FORECASTING GOVERNMENT BOND YIELDS IN THAILAND

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ABSTRACT

Title of Dissertation	FORECASTING GOVERNMENT BOND YIELDS IN THAILAND
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This dissertation aims to comprehensively investigates key macroeconomic factors and bond yield interaction in Thai bond market, and analyzes the impacts of both domestic and international economic factors on the fixed income yields in different maturities of 1-, 3-, 5-, 7-, and 10-year movements, as well as forecasts the future bond yields of different maturities with macroeconomy, including comparing the best predictive yields with each model. Through estimating VAR, Bayesian VAR, and Single Equation (SE) approaches as well as Random Walk (RW) forecast as the benchmark, the results show several key findings:

Overall, fixed income yields generally respond strongest to the economic factor shocks. Explicitly, yield in various maturities responds directly to positive and negative shocks in macroeconomic indicators (i.e., six key variables: fed rate, primary budget deficit, commodity price, capital inflow, VIX index, and liquidity). Generally, it finds that both domestic and international macroeconomic factor shocks have a significant impact on the fixed income yields of various maturities with all models. Regarding the macro shocks from fed rate, commodity price, VIX index, capital inflow, primary budget deficit, and liquidity have a strong impact on the bond yields in all maturities and the impact is transitional, usually dies out after 5 to 10 quarters but the effects of Bayesian VAR approach seem to be long lasting more than 10 quarters. Interestingly, from the results, evidence shows that new economic variables intended into this study, commodity price and capital inflow have a quite strong impact on the bond yields with all maturities as well.

Last, VAR, Bayesian VAR, and SE models are built to forecast future bond yields in various maturities with macroeconomy. It finds that the static forecast (in-sample) with all of three models, the strong evidence results show that the most case of

the BVAR model produces the best predictivity of bond yields in a different maturity, except for only 10-year maturity that the RW forecast beat BVAR model. Most figures of BVAR model of these statistical functions measured are the lowest and for RMSE and Theil of evaluations of all yields are smaller than one signals that the model under consideration strongly outperforms the SE, VAR, and RW models, but the figures of RW forecast (10-year maturity yield) beat all the models. The results reflect that the performance in-sample forecasting is quite good. Besides, for the dynamic rolling forecast (out-of-sample) with both VAR and BVAR models, the evidence results confirm that BVAR model is the best performance in dynamic rolling-window forecasting the bond yields with various maturities for 2-, 4-, and 8-quarter rolling ahead. The statistical evaluations show that the most figures of BVAR with all rolling forecasts appear the lowest and outperform the VAR at all maturities. Hence, the BVAR model produces generally more accurate forecasting future yields than those competitive model in a robust way.

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Wantana Buaban

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ABBREVIATIONS

Abbreviations	Equivalence
GDP	Gross Domestic Product
TGBY	Thai Government Bond Yield
FED	Federal Funds Rate
VIX	Choe Volatility Index
PB	Primary Budget Deficit
ACPI	All Commodity Price Index
VAR	Vector Autoregressive
BVAR	Bayesian Vector Autoregressive
SE	Seigel Equation
RW	Random Walk
NS 1987	Nelson and Siegel (1987)
MS-DNS	Markov-Switching Dynamic Nelson-Siegel
ATS	Affine Term Structure
RMSE	Root Mean Squared Error
Theil	Theil’s Inequality Coefficient

CHAPTER 1

INTRODUCTION

The bond market is the important part of financial markets in Thailand. The domestic fixed income market has grown significantly over the past two decades. Prior to the Asian financial crisis in 1997, the bond market was relatively insignificant accounting for a mere 7.4 percent of GDP in comparison to banks loan and equities market which accounted for 72.2 percent of GDP and 51.6 percent of GDP, respectively. The imbalances amongst the three main pillars of the financial system were caused by the over-reliance on commercial banks as the main source of funding and over investment in stock market as investments options were restricted. Financial system imbalances which, contributed significantly to the financial crisis highlighted the need for the government to urgently reform and implement initiatives to rebalance the financial system. The government through Public Debt Management Office, Ministry of Finance has been committed to rectify the imbalances by developing the domestic fixed income market to be an alternative massive funding and investment source for both public and private sector.

The Thai fixed income market has demonstrated remarkable development since 1997. The government has continued to issue bonds of various maturities with the primary objectives being to finance the annual budget deficit, support economic development, and restructure public debt. The bond market has now become a significant funding source of government and corporate sectors as well as instruments for monetary policy management by the central bank.

With the robustness of the domestic fixed income market, the main pillars of Thai financial markets, namely bank loan, stock market, and bond market have been increasingly more balanced. In figure 1.1 shows that the proportion of bank loans to GDP has declined from 128 percent of GDP in 1997 to 107 percent of GDP as of September 2020, whereas the fixed income market has grown rapidly from 12 percent of GDP in 1997 to 91 percent of GDP at the same period. And for the corporate bond market, the outstanding has expanded from 3 percent of GDP in 1997 to 25 percent of GDP presently. Meanwhile, the equity market capitalization has also grown from 24 percent of GDP to 86 percent of GDP during the same period.

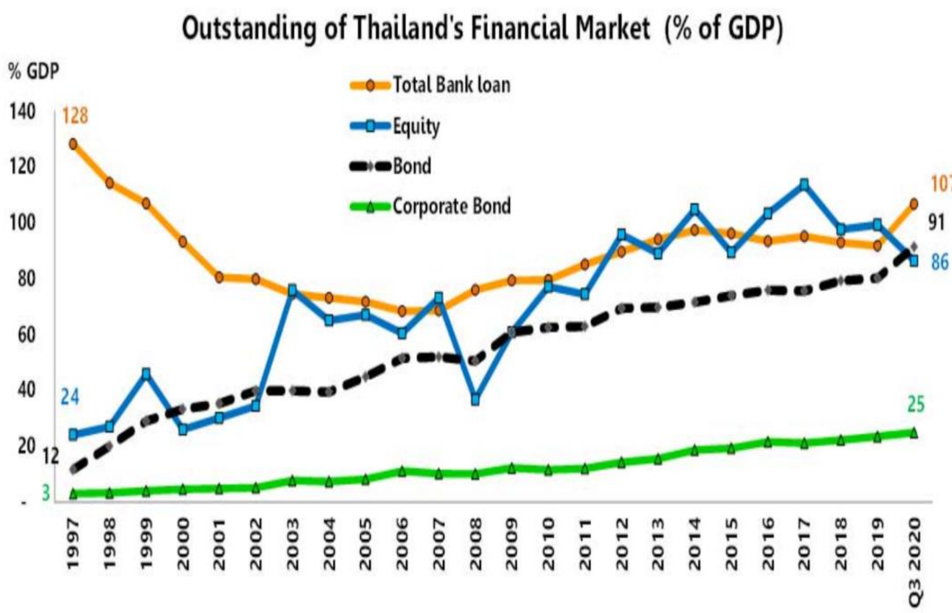


Figure 1.1 Thailand's Financial Market
Source: ThaiBMA, as of September 2020.

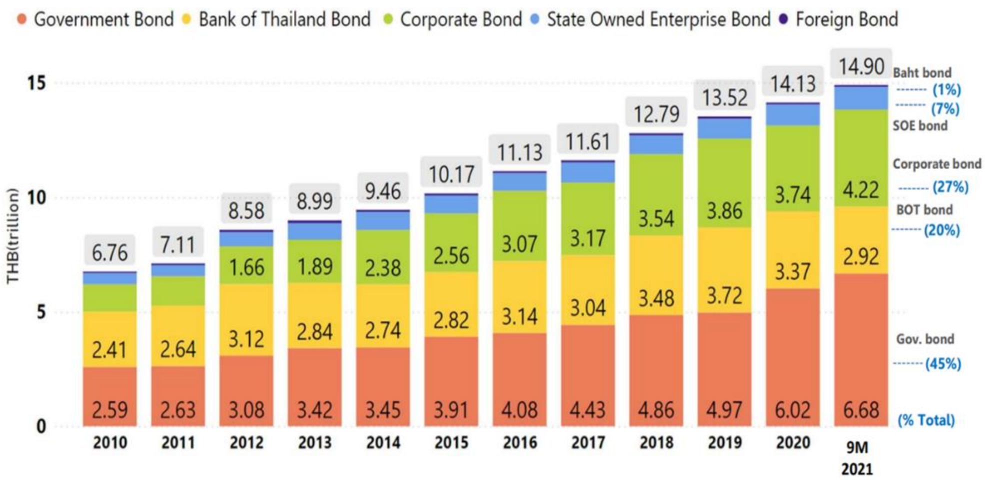


Figure 1.2 Total Outstanding of Thai Fixed Income Market THB 14.9 trillion
Source: ThaiBMA and Public Debt Management Office, as of September 2021.

Currently, the total outstanding of Thai bond market was THB 14.9 trillion (USD 478 billion) as of September 2021 in figure 1.2. The government bonds (including T-bills) dominate the market, accounting for 45 percent of total. Corporate bonds ranked the second, accounting for 27 percent while the central bank bonds accounted for 20 percent and state-owned enterprises (SOEs) bonds accounted for 7 percent. Lastly, foreign bonds accounted for 1 percent of the total outstanding.

