -5.465 | 5.182 | 4.981 | 6.993 |
| | CPI | 1.201 | 4.668 | 5.646 | 17.782 |
| | Exchange rate | -10.848 | -0.139 | 0.663 | 20.785 |
| Malaysia | GDP | -9.084 | 2.153 | 1.910 | 12.227 |
| | Exchange rate | -2.353 | 0.319 | 0.597 | 4.241 |
| Mexico | GDP | -18.901 | 2.510 | 1.450 | 19.619 |
| | CPI | 2.274 | 3.981 | 4.224 | 6.990 |
| | Unemployment | -0.833 | 0.035 | 0.108 | 1.970 |
| Poland | GDP | -5.031 | 6.225 | 6.296 | 15.883 |
| | CPI | -1.207 | 2.365 | 2.654 | 10.603 |
| | Unemployment | 1.000 | 56.000 | 58.890 | 123.000 |
| Russia | GDP | -11.151 | 2.612 | 2.594 | 10.473 |
| | CPI | 2.255 | 7.340 | 8.083 | 16.207 |
| | Unemployment | -3.429 | -0.139 | 0.021 | 3.784 |
| South Africa | GDP | -17.394 | 0.553 | 0.538 | 13.893 |
| | CPI | -1.761 | 4.871 | 4.823 | 11.232 |
| | Exchange rate | -30.061 | 5.534 | 3.499 | 46.589 |
| Turkey | GDP | -9.103 | 5.960 | 5.962 | 22.429 |
| | CPI | 4.344 | 9.236 | 10.887 | 25.848 |

Table 4: Statistical summary of macroeconomic variables

### 4.4 Building and fitting the VAR models

We then build the VAR models based on what was said in the beginning of section 4. Every country has three VAR($p$) models containing the national, euro, and USA yield curves and two or three macroeconomic variables.

China, Turkey and Malaysia have only two macroeconomic variables; therefore, each of them have three VAR(5) models that comprise five time series variables. The rest of the countries have VAR(6) models.

Each country has thus three VAR(5) or VAR(6) models, each one having the following set of equations:

$$\begin{aligned} y_{t,1} =& c_1 + A_{11} y_{t-1,1} + \dots + A_{1p} y_{t-p,1} + B_{11} y_{t-1,2} + \dots + B_{1p} y_{t-p,2} \\ &+ C_{11} y_{t-1,3} + \dots + C_{1p} y_{t-p,3} + D_{11} level_{t-1,i} + \dots + D_{1p} level_{t-p,i} \\ &+ E_{11} spread_{t-1,i} + \dots + E_{1p} spread_{t-p,i} \\ &+ F_{11} curvature_{t-1,i} + \dots + F_{1p} curvature_{t-p,i} + e_{t,1} \end{aligned} \tag{7}$$

$$\begin{aligned} y_{t,2} =& c_2 + A_{21} y_{t-1,1} + \dots + A_{2p} y_{t-p,1} + B_{21} y_{t-1,2} + \dots + B_{2p} y_{t-p,2} \\ &+ C_{21} y_{t-1,3} + \dots + C_{2p} y_{t-p,3} + D_{21} level_{t-1,i} + \dots + D_{2p} level_{t-p,i} \\ &+ E_{21} spread_{t-1,i} + \dots + E_{2p} spread_{t-p,i} \\ &+ F_{21} curvature_{t-1,i} + \dots + F_{2p} curvature_{t-p,i} + e_{t,2} \end{aligned} \tag{8}$$

$$\begin{aligned} y_{t,3} =& c_3 + A_{31} y_{t-1,1} + \dots + A_{3p} y_{t-p,1} + B_{31} y_{t-1,2} + \dots + B_{3p} y_{t-p,2} \\ &+ C_{31} y_{t-1,3} + \dots + C_{3p} y_{t-p,3} + D_{31} level_{t-1,i} + \dots + D_{3p} level_{t-p,i} \\ &+ E_{31} spread_{t-1,i} + \dots + E_{3p} spread_{t-p,i} \\ &+ F_{31} curvature_{t-1,i} + \dots + F_{3p} curvature_{t-p,i} + e_{t,3} \end{aligned} \tag{9}$$

$$\begin{aligned} level_{it} =& c_4 + A_{41} y_{t-1,1} + \dots + A_{4p} y_{t-p,1} + B_{41} y_{t-1,2} + \dots + B_{4p} y_{t-p,2} \\ &+ C_{41} y_{t-1,3} + \dots + C_{4p} y_{t-p,3} + D_{41} level_{t-1,i} + \dots + D_{4p} level_{t-p,i} \\ &+ E_{41} spread_{t-1,i} + \dots + E_{4p} spread_{t-p,i} \\ &+ F_{41} curvature_{t-1,i} + \dots + F_{4p} curvature_{t-p,i} + e_{t,4} \end{aligned} \tag{10}$$

$$\begin{aligned} spread_{it} =& c_5 + A_{51} y_{t-1,1} + \dots + A_{5p} y_{t-p,1} + B_{51} y_{t-1,2} + \dots + B_{5p} y_{t-p,2} \\ &+ C_{51} y_{t-1,3} + \dots + C_{5p} y_{t-p,3} + D_{51} level_{t-1,i} + \dots + D_{5p} level_{t-p,i} \\ &+ E_{51} spread_{t-1,i} + \dots + E_{5p} spread_{t-p,i} \\ &+ F_{51} curvature_{t-1,i} + \dots + F_{5p} curvature_{t-p,i} + e_{t,5} \end{aligned} \tag{11}$$

$$
\begin{aligned}
curvature_{it} =& c_6 + A_{61} y_{t-1,1} + \dots + A_{6p} y_{t-p,1} + B_{61} y_{t-1,2} + \dots + B_{6p} y_{t-p,2} \\
& + C_{61} y_{t-1,3} + \dots + C_{6p} y_{t-p,3} + D_{61} level_{t-1,i} + \dots + D_{6p} level_{t-p,i} \\
& + E_{61} spread_{t-1,i} + \dots + E_{6p} spread_{t-p,i} \\
& + F_{61} curvature_{t-1,i} + \dots + F_{6p} curvature_{t-p,i} + e_{t,6}
\end{aligned} \tag{12}
$$

$y_{t,1}$, $y_{t,2}$, and $y_{t,3}$ are macroeconomic time series variables at time $t$, such as GDP growth QoQ, CPI, and unemployment or exchange rate. If the country has only two macro variables, then $y_{t,3} = 0$ for any value of $t$. In that case, the model is VAR(5) with 5 time series variables. $level_{it}, spread_{it}$, and $curvature_{it}$ are time series variables at time $t$, calculated from the yield curve of the area $i$ (national, euro area or the US) using the equations in section 4.2.1 on page 12. $A, B, C, D, E$ and $F$ are matrices of coefficients to be estimated with an approach defined at the end of this section. $c$ is a vector of constants, and $e$ is a matrix of error terms.