In addition, government bond holders are classified by type of investors as of September 2021 in figure 1.3. The insurance company accounted for 23.64 percent of total. Contractual Funds ranked the second, accounting for 23.25 percent whereas the depository corporation and non-resident accounted for 17.24 and 14.26 percent, respectively. Lastly, Bank of Thailand accounted for 7.76 percent and other investors accounted 13 percent of total holders (household 5.92%, financial institution 3.98%, mutual funds 1.94%, non-profit 0.55% and others 1.45%).

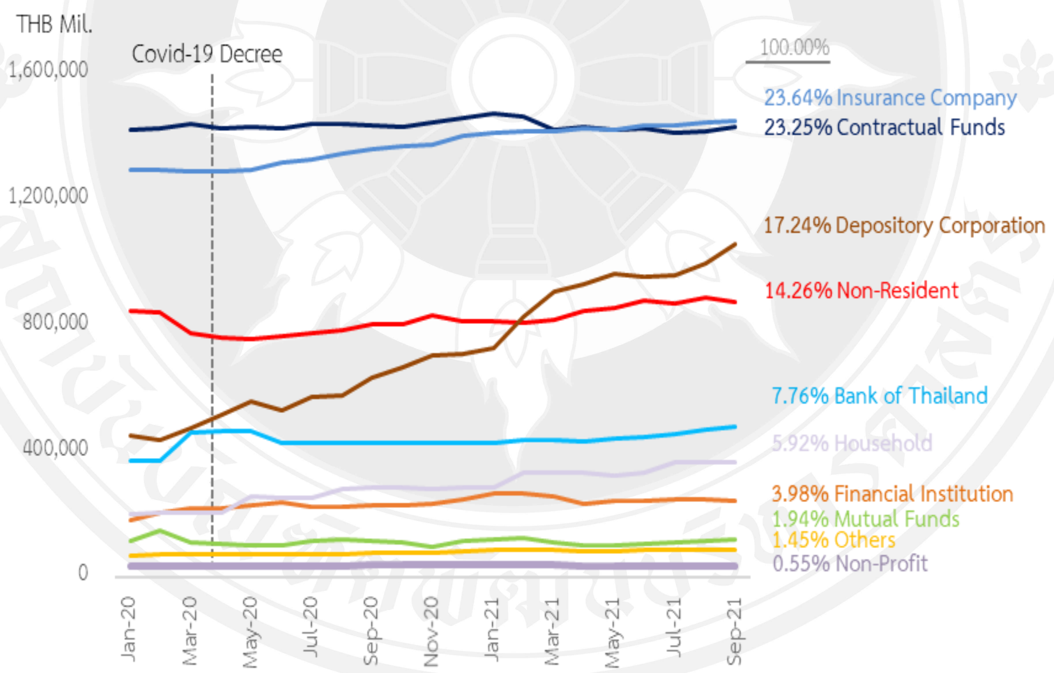


Figure 1.3 Government Bond Holders Classified by Type of Investors

Source: Public Debt Management Office, as of September 2021.

This overall indicates that the fixed income market is an important part and trends to be continued a large market in the future. Additionally, it has become one of three main pillars of the Thai's financial markets for developing actively economy system in an increase financing and investment source. From now onward, economic development in the region, especially for Thailand is going to move forward from traditional sources to a key role of the bond market with financial liberalization. This leads to the reason why bond yields have been increasing important index in the financial markets.

1.1 Statement of Problem

Now one of the most important market indexes is the government bond yields in financial markets. The yield curve is a return of bond issued by the government at a different maturity. With trustworthy and reliable in the government, most of investors consider investing in the fixed income as risk-free rate market. The bond yield becomes the minimum requirement of return or a single price for using a measure of the benchmark in debt market for government, fixed income portfolio managers, financial institutions, risk managers, and investors. Although the rate of return of bond is known at the time of being issued, then, is neutral to the uncertainty (Caballero et al., 2017). Changing in the yield curve will affect directly to fixed income market and other market indexes. Additionally, the slope of the spot curve contains the information about the economic environments and also the shape of the yield curve can be interpreted market conditions such as a business cycle (i.e., a recession or a boom).

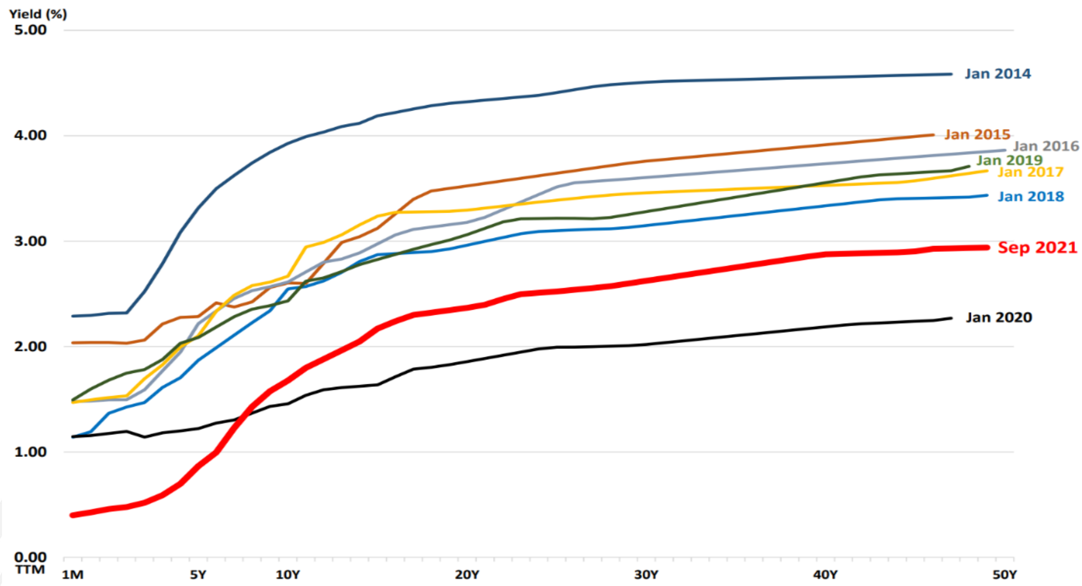


Figure 1.4 Thai Government Bond Yield Curve 2014 - 2021
Source: Public Debt Management Office, as of September 2021.

Especially, the yield curve affects directly to the borrowing cost of government for an investment in infrastructure projects and restructure public debt in portfolio, including the cost of funding of private sector. Fluctuations in nominal bond yields movements generate the borrowing cost problems of government, as well as it also influences on the public debt management, especially for refinancing of government debt and risk management in portfolio benchmark. It is therefore of great interest of diverse market participants, namely policy makers, investors, and risk managers to accurately predict the yields movements. For policy makers understanding the changing in future yields may help their decision making concerning macroeconomic monetary and fiscal policy. And also for investors or speculators, forecasting future yields may result in the higher portfolio returns.

However, the bond yield movements, like other high frequency financial economic data, are complicated to explain. Fundamental economic theories seem unable to clarify movements in fixed income yields behavior. In sprit of its growing importance, the impacts of macroeconomic shocks that drive yield movements remains mainly based on event-specific analyses and observations. It also is very challenging to produce accurate yields with different maturities and their predictions are crucial for policy marker, treasurers, bankers, risk managers, and fixed income portfolio managers to adjust the bond yield fluctuations. Particularly, in order to forecast the yields accurately, it requires a good model which allows economic indicators both domestic and global variables to interact with the yield movements. It allows for investigating the effects of macroeconomic factors on the yields in different maturities and forecasting future bond yields as well.

Furthermore, the order of the economy system in globalization has been changing rapidly and interdependencies linkages between domestic and international financial market, in particular the rise of some shocks in new economic factors such as commodity price and capital inflow. This trend may indicate some shocks in the order of macroeconomic variables to the yields as well. It is worthwhile to consider a joint macro-finance perspective because the dynamic of the yields and the state of the macroeconomy are jointly related. Thus, the factorial determinants of yields with a different maturity fluctuation in the bond market and forecasting the future bond yields with macroeconomy need to be explored in order to verify this statement.

In order to reduce the vulnerability of the yield movements to economic shocks as well as to achieve producing accurately forecasts the future fixed income yields – in sense that its benefits outweigh risks associated and uncertainty. However, this dissertation focuses on the effect shocks of economic indicators on the yield movements in each maturity and consider choosing the model fit as well as forecasting performance of the yields. Generally, macroeconomic policies such as fiscal policy, monetary policy, and including Federal funds rate, capital inflow, and commodity price are used as the main to stabilize the economy environment and most of these are widely considered to be the set of economic factors required to capture economic dynamics (Kozicki & Tinsley, 2001; Rudebusch & Svensson, 1999). Hence, many economists are interested in studying on the effect shocks of domestic and international macroeconomic indicators on the fixed income yield movements, and also these factors are used to forecast the future yields in the bond market indexes.

In fact, however, the main problem is that the bond yield movements, likely to other high frequency financial economic data as mentioned previously, are complicated to predict accurately. Albeit most of evidence existing literatures find that there are the movement in yields with various macroeconomy, particularly for the US treasury yields and the others but is yet unclear in the evidence of determinants of the yields in government bond movements in Thai bond market aftermath the Asian financial crisis in 1997.

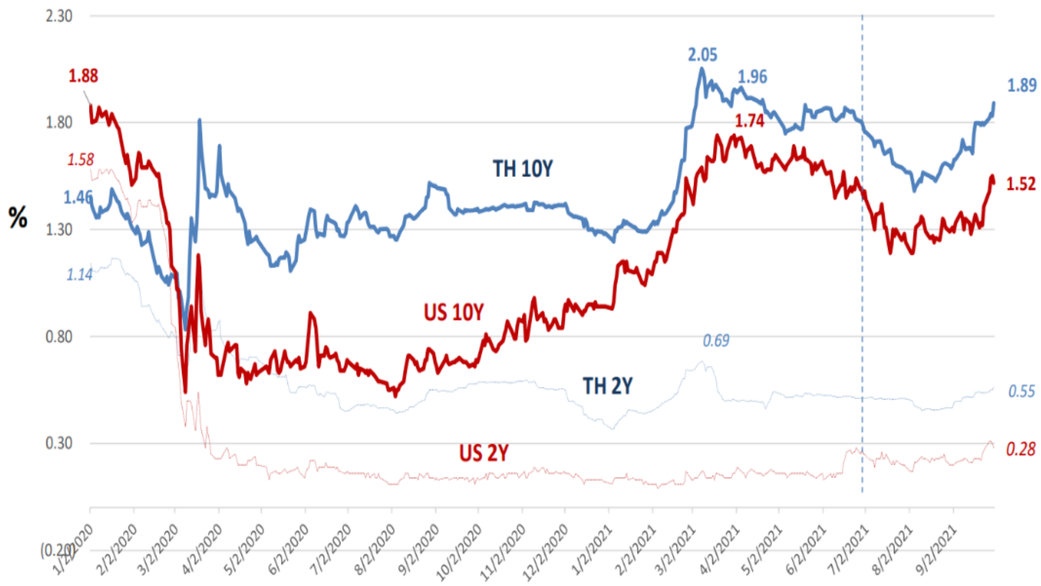


Figure 1.5 TH 10Y and US 10Y Bond Yield Movement
Source: ThaiBMA and Public Debt Management Office, as of September 2021.

1.2 Motivation

In the context of the fixed income yield which is one of the most important market indexes in the financial market with financial liberalization. The bond yield becomes to minimum requirement of return or benchmark, it is crucial for government, fixed income portfolio managers, financial institutions, risk managers, and investors to timely estimate and understand both magnitude and duration of effects of domestic and international economic shocks on the yields with all maturities. All of these are important factors to analyse and examine how macroeconomic indicators affects bond yields and its variability. The obtained information in turn can help policy makers, investors, and risk managers to conduct adequate tools in order to manage and monitor such risk, reduce and avert further increase of vulnerability the yield movements. However, it is challenging to predict the effects of economic indicator shocks on the yields with various maturities and forecasts the future yield curve in the debt market.

Empirically, for the case of bond yields, there are a wide of studies covering the related topics. They can be classified into several specific topics, such as research on forecasting future yields of different maturities with various models and evidence and impact of macroeconomic indicators on the yields in all different maturities. However, these studies have mostly dealt with these topics separately, even in the same topic as forecasting government bond yields with different approaches, and the impacts of economic factor shocks on the yields of different maturity movements.

Therefore, this dissertation aims to employ macroeconomic factor models which allow for analyzing various aspects of economic indicators and the yield movements interaction to achieve three objectives of the dissertation:

1. Investigating the relationship between macroeconomic factors and government bond yields in the Thai bond market.

2. Analyzing the effect shocks of domestic and international macroeconomic factors on the yield movements in each maturity.

3. Forecasting the future government bond yields with various approaches in the Thai bond market.

The first objective is to investigate the association between the economic indicators and the yields of all maturities. I will primarily examine macroeconomic variables and government bond yields in the Thai bond market. This study obtains the six key variables, namely fed rate, primary budget deficit, commodity price index, capital inflow, VIX index, and liquidity, which some variables are widely considered to be the fundamentals needed to capture basic macroeconomic dynamics. The yields with macro factors use these methods transition equation summarizing the dynamics of the vector of variables, and a linear measurement equation relation to the observed yields to the variables. The estimate results will provide several implications for policy makers and private sectors. For example, information of economic indicators and the yield movements interaction are important for policy institution, investors, and risk managers to closely monitor the associated risks and manage their portfolio investments.

After investigating an overview about movement in yields of different maturity and macroeconomic linkages, the second objective will focus on the effect of domestic and international shocks on the yield movements which all market participants recently have been increasingly concerning. In the current economic environment, fiscal and monetary policy which will reflect to dynamic of macro factors adopted in our country and other countries in the world, especially for the Federal fund rate are possibly to affect the bond yields in financial market indexes. The effect shocks of economic indicators play a significant role of the fixed income yield movements. Following the estimation results of the second study objective which finds macroeconomic shock have a strong impact on the government bond yields in all different maturities and suggests that the bond market may be needed to mitigate the risks arisen from the inverse impacts. However, it is difficult to explain the degree of response of the bond yields to shocks of the macro variables. Hence, the third objective is to attempt constructing good models of the yield curve for forecasting performance, the resulting models are very different in form and good fit. Based on different study, there is apparent large gap between the yield models proposed by macroeconomists, which focus on the role of economic factors in the determinants of the yields, and the models provided by financial economist, which avoid any explicit role for such determination (Diebold et al., 2006). Thus, what can be done in this dissertation is to consider the most suitable approaches for forecasting the future government bond yields with macroeconomy, then comparing the best predictive yields with each model. The differences between actual and forecast will provide information about the best performance of the bond yield movements accuracy.

As mentioned previously, macroeconomic factor models are required to achieve the study objectives. However, it is really challenging to build such models that are able to capture the interaction between the yields and economic factors from both domestic and international shocks through different policies and from various sources in a global environment. Explicitly, these indicators are classified into 2 groups: first group, the common factors – macroeconomic dynamics are widely used to capture the yields such as fed rate, primary budget deficit, VIX index, and liquidity shocks; second group, new factors – economic factors used for the first time in predicting the yields such as commodity price and capital inflow. In the existent literature, there are two main approaches in modelling forecasts the yields. The first approach is traditional and classic models that seem not to be suitable for this study and the second approach is to construct and parameterize a linear model or new model such as VAR model, Bayesian VAR model, and Single Equation model as well as Random Walk forecasts as a benchmark.

Therefore, the three main approaches will be used in this dissertation (i.e., focusing on BVAR model, VAR model, Single Equation model, and Random Walk), because they allow studying the relative importance of different shocks, economic shocks transmission mechanism at the yields with all maturities; furthermore, they also allow investigating the impacts of both domestic and international macroeconomic factors on the fixed income yield movements. Additionally, they allow the forecasting future yields of different maturities and then, compare the empirical forecasting performance of the proposed competitive linear models with fixing an in-sample and out-of-sample forecast horizon. However, these all models, this dissertation will focus on Bayesian VAR approach and the others are competitive approaches. Theoretically, Bayesian VAR model – built on VAR approach, is constructed by Litterman (1980), Doan et al. (1984), Litterman (1986), and Spencer (1993) to analyze indeed lots of factors. It can also overcome the curse of dimensionality and the number of data limitation which happened in traditional VAR and other approaches. The BVAR parameters are treated as random variables, and prior probabilities are assigned to them. Thus, it becomes the most popular one approach because its exploits more than the others. In short, "**Bayesian VAR**" is advanced econometric technique suitable for investigating associations between economic indicators and the yield movements and forecasting the best performance of the bond yield movements accuracy.

1.3 The Study is Structured as Following

Chapter 1: Introduction

Chapter 2: Review Related Theories and Methodologies

Chapter 3: Data and Methodology

Chapter 4: The Impact of Macroeconomic Factors on Bond Yields in Thailand

Chapter 5: Forecasting Government Bond Yields in Thailand: a Bayesian VAR Approach

Chapter 6: Conclusion and Policy Implication

CHAPTER 2

REVIEW RELATED THEORIES AND METHODOLOGIES

In this chapter, various strands of related literatures with focusing on the case of fixed income yields in the debt market are reviewed in order to have a wide understanding about how economic shocks are empirically and theoretically transmitted and affect the bond yields as well as how to forecast the future fixed income yields with several models. It starts with reviewing the term structure of interest rates integration theories to examine how it is essential in the financial markets and whether internal and external shocks of macroeconomic can be transmitted into bond yield movements. Then, it continues to review the literatures explaining how to forecast the yield movements using different models

2.1 Overview about Benefits and Drawbacks of Yields Curve Projection

There are several market indexes in financial markets. One of the most importance market indexes is the bond yields in debt market. Theoretically, the yield curve, also known as the term structure of interest rates, is the relation between interest rates or fixed income yields and different terms or maturities. Interest rates play several essential roles within the macroeconomy. One of them is being a key policy instrument of central banks to steer the state of the economic environment. The yield curve is a return of bond issued by the government at a different maturity. With trustworthy and reliable in the government, most of investors consider investing in the bond as risk-free rate market. Many countries have large debt and stock markets and receive vast inflows of foreign capital, playing an essential role in the international capital market. Thailand receives attention as it has large debt market, with liquid derivative markets, and thus represents interesting opportunities for both domestic and external investors.