Table 5 is a summary of the VAR models:

| Country | Macro variables | Yield curve type ($i$) | Quarters ($t$) | Observations | Start | End |
|---|---|---|---|---|---|---|
| Brazil | GDP<br>CPI<br>Exchange rate | National | 52 | 312 | 2009 Q1 | 2021 Q4 |
| | | Euro area | 70 | 420 | 2004 Q3 | 2021 Q4 |
| | | USA | 100 | 600 | 1997 Q1 | 2021 Q4 |
| China | GDP<br>CPI | National | 78 | 390 | 2002 Q3 | 2021 Q4 |
| | | Euro area | 70 | 350 | 2004 Q3 | 2021 Q4 |
| | | USA | 78 | 390 | 2002 Q3 | 2021 Q4 |
| India | GDP<br>CPI<br>Exchange rate | National | 66 | 396 | 2005 Q2 | 2021 Q3 |
| | | Euro area | 66 | 396 | 2005 Q2 | 2021 Q3 |
| | | USA | 66 | 396 | 2005 Q2 | 2021 Q3 |
| Indonesia | GDP<br>CPI<br>Exchange rate | National | 69 | 416 | 2004 Q4 | 2021 Q4 |
| | | Euro area | 70 | 420 | 2004 Q3 | 2021 Q4 |
| | | USA | 70 | 420 | 2004 Q3 | 2021 Q4 |
| Mexico | GDP<br>CPI<br>Unemployment | National | 56 | 336 | 2008 Q1 | 2021 Q4 |
| | | Euro area | 56 | 336 | 2008 Q1 | 2021 Q4 |
| | | USA | 56 | 336 | 2008 Q1 | 2021 Q4 |
| Poland | GDP<br>CPI<br>Unemployment | National | 87 | 522 | 2000 Q1 | 2021 Q3 |
| | | Euro area | 69 | 416 | 2004 Q3 | 2021 Q3 |
| | | USA | 103 | 618 | 1996 Q1 | 2021 Q3 |
| Russia | GDP<br>CPI<br>Unemployment | National | 52 | 312 | 2009 Q1 | 2021 Q3 |
| | | Euro area | 70 | 420 | 2004 Q3 | 2021 Q3 |
| | | USA | 100 | 600 | 1997 Q1 | 2021 Q3 |
| South Africa | GDP<br>CPI<br>Exchange rate | National | 74 | 444 | 2003 Q2 | 2021 Q3 |
| | | Euro area | 69 | 416 | 2004 Q3 | 2021 Q3 |
| | | USA | 69 | 416 | 2004 Q3 | 2021 Q3 |
| Turkey | GDP<br>CPI | National | 47 | 235 | 2010 Q2 | 2021 Q4 |
| | | Euro area | 70 | 350 | 2004 Q3 | 2021 Q4 |
| | | USA | 92 | 460 | 1999 Q1 | 2021 Q4 |
| Malaysia | GDP<br>Exchange rate | National | 79 | 395 | 2002 Q1 | 2021 Q3 |
| | | Euro area | 69 | 345 | 2004 Q3 | 2021 Q3 |
| | | USA | 77 | 385 | 2002 Q3 | 2021 Q3 |

Table 5: Summary of VAR models. The second column lists the macroeconomic variables available for the corresponding country. Some countries (China, Turkey, etc). do not have timely data on their exchange rates on the internet.. The last four columns show the time frame of the time series variables for each country's VAR(p) models. The number of observations can be retrieved by multiplying the number of variables in the VAR model by the number of quarters.

The VAR models' timeframe is mostly limited by the availability of yield curve data, which does not go back in time as far as GDP or CPI growth. For instance, no information regarding the euro area yield curve can be retrieved before the third quarter of 2003. Turkey's VAR model with its national yield curve is restricted to 2010 and beyond for similar reasons.

After building and fitting the VAR($p$) models, we estimate the coefficients of the models within a confidence interval of 95% using the ordinary least squares (OLS) method.

Consider the following equation, which constitutes part of a VAR(p) model:

$$y_t = c + A_1 y_{t-1} + A_2 y_{t-2} + \ldots + A_p y_{t-p} + e_t$$

The variables ($A_1 ... A_p$) are respectively the coefficients of ($y_{t-1} \ldots y_{t-p}$), with the integer $p > 0$.

VAR models can be summarized using matrices, and $B$ is the matrix of constants to be estimated:

$$Y = BZ + U$$

We estimate $B$ using this approach:

$$\hat{B} = YZ\prime(ZZ\prime)^{-1}$$

We will then run Granger causality tests between each yield curve's term structure and all macroeconomic variables. The Granger test, while not detecting a true causal effect, is nonetheless a useful way to assess the forecasting performance of the yield curve. We will also control for adjustments in the Federal Reserve's funds rate, which can sway economic variables in emerging markets (see Literature review).

After that, we will then analyse the impulse responses and forecast error variance decompositions for all VAR models, and display some of them to discover how a shock in one of the yield curve's factors affects macro variables.

### 4.4.1 Overview of yield curve data

Table 6 is a summary of the transformed yield curve data for all selected emerging markets, plus the euro area and the United States. The yield curve components/factors presented in this table were calculated with the empirical method described in section 4.2.1 on page 12. The columns show the minimum, median, mean and maximum values for each component of all the yield curves. The countries that have been experiencing high inflation in the past or in the present (such as Poland, Russia or Turkey, among others) typically have higher maximum values for the level than other nations.