Recently, the benefits of fixed income yield become the minimum requirement of return or a single price using a measure of the benchmark in the debt market for government, fixed income portfolio managers, financial institutions, risk managers, and investors. Although the rate of return of bond is known at the time of being issued, it is neutral to the uncertainty (Caballero et al., 2017). Therefore, it is the great interest of various market participants such as investors, policy makers, and risk managers to accurately predict interest rates movements. For investors, forecasting future yields may result in higher portfolio returns. However, for policy makers understanding the change in future yields may help their decision making concerning macroeconomic monetary and fiscal policy.

Explicitly, drawbacks and risks for participating in the markets, changing in the yield curve will affect directly to fixed income market and other market indexes, especially increasing the cost of funding. Besides, it also reflects directly to the costs of a new government borrowing for an investment in infrastructure projects and refinancing debt in portfolio. Fluctuation in nominal bond yield movements generate the cost problems for new government borrowing, as well as it also affects the public debt management, especially refinancing of government debt, funding needs for infrastructure, and risk management in portfolio benchmark.

Hence, in attempt to examine the determinants of economic indicators to drive on the yields with a different maturity and developed models are able to properly capture the behavior of the yield curve with and without macroeconomy for the benefits of all participants in the debt market. In a current literature, indicates that the Federal fund rate is the most significant indicators to the yield movements which plays a key role in the forecasting future yields. It means that when changing in Federal fund rate is up and down fluctuation, it probably leads to the yield movements.

2.2 The Impact of Macroeconomic Factors on Yield Movements

In this section, we will review how macroeconomic shocks and yield interaction with considering a significant effect on the yields and generating more risk and uncertainty for yield curve in the markets. Theoretically, as an open economy is deeply linked with other economies in both real market and financial market, it has effect of domestic and international macro shocks on debt market, and capital market. We then will review the literatures related to the impact of economic factors on yield volatility which is an indicator for the uncertainty. The relationship between macro variables and yield movements are also investigated.

Regrading to the impact of economic indicators on the fixed income yields, Diebold et al. (2005) argue that there is the nature of linkages between the macro-finance factors driving the bond yield curve and macroeconomic fundamentals. The impact of macroeconomic factors has directly significant to future movements in the government bond yield curve and evidence for a reverse influence. Additionally, Akram and Das (2014) state that low short-term interest rates (monetary policy) have been the key reason for Japanese government bond low nominal yields. Similar to Dai Hung (2020) finds that the impacts of macroeconomic variables (i.e., inflation rate, economic growth, and monetary supply) also drive the government bond yield curve. Also Akram and Das (2019) examine that in India the short-run interest rate plays role of diver of the long-run fixed income yield holds over the long-run. While the government debt ratio does not have adverse effect on India government bond yields in the same period. Moreover, Perović (2015) finds that the magnitude of effects of government debt and primary balance on long-term government bond yields in 10 Central and Eastern European countries, have more significant. One percentage point increase in the stock of government debt is related with an increase in government bond yields of 2.7 – 4 basis points, while a one percent point increase in the primary deficit to GDP ratio is associated with an increase in government bond yields of 12.9 – 24.3 basis points. In addition, many academics argue that common factors such as debt to GDP ratio, fiscal deficit, current account deficit, interest rate, unemployment, VIX index, generalized risk aversion, and inflation, have a more significant as determinants of government bond yields (Bernoth et al., 2004; Longstaff et al., 2011; Mody, 2009; Schuknecht et al., 2010).

On the other hand, some academics argue that aggregate demand shocks and monetary policy shocks of a small and open economy have relatively large and persistent effects on long-term yields. Similarly, find that aggregate demand shocks of Canada and USA economy have relatively large and persistent effects on long-term yields, whereas aggregate supply shocks do not have significant effects. Monetary policy shocks in Canada, however, have large and more effects on long-term yields than those found for the USA (Lange, 2005). Additionally, increase in foreign capital inflows to emerging countries due to higher financial integration might be investment opportunities in the international debt market; this consequently leads to more volatility of bond yields. The existing literature also do provide an unclear conclusion about the theoretical impact of capital inflow linkage on the fixed income yields in the debt market. Such as, Cebula (1997) finds that the impact of net international capital inflow is significant, as domestic interest rates in France may not only reduce longer term interest rates but may also offsets a large segment of the long-term yield impact of that nation’s government budget deficit.

To examine the vague conclusion about the association between economic factors and yield movements in the debt market, many academics continue to investigate this matter in more comprehensive scop and find out that the effect of macroeconomic variable shocks on the yield movements depend on various indicators.

2.3 Forecasting Yields with and without Macroeconomy Factors

The literatures related to the forecasting future bond yields of different maturities with and without macroeconomic factors. Most of the literature studies apply various economic models to compare the performance forecasting the bond yields with in-sample and out-of-sample forecast horizon. They can be categorized into 2 strands of literatures.

In the first strand of literatures, it states that an increase in volatility of government bond yields may cause movement in the yields, it then leads to study for forecasting future yields without economic factors. Diebold and Li (2006) apply the Nelson-Siegel model and variety of the models with regarding the yields to forecast the term structure of government bond yields. This study examines out-of-sample forecasting performance of the yields by using U.S. Treasury. They find that Nelson-Siegel yield curve as a three-factor dynamic model (level, slope, and curvature) forecast appear much more accurate at long horizons than the random walk (RW), but the 1-month ahead forecast no better than the RW and the other model’s performance (slope regression, Fama-Bliss forward rate regression, Cochrane-Piazzesi (2002) forward curve regression, univariate autoregressive (AR), vector autoregressive (VAR), and Error Correction Model (ECM)). Similarly, Koopman et al. (2010) apply the time-varying parameters in a dynamic Nelson-Siegel model for the simultaneous analysis and prediction of yields of a different maturity – called the term structure- with US Treasury yields covering the period from January 1972 to December 2000 (Dataset is the same as used by Diebold et al. (2006)). They find empirical evidence that the time-varying loading and volatilities in the dynamic Nelson-Siegel effect to significant increases in model fit. This leads to improve the forecasts of the yield curve accurately, although the dataset is missing. Vicente and Tabak (2008) also study different models for the forecasting the fixed income yields in Brazil with 4 interest rates swap maturing in months. They compare the accuracy of out-of-sample forecasting of Diebold-Li (2006) model, an affine term structure model, and RW benchmark by using mean squared errors and Diebold-Mariano statistics. They suggest that the Diebold-Li (2006) model produces superior forecasts than the other models, particularly at the long-term horizon for short-term yields. In additional to Hevia et al. (2015), also use a Markov-switching Dynamic Nelson-Siegel model (MS-DNS) for forecasting the US yield curve that depends on circles of economy such as a recession, a boom, and on the stance of monetary policy. They find that Markov-switching framework seems to capture the shape of the yields curve changing over time in ways and yield curve is substantially flatter during recessions than in booms for the sample. Finally, they find that MS-DNS model outperforms the single-regime dynamic Nelson-Siegel model and other models of the yield curve.

In the second strand of literatures, it states that impact of volatility on economic factors may cause to movements in fixed income yields in the bond market. This leads to study for forecasting the future yields with economic factors. Such as, Carriero et al. (2012) introduce a new statistical model for entire the term structure of interest rates (US treasury dataset using rolling estimation window of 120 months, period from 1985 to 2003) and compare its forecasting performance of the proposed model relative to most of the existing alternative specifications (RW, AR, VAR, Fama and Bliss (1987) (FB), Cochrane and Piazzesi (2005) (CP), affine term structure model (ATSM), Dynamic Nelson and Siegel model (Diebold and Li, 2006, (DL)), and Bayesian VAR). They find that the proposed Bayesian VAR approach produces competitive forecasts, systematically more accurate than RW forecast at all maturities and forecast horizon, even though the gains are small, and it outperforms all models. Moreover, they find that in the class of linear models, powering up produces overall better forecast than the other models (direct approach), both for AR and VAR models. Almeida et al. (2017) apply segmented term structure models to forecast bond yields and compare with successful term structure benchmarks based on out-of-sample forecasting performance of segmented term structure models by using U.S. Treasury with 8 maturity yields covering period from 1985 to 2012. They use several models to measure the rolling-window forecast performance with RW, are DL, Svensson model (DSM), polynomial segmented model (Bowsher and Meeks (2008) (BM)), affine Gaussian, weak segmented (NS4), and strong segmented (NS4S), all with AR factor dynamics. They find that series of out-of-sample forecast with US Treasury yields, the segmented models provide significantly smaller RMSE than those produced by the RW and some other established term structure models. Also Koopman and van der Wel (2013) apply dynamic factor yield curve models with economic factors for forecasting the US Treasury yields. This study uses a monthly time series panel of unsmoothed Fama-Bliss zero yields with different maturities covering from 1970 to 2009. They find that there is the relationship between the economic factors and yield curve, and macroeconomic factors can lead to more accurate term structure forecasts.

Additionally, Noteboom (2019) employs extending MS-DNS model to fit and forecast the yield curve in a low interest rate environment with and without linking the yield curve to the macroeconomy (i.e., federal fund rate, inflation rate, and gross domestic product), by using the US Treasury yields from 1986 to 2018. He finds that MS-DNS with regime-switching model allows the transition probabilities to depend on the economic factors produces the most superior forecasts, especially at the short yield curve.

2.4 Methodologies Employed to Forecast the Yield Curve

Regrading to forecast the yield curve, a choice of model plays a key role in accurate forecasts of the fixed income yields. Hence the study of impact of economic factors on the maturity yield movements and forecasting the future yields will also involve in investigating the evidence from these mentioned models.

Based on the existing in macroeconomic and financial literature, there are various approaches to study forecasting the bond yields with a different maturity, these methods can be classified into four clusters. The first cluster contains models based on forward rate regressions which try to forecast the future yields by analyzing the information contained in the present forward rates such as Fama and Bliss (1987) and Cochrane and Piazzesi (2005). The second cluster contains models based on the no-arbitrage restriction - called latent factors -, such as affine term structure model (ATSM) and Gaussian model. The third cluster contains models based on exponential components framework such as Nelson and Siegel (1987), Dynamic Nelson and Siegel (Diebold and Li, 2006), and Markov-switching Dynamic Nelson-Siegel. The last cluster contains models based on a liner model, currently literatures suggest that these are very popular and tend to produce overall good forecasts of economic indicators and yields than other direct approaches such as univariate autoregressive (AR), vector autoregressive (VAR), and Error Correction Model (ECM), especially Bayesian VAR.

In this study, however, the main objective is to model a linear multi-factor system to investigate the relationship between macro factors and yields, and the impact of economic shocks on the yield movements, as well as the accurate forecast the future yields with maturity. The tradition and classic models (i.e., random walk, forward rate, ATSM model, Nelson and Siegel (1987), Dynamic Nelson and Siegel (Diebold and Li, 2006), and Markov-Switching Dynamic Nelson-Siegel) seem not to be suitable, since these models are mostly applied in studying forecast the fixed income yields in the past. Hence, we propose only new linear approaches are applied in this study (i.e., VAR, and Bayesian VAR, as well as Single equation is polynomial lag model), in a detail of these models will be presented in the next chapter. Finally, we will review briefly conceptual related literature covering the case of interesting forecast models that are applied to forecast the yield curve but are not employed in this study. The detailed review regarding to each specific topic will be presented in the corresponding chapters.

2.4.1 Random Walk Model

Random walk is originally modeling for analyzing the stock prices move earlier developed by Kendall and Hill (1953). In earlier theory, some academics suggest that financial data are a random walk, similar to change stock price movements have the same distribution and are independent of each other. Thus, it assumes the past movement of a stock price or market cannot be used to predict its future movement. However, after the RW is mostly applied in studying to forecast the yield curve. The forecast is always “no-change”. It becomes to be a very competitive benchmark in forecasting the term structure of maturity yields. The RW forecast of the maturity yields is presented as following:

$$\hat{y}_{t+h}^{(\tau)} = y_t^{(\tau)} \tag{2.1}$$

In the existing literature, there are many studied that apply the RW approach to study the forecasting the future yield curve in the fixed income market and some studies use its forecast to be competitive benchmark. Carriero et al. (2012) state that the RW forecasts are generally more accurate than most of other models at long horizons, except only Bayesian VAR model. In addition, Duffee (2002) and Diebold and Li (2006) argue that beating a RW forecast of the yield curve is very difficult. Therefore, many researchers will use the RW forecasts as the benchmark with respect to compare the forecasts of all the competing models. However, Diebold and Li (2006) find that Nelson-Siegel yield curve as a three-factor dynamic model (level, slope, and curvature) forecast appear much more accurate than the RW at long horizons. Vicente and Tabak (2008) also study different models for the forecasting the fixed income yields in Brazil by using Diebold-Li (2006) model, an affine term structure model, and RW benchmark. They suggest that the Diebold-Li (2006) model produces superior forecasts than the RW and ATSM models, specially at the long-term horizon for short-term yields.

2.4.2 Forward Rates Model

There are two models based on forward rate regressions which try to forecast the future yields by analyzing the information contained in the present forward rates such as Fama and Bliss (1987) and Cochrane and Piazzesi (2005). The briefly approaches will be presented as follows:

The first approach is Fama and Bliss (1987) (FB), the approach uses the spread between the τ-year forward rate and the 1-year yield forecast the 1-year excess return of the τ-year fixed income. The extension of the Fama-Bliss model uses the following regression model for each maturity τ:

$$\hat{y}_{t+h}^{(\tau)} - y_t^{(\tau)} = \alpha_h + \beta_h(f_{t-h}(h,\tau) - y_{t-h}^{(\tau)}) + \varepsilon_t \qquad (2.2)$$

Where $(f_h(h,\tau)$ as the forward rate at time t for yields between time $t+h$ and $t+h+\tau$. The h-step ahead forecasts $\hat{y}_{t+h}^{(\tau)}$ are then provided by forecasting the change in yields from time t to time $t+h$ using the forward-spot spread at time t:

$$\hat{y}_{t+h}^{(\tau)} - y_t^{(\tau)} = \hat{\alpha}_{\tau h} + \hat{\beta}_{\tau h}(f_{t-h}(h,\tau) - y_t^{(\tau)}) \qquad (2.3)$$

The second approach is Cochrane and Piazzesi (2005) (CP), the approach will imply putting all the available forward rates on the right-hand side of the regression. Imposition of the Cochrane-Piazzesi restrictions produced qualitatively identical result. The forecasts are computed as follows:

$$\hat{y}_{t+h}^{(\tau)} - y_t^{(\tau)} = \hat{\alpha}_{\tau h} + \hat{\beta}_{\tau h} y_t^{(\tau)} + \hat{\gamma} f_t(h,\tau) + \hat{\delta} f_t(h,\tau) \qquad (2.4)$$

In the existent literature, there are several studied that apply the two approaches to study the forecasting the future yield curve. Studies such as Carriero et al. (2012) find that the forward rate regressions both of FB and CP approaches for forecasting the yield curve perform quite good and fit but not as well as the Bayesian VAR. Moreover, the FB forecast quite well for the yields of short maturities, but they cannot beat the RW for yields of longer maturities, especially for longer forecasting horizons. However, as for the internal raking of the two methods, the FB approach seems to systematically outperform the CP approach in out-of-sample forecasting.

2.4.3 Affine Term Structure Model

Affine term structure model (ATSM) is the role to examine stylized facts concerning term structure dynamics and pricing bond derivatives. Generally, ATSM are multifactor dynamic term structure models that the state process X is an affine diffusion, and the short-term rate is affine in X. To aim is to forecast bond yields, then, $A_0(3)$ is a natural choice since in this ATSM family all factors capture information about interest rate. The short-term rate is featured as the sum of three stochastic factors as follows:

$$r_t = \phi_0 + X_t^1 + X_t^2 + X_t^3 \tag{2.5}$$

Where the dynamics of process X under the martingale measure Q is given by

$$\mathrm{d}X_t = -\,\mathrm{k}X_t\mathrm{dt} + \rho \mathrm{d}W_t^Q$$

with W_t^Q being a three-dimensional independent Brownian motion under Q, k a diagonal matrix with K_i in the i_{th} diagonal position, and ρ is a matrix responsible for correlation among the X factors.

The empirical literature of the ATS model, Vicente and Tabak (2008) study different models for fitting and forecasting the fixed income yields. They find that the forecasts of the ATSM follow Duffee (2002) for predicting the maturity yields seem to low performance than most of the RW and the Diebold and Li (2006). Additionally, Carriero et al. (2012) find that the ATSM produces quite poor forecasting at 1-step ahead horizon, then it improves at longer horizons, but it can beat the RW model only for yields of short maturity. However, it performs much worse than the Bayesian VAR in the remaining cases.