| Yield curve | Factor | Min (%) | Median (%) | Mean (%) | Max (%) | Yield curve | Factor | Min (%) | Median (%) | Mean (%) | Max (%) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Level | 6.710 | 11.439 | 11.048 | 16.065 | | Level | 1.225 | 5.199 | 5.154 | 12.691 |
| Brazil | Spread | -1.427 | 1.912 | 1.706 | 4.628 | Poland | Spread | -7.893 | 1.080 | 0.384 | 2.599 |
| | Curvature | -2.547 | 1.127 | 1.043 | 7.143 | | Curvature | -4.201 | 0.209 | 0.079 | 1.870 |
| | Level | 2.627 | 3.499 | 3.533 | 4.778 | | Level | 5.877 | 7.710 | 8.098 | 13.147 |
| China | Spread | 0.191 | 0.748 | 0.965 | 2.408 | Russia | Spread | -11.698 | 0.590 | 0.309 | 6.783 |
| | Curvature | -0.637 | 0.192 | 0.262 | 1.296 | | Curvature | -9.024 | 0.177 | 0.070 | 7.742 |
| | Level | 5.895 | 7.649 | 7.483 | 8.878 | | Level | 6.310 | 8.562 | 8.516 | 10.228 |
| India | Spread | -2.109 | 0.831 | 1.051 | 4.004 | South Africa | Spread | -3.460 | 1.716 | 1.385 | 5.903 |
| | Curvature | -1.158 | 0.629 | 0.747 | 3.663 | | Curvature | -3.490 | 0.318 | 0.196 | 3.300 |
| | Level | 5.427 | 8.030 | 8.593 | 14.955 | | Level | 6.650 | 10.140 | 11.420 | 22.870 |
| Indonesia | Spread | 0.242 | 1.316 | 1.541 | 3.513 | Turkey | Spread | 16.917 | 0.470 | -0.425 | 14.450 |
| | Curvature | -0.662 | 0.354 | 0.452 | 1.623 | | Curvature | 11.493 | 0.448 | 0.086 | 16.207 |
| | Level | 8.172 | 11.814 | 11.737 | 15.322 | | Level | -0.552 | 1.946 | 1.928 | 4.456 |
| Malaysia | Spread | -0.344 | 2.721 | 3.061 | 7.313 | Euro | Spread | 0.125 | 1.119 | 1.242 | 3.044 |
| | Curvature | -2.353 | 0.319 | 0.597 | 4.241 | | Curvature | -0.488 | -0.197 | -0.072 | 0.892 |
| | Level | 5.017 | 6.797 | 6.805 | 8.907 | | Level | 0.642 | 4.063 | 4.111 | 8.104 |
| Mexico | Spread | -0.740 | 1.655 | 1.535 | 3.501 | USA | Spread | -0.692 | 1.644 | 1.699 | 3.626 |
| | Curvature | -11.350 | 0.445 | 0.421 | 1.992 | | Curvature | -0.765 | 0.613 | 0.609 | 2.271 |

Table 6: Statistical summary of transformed yield curve data

# 5 Results

Table 7 summarizes the estimations from all VAR models. For each emerging market, the components of the three yield curves are listed, along with the macroeconomic variables they could forecast with a confidence level of 95% or more (or a $\rho$-value equal to or smaller than 0.05). The number in the cells indicate how many times the component was lagged to get the result (up to 4 horizons), and the stars represent the level of significance.

| | | Brazil | | | | | Mexico | | |
|---|---|---|---|---|---|---|---|---|---|
| **Yield curve** | **Factor** | **GDP** | **CPI** | **Exchange rate** | **Yield curve** | **Factor** | **GDP** | **CPI** | **Unemployment** |
| National | Level | | 1* | 4* | National | Level | | | |
| | Spread | | | | | Spread | | | |
| | Curvature | | 1* | 4* | | Curvature | | | |
| Euro | Level | | | | Euro | Level | | | |
| | Spread | | | | | Spread | | | |
| | Curvature | | | 2* | | Curvature | | | |
| USA | Level | 1* | | 4** | USA | Level | 1*, 4* | 1* | 1**, 2* |
| | Spread | | | | | Spread | 4** | | 1**, 2**, 3* |
| | Curvature | 1** | | 4* | | Curvature | | | 2*, 3*, 4* |
| | | **China** | | | | | **Poland** | | |
| **Yield curve** | **Factor** | **GDP** | **CPI** | | **Yield curve** | **Factor** | **GDP** | **CPI** | **Unemployment** |
| National | Level | | | | National | Level | 4* | | |
| | Spread | | 3* | | | Spread | | | |
| | Curvature | 4* | | | | Curvature | 4* | | |
| Euro | Level | | | | Euro | Level | | 2* | |
| | Spread | | | | | Spread | | | |
| | Curvature | | | | | Curvature | | | |
| USA | Level | | | | USA | Level | 1* | | |
| | Spread | | 2* | | | Spread | | | |
| | Curvature | | | | | Curvature | | | |
| | | **India** | | | | | **Russia** | | |
| **Yield curve** | **Factor** | **GDP** | **CPI** | **Exchange rate** | **Yield curve** | **Factor** | **GDP** | **CPI** | **Unemployment** |
| National | Level | 1**, 3* | 4* | | National | Level | | 1* | |
| | Spread | | | | | Spread | | 3* | |
| | Curvature | 1** | | | | Curvature | | | |
| Euro | Level | 2*, 3**, 4* | 4* | | Euro | Level | 1***, 2**, 3*, 4* | 4* | |
| | Spread | | 3*, 4* | | | Spread | 1* | | |
| | Curvature | | | | | Curvature | 3* | 4* | |
| USA | Level | | | | USA | Level | 1*, 4* | | |
| | Spread | | | | | Spread | | 4* | |
| | Curvature | | | 4* | | Curvature | | 4* | |
| | | **Indonesia** | | | | | **South Africa** | | |
| **Yield curve** | **Factor** | **GDP** | **CPI** | **Exchange rate** | **Yield curve** | **Factor** | **GDP** | **CPI** | **Exchange rate** |
| National | Level | | | | National | Level | | | |
| | Spread | | | | | Spread | | | 1*, 2* |
| | Curvature | | | | | Curvature | | | 2* |
| Euro | Level | 3* | 1*, 2* | | Euro | Level | | | |
| | Spread | | 1** | | | Spread | | | |
| | Curvature | | | | | Curvature | | | 1**, 2* |
| USA | Level | | 1* | 3* | USA | Level | | | 3*, 4** |
| | Spread | | | 2*, 3*, 4* | | Spread | | | |
| | Curvature | | | | | Curvature | | | 4* |
| | | **Malaysia** | | | | | **Turkey** | | |
| **Yield curve** | **Factor** | **GDP** | **Exchange rate** | | **Yield curve** | **Factor** | **GDP** | **CPI** | |
| National | Level | 4** | | | National | Level | 4* | 4** | |
| | Spread | 4** | | | | Spread | 4*** | | |
| | Curvature | 4* | | | | Curvature | 4* | | |
| Euro | Level | 3* | 4** | | Euro | Level | 2* | | |
| | Spread | 1* | | | | Spread | | | |
| | Curvature | | 4*** | | | Curvature | | | |
| USA | Level | 1* | 3* | | | Level | 1***, 2** | 2* | |
| | Spread | 1* | | | | Spread | | | |
| | Curvature | | | | | Curvature | | 3* | |

Table 7: Summary of the coefficient estimation results. The cells show the number of lags and the confidence level. For instance, the Brazil CPI growth can be forecasted by the level component of the national yield curve with four lags only (equal to four quarters or one year) and with a confidence interval of 95%.

Signification codes: ***: $\rho \leq 0.001$, or a confidence level of 99.99%, **: $\rho \leq 0.01$, or a confidence level of 99%, *: $\rho \leq 0.05$, or a confidence level of 95%.

## 5.1 Estimation of the coefficients

The estimated coefficients, summarized in the table 7 on page 21, show that the performance of the national yield curves is mixed. Malaysia and Turkey's yield curve seem to be performing the best among all countries, being able to forecast GDP, CPI, and exchange rate growth QoQ with four lags (equivalent to the yield curve being lagged by one year). On the other hand, Mexico and Indonesia's curves are woefully ineffective in forecasting variables and are outperformed by USA's curve or the euro area's.