2.4.4 Nelson and Siegel (1987) Model

Nelson and Siegel (1987) (NS 1987) model give a static description of the yield curve in the form of a factor model. The NS 1987 curve are well-known to ultimate forecasting purposes, and the three coefficients in the NS 1987 curve may be interpreted as latent level, slope, and curvature factors. In addition, the nature of the factors and factor loadings implicit in the NS provides consistency with various empirical properties of the yield curve. The NS function form, which is a convenient and parsimonious three-component exponential approximation, then the NS form with the forward rate curve is presented as follows:

$$f_t(\tau) = \beta_{1t} + \beta_{2t}e^{-\lambda_t\tau} + \beta_{3t}\lambda_t\tau e^{-\lambda_t\tau} \tag{2.6}$$

The NS forward rate curve can be viewed as a constant plus a Laguerre function, which is a polynomial time an exponential decay term and is a popular mathematical approximating function. The corresponding yield curve using the three-factor model is expressed in term of a small set of unobserved factors:

$$y_t(\tau) = \beta_{1t} + \beta_{2t}\left(\frac{1-e^{-\lambda_t\tau}}{\lambda_t\tau}\right) + \beta_{3t}\left(\frac{1-e^{-\lambda_t\tau}}{\lambda_t\tau} - e^{-\lambda_t\tau}\right) + \varepsilon_t(\tau) \tag{2.7}$$

Several of empirical literature related to the NS model, Diebold and Li (2003) find that Nelson-Siegel yield curve with no-arbitrage pricing as a three-factor dynamic model (level, slope, and curvature) forecast appears much more accurate at long horizons than the RW, but the 1-month ahead forecast no better than the RW and the other model's performance (slope regression, Fama-Bliss forward rate regression, Cochrane-Piazzesi (2002) forward curve regression, univariate autoregressive (AR), vector autoregressive (VAR), and Error Correction Model (ECM)). Similar to Diebold et al. (2006) state that the NS form guarantees positive forward rates at all horizons and a discount factor that approaches zero as maturity increases.

2.4.5 Dynamic Nelson and Siegel Model

A main drawback of the Nelson-Siegel model is its poor out-of-sample forecasting performance. This is because of the latent Nelson-Siegel factors tend to vary over time. Thus, Diebold and Li (2006) dynamically extend the Nelson and Siegel model by allowing for time-varying latent factors at each time *t*, called Dynamic Nelson and Siegel (Diebold and Li, 2006) (DNS-DL). They showed very well results in term of out-of-sample yield curve forecasting. Diebold and Li (2006) interpreted the NS 1987 equation in a dynamic fashion as a latent factor model in which β_{1t}, β_{2t}, and β_{3t} are time-varying level, slope, and curvature factors and the terms that multiply these factors are factor loadings. For instance, the loading on β_{1t} is constant and equal to one for all maturities. A raising in β_{1t}, thus, results in an equal increase in rate of return across all maturities. Hence, the loading on β_{1t} may be interpreted as a long-term or level factor. For the loading on β_{2t} and β_{3t}, it is useful to consider the limit of the DNS-DL model.

The forecasts of the factors at time t+h is available, the forecast of the yields can be retrieved simply by exploiting again the cross-sectional dimension of the system. This gives the DNS-DL 2006 model as follows:

$$\hat{y}_{t+h}^{(\tau)} = \hat{\beta}_{1t+h} + \hat{\beta}_{2t+h}\left(\frac{1-e^{-\lambda_t \tau}}{\lambda_t \tau}\right) + \hat{\beta}_{3t+h}\left(\frac{1-e^{-\lambda_t \tau}}{\lambda_t \tau} - e^{-\lambda_t \tau}\right) \tag{2.8}$$

In the existing literature covering the DNS model, Carriero et al. (2012) find that the models based on the NS approach, overall, the DNS-Diebold-Li model based on the univariate autoregressive factor works better than the one based on the VAR factor specification, exception the forecasts of short maturities at short horizons, however, both are outperformed by the RW. Furthermore, Vicente and Tabak (2008) find that the DNS-Diebold-Li model produces superior forecasts than the RW and ATSM models, specially at the long-term horizon for short-term yields. However, Noteboom (2019) finds that the DNS-Diebold-Li model tend to provide more extreme estimates of the latent factors. Such as the estimated factor is more positive when the empirical proxy is positive, and more negative when the proxy is negative.

2.4.6 Markov-Switching Dynamic Nelson-Siegel Model

Markov-Switching Dynamic Nelson-Siegel Model (MS-DNS) is baselined the DNS-DL model by allowing for regime-switching. The concept of the MS-DNS model follows the Bernadell et al. (2005) which lets the MS-DNS model switch between two regimes, called regime-switching model. The first regime is a period with normal interest rate levels and a nearly flat yield curve. The second regime, interest rates of short term are consider lower showed by a steep curve. In addition to the main feature of the MS-DNS model is that the yield curve depends on a variable that can be interpreted by capturing discrete changes in economic conditions, for instance, it is able to capture that the slope of the yield curve is different at the different economic cycles. The arbitrage-free MS-DNS model conditional on regime i = 0 and 1, can be presented as follows:

$$y_t(\tau) = -\frac{A_i(\tau)}{\tau} + \beta_{1t} + \beta_{2t}\left(\frac{1-e^{-\lambda_t \tau}}{\lambda_t \tau}\right) + \beta_{3t}\left(\frac{1-e^{-\lambda_t \tau}}{\lambda_t \tau} - e^{-\lambda_t \tau}\right) + \varepsilon_t(\tau) \qquad (2.9)$$

The empirical literature related to the MS-DNS model, Hevia et al. (2015) find that the behavior of the US yield curve is relatively easy and flexible enough to match the changing shapes of the yield curve over time. Moreover, they find that the forecasting performance of Markov-switching model that extends to the standard DNS model with regime shifts outperform the single-regime Nelson-Siegel model of yield curve. In addition, Noteboom (2019) finds that the MS-DNS with regime-switching model produces the yield considerably better both in-sample and out-of-sample than the baseline DNS- Diebold-Li and only able to forecast the short yield curve better than a random walk.

In conclusion, most of the previous studies have dealt with the effect of economic factor shocks on the fixed income yield movements and forecast the future yields with different maturities by using various approaches. However, there are still no study employed by the linear models, especially Bayesian VAR model for accurate predicts the future rate of return on Thai government bond in the debt market.

CHAPTER 3

DATA AND METHODOLOGY

3.1 Why Include the Macro Factors Listed in this Study?

In this section, we need to consider selection of the macro factors listed in this study because used variables are very important to investigate the relationship between the macroeconomic factors and government bond yields and to predict future bond yield movements in the Thai bond market. Thus, this chapter mainly aims to explain the reasons for choosing the suitable macroeconomic factors listed and also discusses each factor of the models and show how the yields can be influenced by changes in these factors and forecasting the yield changes. Hence, it requires to macro variables where internal and external shocks of macro variables can be transmitted into bond yield changes in the Thai bond market.

We next discuss the macroeconomic factors used in this study. Why we employ these variables to estimate and forecast future bond yields. We have many reasons including the macro factors listed in this study such as fed rate, primary budget deficit, commodity price, VIX Index (CBOE Volatility Index), capital inflow, and liquidity.

Generally, macroeconomic policies such as fiscal policy, monetary policy, and including Federal funds rate, capital inflow, and commodity price are used as the main variables to stabilize the economy environment and most of these are widely considered to be the set of economic factors required to capture economic dynamics (Kozicki & Tinsley, 2001; Rudebusch & Svensson, 1999). Hence, many economists are interested to employ these variables in studying on the effect shocks of domestic and international macroeconomic indicators on the fixed income yield movements, and also these factors are used to forecast future yields in the bond market. In additional, many existing of literatures suggest that these macro factors have effect on the government bond yield movements, especially U.S. Treasury yields and other yields in many countries.

Moreover, some papers strongly suggest that the Federal fund rate are possibly to affect the bond yields in financial market indexes because in the current economic environment, fiscal and monetary of U.S. policy which will reflect to dynamic of macro factors adopted in our country and other countries in the world.

In contrast, some macroeconomic variables such as policy rate, exchange rate (FX rate), SET index, output growth and so on, are not includes in this study. Although some literatures suggest that some variables may drive the bond yield curve in some countries, but it depends on factors and size of their domestic bond markets. Moreover, we find that a few papers use the number of variables and different variables in each studying on the effect shock of macro factors on bond yields.

In Thailand, we have already chosen from a variety of macro variables by using Walt test and confidence bands test with 90% to consider and ascertain whether the joint impact of these macro variables have a significant influence on the yields in Thai bond market or not. We find that these economic variables that are not included, do not have an impact on yield movements in Thai bond market, while six macro variables as mentioned previously, have influence on the bond yield movements.

Thus, it is cleared that effect shocks of economic indicators play a significant role of the yield movements in Thai domestic bond market. Finding macroeconomic shock have a strong impact on the government bond yields in all different maturities and suggests that the bond market may be needed to mitigate the risks arisen from the inverse impacts. We, then, classified these indicator variables into 2 groups: first group, the common factors – macroeconomic dynamics are widely used to capture the yields such as fed rate, primary budget deficit, VIX index, and liquidity shocks; second group, new factors – economic factors used for the first time in predicting the yields such as commodity price and capital inflow.

3.2 Data Description

In this part, we next discuss the data used in this study. We study the Thai fixed income yield data. Then we will describe the economic factors which are used to estimate the univariate and multivariate models and elaborate on the relationship between these variables and the maturity yields. The data defined and collected are presented as follows:

Government bond yield is defined as a return on bond issued by government at a different maturity. The yield is the minimum requirement of return or a single price for using a measure of benchmark in debt market. This data is collected from the ThaiBMA.

Federal funds rate (Fed rate) is defined as policy interest rate set by the Federal Open Market Committee in the US economy. It affects monetary and financial conditions to broader economy in the world, including Thai economy. This variable is expected key drivers for changes in bond yields and the linkage between the bond yields and fed rate. This data is collected from the Bank of Thailand.

Primary Budget is collected from the Fiscal Policy Office (FPO) and the Comptroller General's Department (CGD). This data is calculated from the difference between revenue and expenditure plus the non-budgetary balance and financing (a budget deficit).

Capital inflow is defined as a net capital flow. This data is calculated from the difference between inward and outward movement of funds. The capital inflow is inward movement of funds into a host country from foreign countries. It consists of foreign direct investment (acquisition of a local firm), portfolio investment in financial securities (bonds and equities), borrowing of government from international banks or governments to finance a balance of payments deficit, and short-term deposits with money market and banking institutions. In contrast, capital outflow is outward movement of funds from one country to another country for a variety of reasons as mentioned above. This data is collected from the Bank of Thailand.

Commodity price is defined both fuel and non-fuel price indices such as crude oil, gold, and agricultural product prices and it play a key role in supporting the economic and social development. This variable is expected key drivers for changes in fixed income yields and the linkage between the bond yields and commodity price. This data is collected from International Monetary Fund (IMF primary commodity prices).

VIX index (Choe Volatility Index) is defined as a real-time index, representing the market's expectations for the strength of near-term price changes of the S&P 500 index is used to capture its impact on the fixed income yields. This variable is derived from the prices of S&P 500 index with near term expiration dates, it produces a 30-day forward projection of volatility. This data is collected from the Stock Exchange of Thailand.

Liquidity is defined as cash or an asset that can be converted into ready cash in financial markets. This data is collected from the Bank of Thailand.

3.2.1 Thai Treasury Yields

We use end of the quarter Thai bond yield data from 1998: Q1 to 2020: Q4. This yield data is used the nominal of fixed income yields with maturities of 1-, 3-, 5-, 7-, and 10-year from the ThaiBMA. This database provides Treasury yields estimate based on the new linear models. An important reason to particularly study to forecast the future government bond yields in Thai bond market.

In Figure 3.1 presents a plot of the yield movements against maturity and time. It shows that yields vary significantly over time and that interest rates fluctuate and are extremely low from the start of the global financial crisis in 2008. Currently, the yields with all maturities are still extremely low since 2020 until now. In addition, it is evident that the fixed income yield is not constant over time but can take a variety of shapes. In a half of this year, the yield curve is nearly steeply upward sloping during the Covid-19 crisis due to most of investors tend to invest in the short term of maturity more than the long term because of risk-off and holding a low risk of asset.

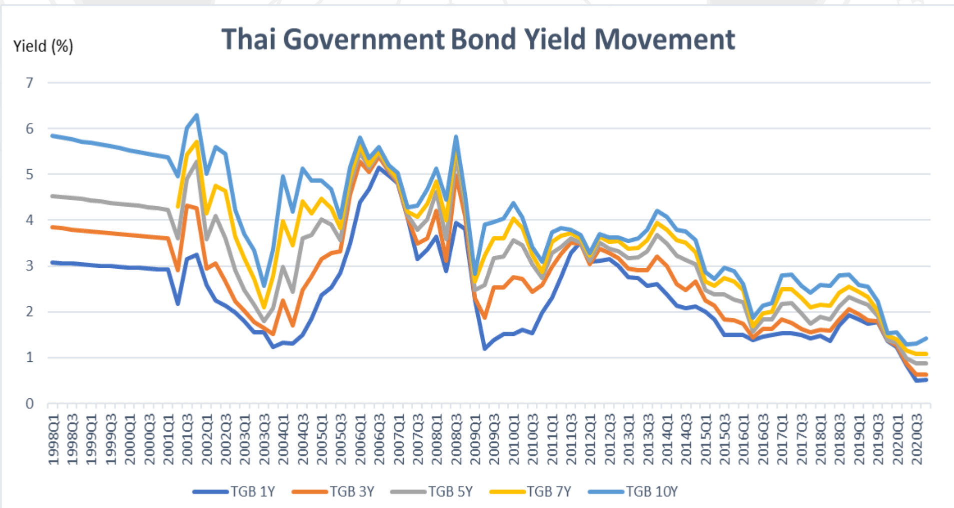


Figure 3.1 Thai Government Bond Yield Movement 1998 - 2020

Source: Authors' calculation.

Table 3.1 Summary Statistics Thai Treasury Yields (in %)

Maturity	Mean	Std. dev.	Minimum	Maximum
1-year	2.394	0.989	0.500	5.150
3-year	2.845	1.079	0.630	5.400
5-year	3.272	1.131	0.870	5.490
7-year	2.926	1.593	1.080	5.710
10-year	3.988	1.293	1.290	6.300

Source: Authors' calculation.

Table 3.1 presents summary statistics of the Thai Treasury yield data, spanning the period 1998 to 2020, measured in percent on a quarterly basis. For each maturity, it shows the mean, standard deviation, minimum, and maximum of the Treasury yields. The statistics show that most of statistics of the short-term yields are quite lower than long-term yields. In general, the yield curve is upward sloping, and that the long end is less volatile and more persistent over time than the short end.

3.2.2 Macroeconomic Factors

As macroeconomic factors, we consider the primary budget deficit (PB), fed’s policy rate (FED), all-commodity price index (ACPI), capital inflow, VIX index (CBOE volatility index) and liquidity which are all obtained from the database of the Ministry of Finance, Bank of Thailand, and the Stock Exchange of Thailand. In addition, some variables are obtained from International Monetary Fund and CEIC Database. We consider these factors as they are widely considered to be the common set of economic fundamentals required to capture macroeconomic dynamics, and also include the new indicators such as commodity price, and capital inflow into this study. The six variables namely represent the fiscal policy instrument, the monetary policy instrument, the financial market indexes, and international indicators, respectively. Most of dataset for domestic and international factors are available at a monthly frequency, but they are converted to base on a quarterly basis covering the period from 1998: Q1 up to 2020: Q4.

Table 3.2 Summary Statistics Economic Indicators

Macro Factors	Mean	Std. dev.	Minimum	Maximum
PB	-5670.26	141905.90	-366393.00	350417.30
FED	1.75	1.72	0.25	6.25
ACPI	109.64	42.82	42.92	199.57
Capital Inflow	-15457.20	111850.90	-321442.40	201502.00
VIX	20.63	8.55	9.51	53.54
Liquidity	11819377.00	5298855.00	5354371.00	22429834.00

Source: Authors' calculation.

In Table 3.2 presents summary statistics of the economic indicators. The key indicator shows that the average FED is nearly to zero and quite volatile around its mean, and also its minimum value is quite low to zero at 0.25 percent during this period, in 2020 which reflects to the financial markets. In addition, the capital inflow is quite volatile in some period around its mean and minimum value is negative which leads to quite volatile in the financial market indexes.

3.3 Why is Bayesian VAR the Most Suitable Approach for the Study?

In doing research, we need to consider choosing the most suitable approaches in accordance with the objectives of each study, because every approach has its own advantages and disadvantages. Hence, this chapter mainly aims to explain the reasons for choosing Bayesian VAR approaches, comparing to the competitive models such as Vector Autoregression (VAR) approach, and Single Equation (SE) approach as well as Random Walk (RW) forecasts as the benchmark.

As mentioned above in the introduction, this study has three main objectives. The first objective is to investigate the relationship between the macroeconomic factors and government bond yields in the Thai bond market. The second objective is to examine the effect shocks of domestic and international macroeconomic factors on the future yield movements in each bond maturity. The third objective is to forecast the future government bond yields in Thai bond market. Therefore, to achieve those objectives, it requires to model a multi-factors where internal and external shocks of macro variables can be transmitted into bond yield movements in the Thai bond market.

According to the objectives of the study, the most suitable models used in this study is to compare the best predictability of the Bayesian VAR against the standard VAR model, SE model and RW forecast model. In addition, this study also discusses each factor of the model and show how the yields can be influenced by changes in these factors and forecasting the yields changes. Hence, there are necessary to study current development of dynamic approaches, SE, VAR, and Bayesian VAR approaches are chosen according to the following reason.

VAR model allows for estimating the multi-factors of internal and external shocks and their impacts on government bond yields movements. Moreover, it can also provide the forecasting future yields of different maturities. However, standard VAR model has severe limitation of estimated factors. For example, in traditional VAR model, there are data limitations such a strategy encounters and overparameterization problem, due to the number of estimated parameters ($p(k-1)$) rapidly reduces the degree of freedom of the VAR system and it cannot add more the number of a large variable (Bernanke et al., 2005). As the result, it may not provide the best value of performance accuracy for estimating the shocks.

In contrast, Bayesian VAR model is developed to analyze indeed lots of factors. It allows for investigating the impact of macroeconomic variables on the yields in all different maturities and forecasting future the yields as well. Additionally, it can also overcome the curse of dimensionality and the number of data limitation which happened in traditional VAR and other approaches. Now, it becomes the most popular one approach because its exploits more than the others. Therefore, it is possible and flexible to forecast the methodology best performance of the bond yields movements accuracy.