Those results may confirm Mehl (2009)'s hypothesis that foreign yield curves, for those countries at least, have more forecasting power than national ones due to financial linkages. For instance, you would expect Mexico to have firm financial links with America, or Russia with the euro area prior to the war in Ukraine. In both cases, the euro yield curve does have significant predicting power. However, this is not the case with Turkey and Poland, who maintain close economic ties with the rest of Europe.

Outside of selected European countries, the euro area yield curve is effective in India, Indonesia, and Malaysia, performing better than national or American curves in those Asian nations. The European Union is the largest (or one of the largest) trading partners for such nations.

America's yield curve, meanwhile, performs well in neighbouring Latin American countries such as Brazil and Mexico and is also significant in Poland and Indonesia.

We also confirm the fact that the curvature and the level can be as useful as the spread, as claimed by Møller (2014). All three components of the curve should therefore be utilized to forecast macroeconomic data.

Another theory that is confirmed is the fact that the GDP can best be forecasted with a one-year horizon, or with four lags. This is best exemplified by Turkey, Poland or Malaysia, among others.

Finally, as we pointed out in section 3.5 on page 8, hikes in the Federal Reserve's federal funds rate can trigger capital outflows in emerging markets and even spark financial crises. After controlling for changes in the federal funds rate by including the variable in our models, no significant correlation between it and other macro data was detected.

## 5.2 Granger causality test results

Granger causality tests are a statistical hypothesis test used to assess whether past values of a variable $X$ can forecast present or future values of another variable Y. We have the following hypotheses:

$$H0\text{: } X \text{ does not Granger-cause } Y$$

$$H1\text{: } X \text{ Granger-causes } Y$$

Note that this test does not measure a real causality effect, but a correlation between X and Y. For this reason, we say that, when H0 is rejected, X Granger-causes Y, or X forecasts Y, and not X causes Y. This test is nevertheless a useful way to assess the forecasting power of the yield curve.

Table 8 shows the results of the Granger causality test with every country-yield curve pair and the corresponding $\rho$-values. Non-significant $\rho$-values (superior to 0.05) are highlighted in red, while some of the results with a very significant $\rho$-value (inferior to 0.01) are in yellow.

The test results show that the three types of yield curves could predict almost all macroeconomic variables in every country, with exceptions highlighted in red.

The strongest correlations seemed to be between the euro area yield curve and Russia/Poland, the American yield curve and Mexico, and Turkey's domestic yield curve with its own macro variables. For each of those international pairs, there seems to be solid international financial linkages that is determined by geographical proximity. The confidence level exceeded 99% at times for the country-yield curve pairs that are highlighted in yellow. For those country-curve pairs, the $\rho$-value is lower than 0.001 (which is close to a confidence interval of 100%)

By contrast, there are only a few circumstances where the yield curve does not Granger-cause macro variables. This is the case for the USA yield curve and Russia, Poland, and the euro area yield curve and Mexico, China, Turkey. Those country-curve pairs are highlighted in red, and they have a $\rho$-value superior to 0.05 – inferior to the 95% confidence interval. On a national basis, the Indonesia yield curve was ineffective.

Those outcomes confirm the coefficient estimations in table 7 on page 21, in that the euro area yield curve cannot forecast the Turkish economy. This

| Country | Yield curve | $\rho$-value | Country | Yield curve | $\rho$-value |
|---|---|---|---|---|---|
| Turkey | National | 1.97E-05 | Mexico | National | 0.01777 |
| | Euro | 0.2748 | | Euro | 0.0868 |
| | USA | 0.005603 | | USA | 2.77E-11 |
| Malaysia | National | 0.000249 | Brazil | National | 0.09445 |
| | Euro | 0.000993 | | Euro | 0.004516 |
| | USA | 0.002906 | | USA | 0.001139 |
| South Africa | National | 0.009636 | China | National | 0.000471 |
| | Euro | 0.007289 | | Euro | 0.1482 |
| | USA | 0.04744 | | USA | 0.02768 |
| Russia | National | 0.01215 | India | National | 0.01503 |
| | Euro | 4.27E-07 | | Euro | 0.000749 |
| | USA | 0.000474 | | USA | 0.01218 |
| Poland | National | 0.004323 | Indonesia | National | 0.3431 |
| | Euro | 0.000507 | | Euro | 0.001319 |
| | USA | 0.1755 | | USA | 0.000226 |

Table 8: Granger test $\rho$-values

absence of financial linkage between the two areas should be further confirmed and explained in future studies.

### 5.3 Impulse response functions

In a VAR model with two or more time series variables, impulse responses describe the evolution of a variable in response to a shock (the impulse) in other variables in a VAR model. In the case of this paper, it shows the estimated response of a country's macroeconomic variable, surrounded by a 95% confidence interval, following a one percentage point shock in any of the three yield curve components over a ten period horizon following the shock (equivalent to ten quarters or two years and a half). The red dotted lines on the graph represent the higher and lower estimates of the 95% confidence interval.

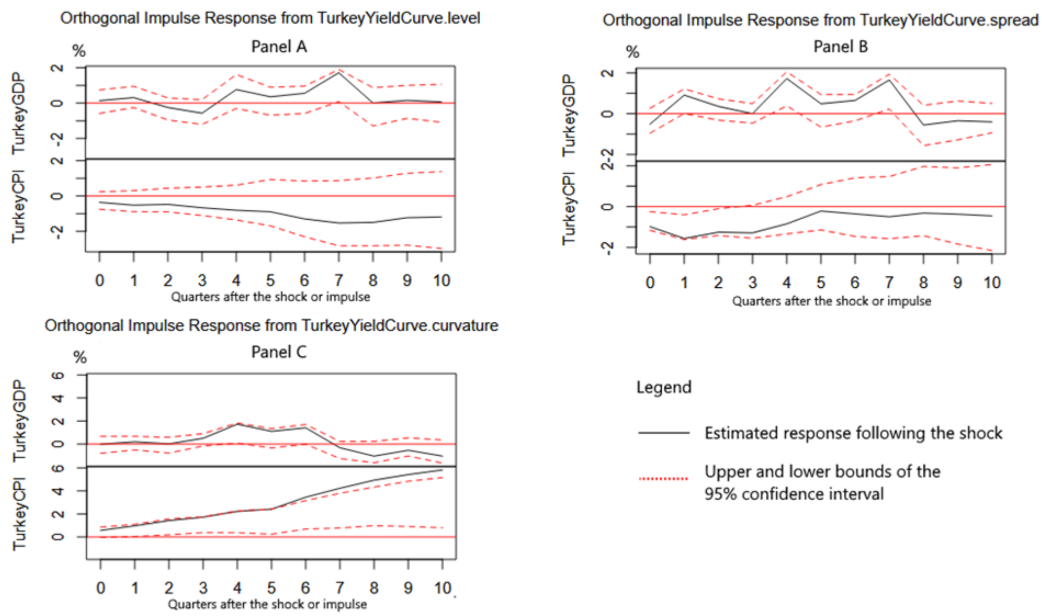


Figure 4: Impulse responses for Turkey's macro variables from a shock in national yield curve factors at time 0. The black lines are the estimated responses of the GDP or CPI QoQ growth from a shock in the spread, level, or curvature up to ten quarters. The dotted red lines represent the upper and lower bounds of the 95% confidence interval. The x-axis shows the number of quarters (up to ten quarters or two and a half years) following the shock at time 0. In theory, the effect from the shock on the affected variables can last for an infinite number of quarters.

Figure 4 shows the Turkish GDP and CPI growth QoQ's response when the spread, lag, and curvature rises by a percentage point. Both variables fall in the short term, but GDP growth bounces back after a quarter and the CPI growth remains subdued. The level exerts the same effect, which could also reflect tightening fiscal policy, and a shock in the curvature seems to raise CPI growth.

According to Engstrom and Sharpe (2019), when a country's central bank raises interest rates, its yield curve's term spread increases as well due to market expectations. The figure 4 could denote how economic activity slows and inflation weakens when a central bank raises interest rates, if we assume that variations in term spread correctly reflect monetary policies.

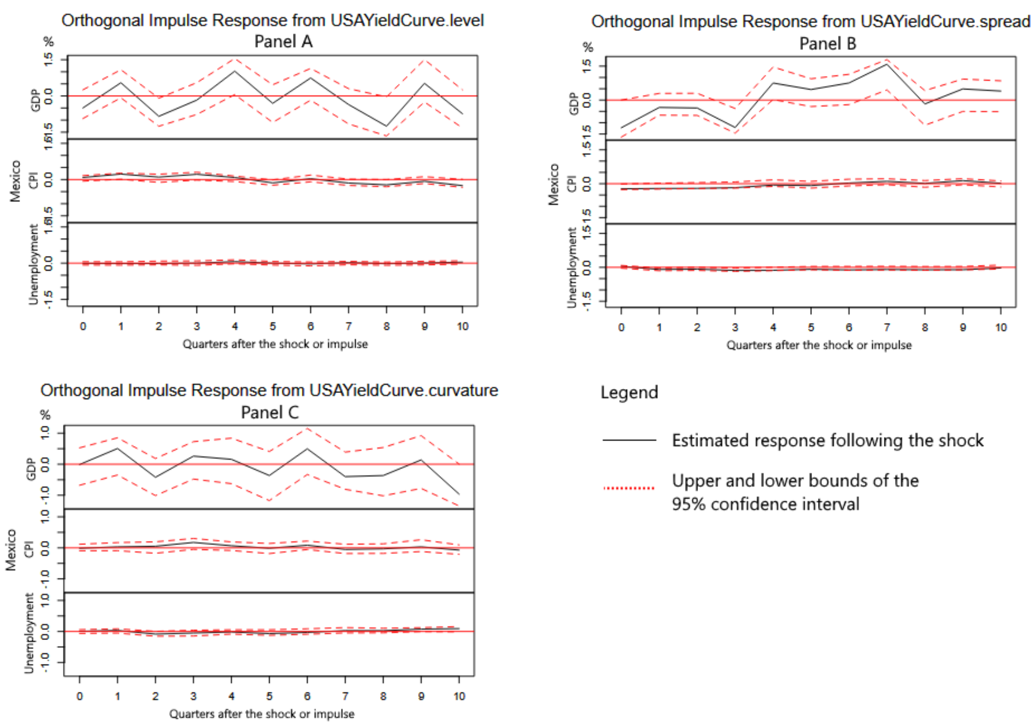


Figure 5: Impulse responses for Mexico's macro variables from a shock in USA yield curve factors

For Mexico's response to a shock in the USA yield curve, the effect is more pronounced for GDP growth QoQ: it only grows back after four quarters (16 months), while the shock does not affect CPI or unemployment growth significantly.

The American yield curve curvature and level's impact on the same variables are, in this case, insignificant or difficult to interpret. Mexico's GDP growth drifts up and down while the CPI is unaffected. The unemployment rate does not respond to a shock in any of the yield curve components.

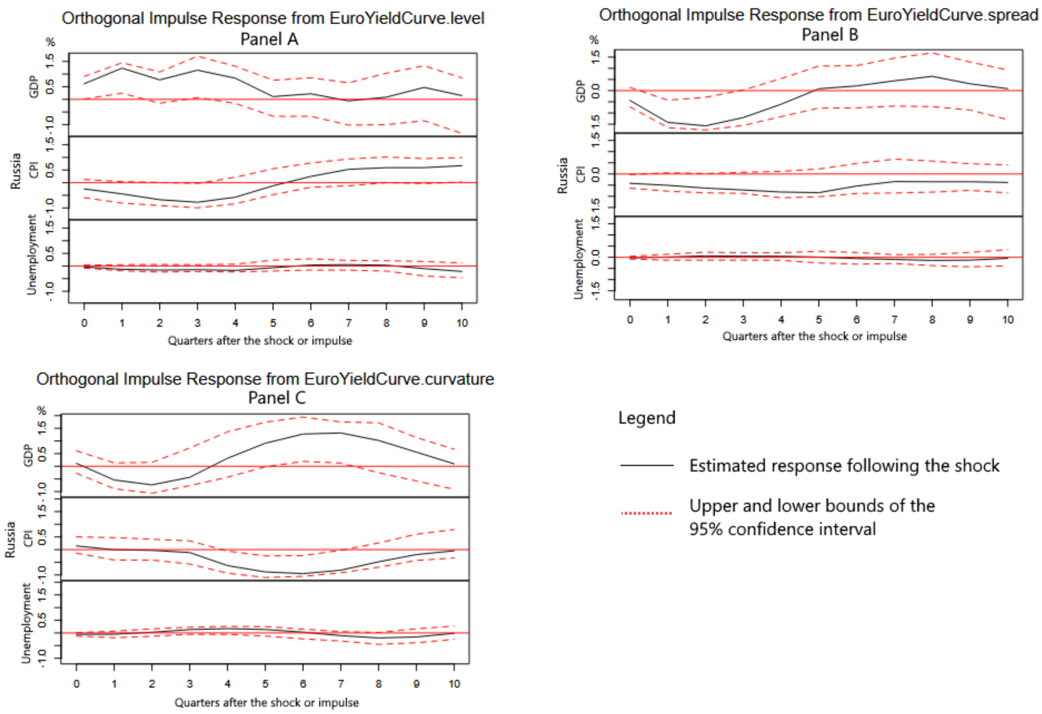


Figure 6: Impulse responses for Russia's macro variables from a shock in euro area yield curve factors

For the impact of a euro area spread shock on Russian's economy, it resembles that of Turkey in figure 4. CPI growth falls in the long term while GDP growth contracts for about five quarters/horizons (more than a year), before bouncing back. However, GDP growth rises with a shock of one percentage point of the level. The curvature exerts roughly the same influence as the spread, but unemployment does not seem to be affected in any case whatsoever.

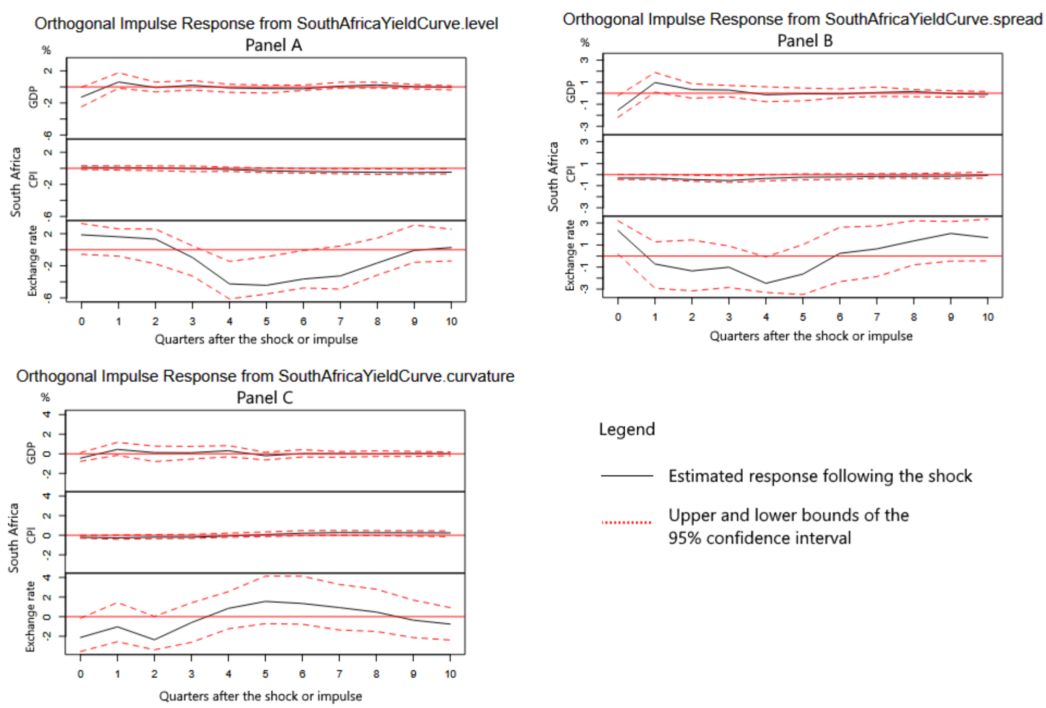


Figure 7: Impulse responses for South Africa's macro variables from a shock in national yield curve factors

Corresponding with the coefficient estimations at the beginning of this chapter, the level is particularly useful for predicting the exchange rate in South Africa. A shock in that component leads to a rising exchange rate in the short-term before falling. The level reflects inflation expectations, which correspondingly devalues the currency over time. The curvature induces the opposite behavior.

### 5.3.1 Impulse response conclusions

Whenever there is a shock in the spread or level, GDP falls in the short term but rebounds after two quarters or more, CPI growth tends to fall over the long-term, and the unemployment rate is unaffected. The curvature tends to apply the opposite effect.

Impulse responses give us some insight about the relationship between the term structure and the economy. In accordance with standard macroeconomic theory, a rise in the spread seems to denote tightening fiscal policy and brings about a fall in the growth rate of inflation. The curvature reflects short-term changes in central bank policy (such as increasing interest rates), and the level is linked with inflation.

## 5.4 Forecast error variance decompositions

Forecast error variance decompositions, or FEVDs, show the percentage of the forecast error variance of a variable that is affected by a 1% exogeneous shock in another variable. In other words, it helps us understand how the time series variables in a VAR model influence each other. The following charts display the percentage (vertical axis) of the variation in the forecast error of macro variables that can be attributed to shocks in given yield curve factors for ten quarters/horizons (horizontal axis) after the shock.

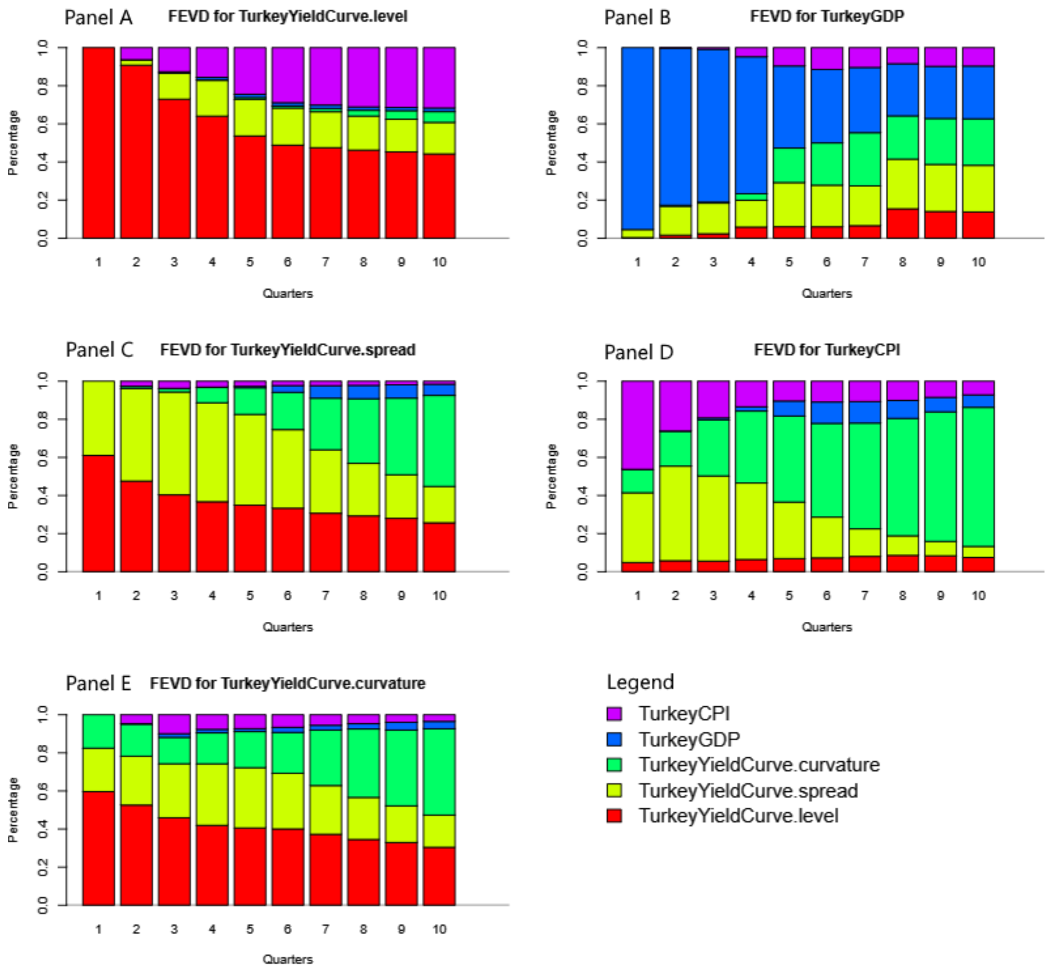


Figure 8: Forecast error variance decomposition results for Turkey from a shock in national yield curve factors. We can observe how Turkey's macroeconomic variables (panel B and D) and yield curve factors (panel A, C, and E) are influenced by past values of themselves. However, we shall only interpret the FEVD charts for macroeconomic variables. As an example, 20% of the variation in the forecast error of Turkey's GDP growth QoQ can be attributed to the national spread over five quarters (see panel B). For the CPI (panel D), this relation is even more apparent; nearly half of its variation is determined by the spread. After several quarters, the curvature becomes more dominant at the spread's expense when it comes to influencing the CPI variable (panel D).

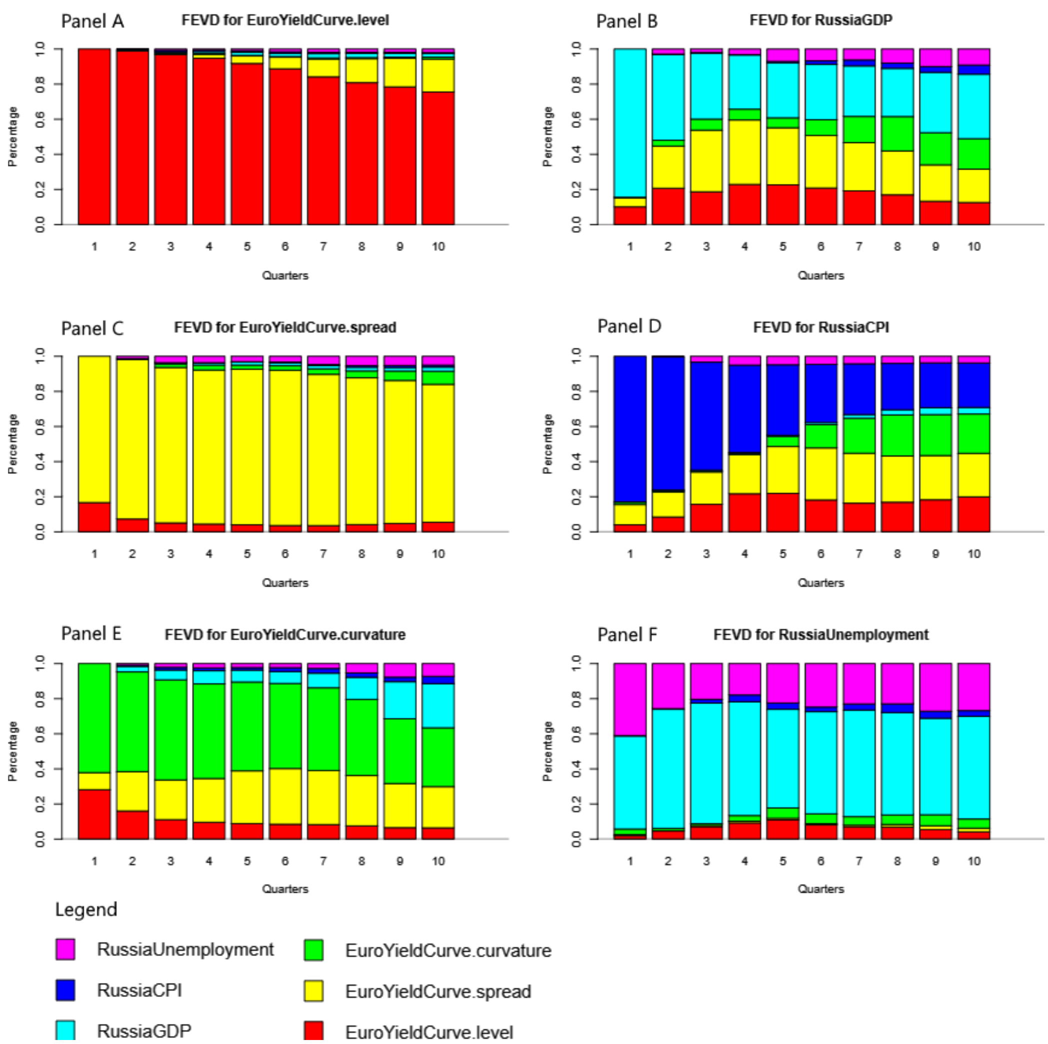


Figure 9: Forecast error variance decomposition results for Russia from a shock in euro area yield curve factors. The graphs show that Russia's macroeconomic data is influenced by the euro area yield curve in much the same way. It seems that, in the short term, the GDP and CPI variables (panel B and D) are swayed by shocks in the spread component, with the curvature playing a larger role over longer-term horizons. The level's power is negligible. Finally, the unemployment rate is largely affected by GDP and not by yield curve factors. Panel F suggests that the unemployment rate is mostly affected by GDP rather than anything else.

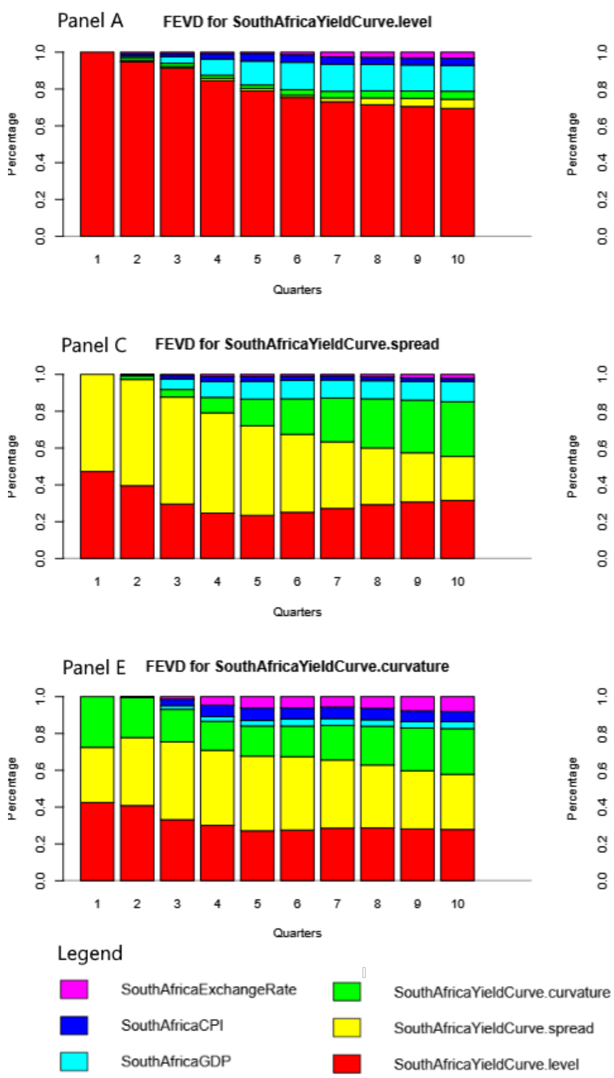


Figure 10: Forecast error variance decomposition results for South Africa from a shock in national yield curve factors. Here, the spread is significant for GDP and CPI (panel B and D), and the level also becomes more prominent at longer horizons (panel B). The exchange rate (panel F) is mostly influenced by the level among yield curve factors, particularly at longer horizons.

# 6 Final conclusions and limitations

After reviewing the results of our tests, we can conclude that the entire term structure yield curve can be used to forecast macroeconomic variables in emerging markets (albeit with varying forecasting power depending on the country-curve pair). Most countries' term structures have significant predicting power. The Granger causality tests in section 5.2 show more favorable results than the coefficient estimates. For instance, the Mexico yield curve Granger-causes its corresponding macroeconomic variables, but according to the coefficient estimates, no Mexican economic component could successfully be forecasted.

Our hypotheses were as follows:

$H0$: Emerging economies' macroeconomic data cannot be forecasted by their national, European, and American yield curves.

$H1$: Emerging economies' macroeconomic data can be forecasted by their national, European and American yield curves.

Based on the results of this paper, we can safely reject the first hypothesis, and we confirm that emerging economies can be forecasted by the three yield curves.

The impulse responses and FEVDs from section 5.3 onwards show how a shock in any of the yield curve's components how the spread in particular influences GDP and CPI. These tests suggest that a shock in the spread, curvature or level are likely affect macroeconomic data in line with economic theory. Shocks in the spread and level components in particular can explain variations in the GDP or CPI over a short-term horizon. The spread rises whenever there is inflation and central banks are forced to crank up interest rates to tame it. The level's role is like the spread, because it rises in line with inflation. The curvature exerts its influence in a similar way to the other factors, and it also contains forecasting power, though we cannot confirm Møller (2014)'s claim that it is more significant than the spread for forecasting GDP.

For certain countries such as Turkey, Russia, or Malaysia, their economic factors can be forecasted with greater signification than others. The links between the euro area yield curve and neighboring countries such as Russia are stronger than for others, and the same could be said between USA's yield curve and Mexico. It seems that geography is a powerful determinant of international financial linkages, as Mehl (2009) implied in his study of emerging markets.

This study has some limitations. The first one involves the choice of time-frames: it could have an impact on the credibility of our results. Turkey's data only goes back as far as 2010, but if previous data had been available the model might yield different conclusions. Therefore we propose that another paper carry out the same analysis but with a rolling window and see if estimates vary over time.

The second limitation concerns the calculation of the three yield curve factors (spread, level, curvature). Those variables were estimated with an empirical method, defined among others by Diebold and Li (2006), which is an approximation of the Nelson-Siegel theoretical framework. But using the Nelson-Siegel model may lead to different values of the yield curve's factors with divergent estimations. It could be useful to perform the same regressions but with Nelson-Siegel estimated parameters and see if the results vary significantly.

The third limitation involves the sample of emerging countries. For practical reasons, we have only picked the ten largest emerging markets by GDP. Another study should assess the yield curves' forecasting performance in smaller emerging economies.

A recommendation to other researchers would be for another paper to assess whether recessions can be forecasted with the same methods employed here. Previous researchers have studied the relation between the yield curve and recessionary events, but at the time of writing nobody has ever tried to predict recessions using the entire term structure in emerging nations.

Finally, we recommend future researchers to consider all components of the yield curve and not just the spread in order to forecast macroeconomic data. Non-linear regressions should be employed to investigate the relationship between economic variables and the entire term structure. They may forecast economic variables more accurately than standard linear techniques, as explained in the Literature review.

## References

Bordo, M. D. and Haubrich, J. G. (2008). Forecasting with the yield curve; level, slope, and output 1875–1997. *Economics Letters*, 99(1):48–50.

Chinn, M. and Kucko, K. (2015). The predictive power of the yield curve across countries and time: The predictive power of the yield curve. *International Finance (Oxford, England)*, 18(2):129–156.

De Backer, B., Deroose, M., and Van Nieuwenhuyze, C. (2019). Is a recession imminent? the signal of the yield curve. *National Bank of Belgium Economic Review*, pages 69–93.

Diebold, F. X. and Li, C. (2006). Forecasting the term structure of government bond yields. *Journal of Econometrics*, 130(2):337–364.

Dombrosky, A. M. and Haubrich, J. G. (1996). Predicting real growth using the yield curve. *Federal Reserve Bank of Cleveland Economic Review*, 32(1):26.

Engstrom, E. C. and Sharpe, S. A. (2019). The near-term forward yield spread as a leading indicator: A less distorted mirror. *Financial Analysts Journal*, 75(4):37–49.

Estrella, A. and Hardouvelis, G. A. (1991). The term structure as a predictor of real economic activity. *The Journal of Finance*, 46(2):555–576.

Estrella, A. and Mishkin, F. (1996). The yield curve as a predictor of u.s. recessions. *Current Issues in Economics and Finance*, 2(7).

Evgenidis, A., Papadamou, S., and Siriopoulos, C. (2020). The yield spread's ability to forecast economic activity: What have we learned after 30 years of studies? *Journal of Business Research*, 106:221–232.

Harvey, C. R. (1988). The real term structure and consumption growth. *Journal of Financial Economics*, 22(2):305–333.

Hoek, J., Kamin, S., and Yoldas, E. (2021). Are rising u.s. interest rates destabilizing for emerging market economies? *FEDS Notes*.

Kumar, R. R., Stauvermann, P. J., and Vu, H. T. T. (2021). The relationship between yield curve and economic activity: An analysis of g7 countries. *Journal of Risk and Financial Management*, 14(2).

Mehl, A. (2009). The yield curve as a predictor and emerging economies. *Open Economies Review*, 20(5):683–716.

Møller, S. V. (2014). Gdp growth and the yield curvature. *Finance Research Letters*, 11(1):1–7.

Plakandaras, V., Gogas, P., Papadimitriou, T., and Gupta, R. (2019). A re-evaluation of the term spread as a leading indicator. *International Review of Economics & Finance*, 64:476–492.

Stock, J. H. and Watson, M. W. (2001). Vector autoregressions. *The Journal of Economic Perspectives*, 15(4):101–115.

Uribe, M. and Yue, V. Z. (2006). Country spreads and emerging countries: Who drives whom? *Journal of International Economics*, 69(1):6–36. Emerging Markets.

Wheelock, D. and Wohar, M. (2009). Can the term spread predict output growth and recessions? a survey of the literature. *Federal Reserve Bank of St. Louis Review*, 91:419–440.