Hence, the methodology used in the study is to compare the Bayesian VAR, which allows an unmodified Bayesian statistical procedure to obtain the best predictive value with the VAR model and SE model for competitive models, which has previously been widely used.

3.4 Standard VAR Modelling

In this study, VAR model is also used to explain movements in the government bond yield. The VAR is a standard tool for forecasting macroeconomic time series, in large part because VAR produce dynamic forecasts that are consistent across equations and forecast horizons. Then, we allow the VAR approach introduced by Sims (1980), and Bernanke and Kuttner (2004). This approach is considered as alternative to the large scale macro-econometric models. According to Sims (1980), all variables appearing in the structural models could be endogenous in reduced-form VAR and empirical research should use small-scale models identified through a small number of constraints.

The reduced-form VAR model is defined by the following dynamic equation:

$$Y_t = A(L)Y_{t-1} + \varepsilon_t \tag{3.1}$$

Where

- Y_t denotes the vector of endogenous variables,
- L represents lag operator, A(L) is a matrix of reduced-form coefficients relating past variable values to current values,
- And ε_t is a vector of reduced-form errors with covariance matrix $\sum_{\varepsilon}$.

The applications of the VAR model in studying are the interaction between the economic factors and bond yields in different maturities. It also can be measured by the bond yields in response to domestic and external economic shocks. They are usually through impulse responses, measuring the effects of the different shocks on the variables of study, and variance decomposition, measuring the relative importance of the different shocks to variation in the different variables. In addition, the different shocks in a VAR model can be analyzed by using the long-term restrictions. The characteristic of VAR enables researchers to distinguish a non-stationary variable into a trend (the non-stationary component of variable due to shocks which have a permanent effect) and a cyclical component. It is the stationary component of variable because of shocks which have only short-term effects. This authorizes for a more flexible explication of macroeconomic fluctuations.

Notwithstanding, the predicted reduced-form VAR is criticized for lack of economic structure disclosed in the model. Thus, there would be various alternative implication for the estimation results from the same dataset. Consequently, to overcome these limitations, two important extensions of the reduced-form VAR has been proposed Bayesian VAR and structural VAR.

VAR model

In this part, the VAR model is set up by estimated multivariate model and linking them with a matrix of predetermined macroeconomic factors. According to a general VAR model, which is employed to analyze the direction of causality macroeconomic factors and the bond yields in different maturities in the Thai bond market. The multivariate time series can be presented in a VAR model of order p.

$$Y_t = \alpha + \delta_1 Y_{t-1} + \delta_2 Y_{t-2} + \ldots + \delta_p Y_{t-p} + \varepsilon_t \tag{3.2}$$

Where

i. Y_t denotes the vector of endogenous variables (macroeconomic factors), including common factors, nominal yields of short-term, medium-term, and long-term Thai government bond (1-year, 2-year, 3-year, 5-year, 7-year, and 10-year maturity yields), primary budget deficit, fed's policy rate, VIX index (CBOE volatility index), and liquidity, and new economic variables added in this research, commodity price index, and capital inflow

ii. α represents a vector of constants

iii. δ_i denotes a matrix of coefficients to be estimated

iv. ε_t is an error vector of random variables with zero mean and covariance matrix

The dynamics of system is explored by Bayesian VAR which allows an unmodified Bayesian statistical procedure to obtain the best predictive value with the VAR. It will be presented in the next sections.

3.5 Bayesian VAR Modelling

The Bayesian VAR approach is originally developed by Litterman (1980), Doan et al. (1984), and Litterman (1986). The Bayesian VAR is built on VAR model by applying Bayesian methods to estimate a VAR. The difference with standard VAR approach lies in the fact that the model parameters are treated as random variables, and prior probabilities are assigned to them. The Bayesian model imposes Theil-Goldberger inaccurate restrictions on the VAR coefficients through the employ of hyper-parameters, so called "**Minnesota prior**" (development of the idea at the University of Minnesota and Federal Reserve Bank at Minneapolis), it reflects the belief that economic structures normally follow a multivariate random walk and in which the econometric equations can be estimated separately, therefore, it is easy to implement.

According to Sims (2007), indicates that the objective aspect of Bayesian inference is the set of rules for transforming an initial distribution into an updated distribution condition on observations. The Bayesian priors are often used to control the otherwise highly over-parametrized the VAR model. The main advantage of Bayesian VAR model is that it avoids the problems of collinearity and over-parameterization that often occur with the applying of VAR model since Bayesian VAR imposes priors on the autoregression (AR) parameters and in correcting coefficient bias resulting from series non-stationarity (Bewley, 2002).

Bayesian VAR model

In the next step, the Bayesian VAR model is set up by stacking the estimated the bond yields in different maturities and linking with a matrix of predetermined economic linkages. The basic idea of Bayesian estimation (Bayesian econometrics) is to think about model coefficients in terms of conditional probabilities rather than about parameters with fixed "true" value and enables to estimate large dimension VAR using Bayesian shrinkage.

In this study, Bayesian VAR model will be used. The general model equation will take the form as:

$$Y_t = \alpha_0 + \sum_{i=1}^{k} \alpha_i(X_i) + \varepsilon_t \tag{3.3}$$

To derive the Bayesian VAR model, we begin by considering a general VAR model of a P dimensional column variable, y_t with M of the form, we can re-write model equation as:

$$y_t = \theta_0 + \theta_m y_{t-1} + \theta_m y_{t-2} + \ldots + \theta_M y_{t-M} + \varepsilon_t \tag{3.4}$$

Where $\mathbf{y_t}$ is $P \times 1$ a vector where P is the number of variables, $\boldsymbol{\theta_0}$ is $P \times 1$ a vector, $\boldsymbol{\theta_m}$ is $P \times P$ a matrix with $m = 1, \ldots, M$, where M is the number of lags, $\boldsymbol{\varepsilon_t}$ is $P \times 1$ vector and the errors $\varepsilon_1, \ldots, \varepsilon_T$ are $iid\ N_p(0, \Sigma)$, and Σ is $p \times p$ positive definite error covariance matrix. Let define:

$$\mathbf{y_t} = \begin{bmatrix} y_{1,t} \\ y_{2,t} \\ \vdots \\ y_{P,t} \end{bmatrix}, \boldsymbol{\theta_0} = \begin{bmatrix} \theta_{01} \\ \theta_{02} \\ \vdots \\ \theta_{0P} \end{bmatrix}, \boldsymbol{\theta}_m = \begin{bmatrix} \theta_{11} & \theta_{12} & \cdots & \theta_{1M} \\ \theta_{21} & \theta_{22} & \cdots & \theta_{2M} \\ \vdots & \vdots & \ddots & \vdots \\ \theta_{P1} & \theta_{P2} & \cdots & \theta_{PM} \end{bmatrix}, \mathbf{x_t} = \begin{bmatrix} y_{1,t-1} & y_{1,t-2} & \cdots & y_{1,t-M} \\ y_{2,t-1} & y_{2,t-2} & \cdots & y_{2,t-M} \\ \vdots & \vdots & \ddots & \vdots \\ y_{P,t-1} & y_{P,t-2} & \cdots & y_{P,t-M} \end{bmatrix}, \boldsymbol{\varepsilon_t} = \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \\ \vdots \\ \varepsilon_{P,t} \end{bmatrix}$$

And

$$Y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_P \end{bmatrix}, \Phi = \begin{bmatrix} \theta_1 \\ \theta_2 \\ \vdots \\ \theta_P \end{bmatrix}, X = \begin{bmatrix} x_1 & x_2 & \ldots & x_M \end{bmatrix}, E = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_P \end{bmatrix}$$

Where

$$\theta_1 = [\theta_{01} \quad \theta_{11} \quad \dots \quad \theta_{1M}]$$
$$\theta_2 = [\theta_{02} \quad \theta_{21} \quad \dots \quad \theta_{2M}]$$
$$\vdots$$
$$\theta_P = [\theta_{0P} \quad \theta_{P1} \quad \dots \quad \theta_{PM}]$$

$$x_1 = \begin{bmatrix} 1 \\ y_{1,t-1} \\ \vdots \\ y_{P,t-1} \end{bmatrix}, x_2 = \begin{bmatrix} 1 \\ y_{1,t-2} \\ \vdots \\ y_{P,t-2} \end{bmatrix}, \dots, x_M = \begin{bmatrix} 1 \\ y_{1,t-M} \\ \vdots \\ y_{P,t-M} \end{bmatrix}.$$

Thus, we have

$$Y = X\Phi + E \tag{3.5}$$

Now, we will discuss on Bayes' Theorem. Let $P(\theta)$ is the probability of θ, $P(\theta/Y)$ is the conditional probability, and $P(Y)$ is the marginal probability. Also, define the joint probability of obtaining such θ on data Y by $P(\theta \cap Y) = P(\theta/Y)P(Y)$ and vice versa. Hence, we get

$$P(\theta/Y) = \frac{P(Y/\theta)P(\theta)}{P(Y)} \tag{3.6}$$

$P(\theta)$ and $P(\theta/Y)$ are, respectively, the prior and posterior distribution of θ, given the observed data Y. In the parameter space, we have $P(Y) = \int P(Y/\theta)P(\theta)d\theta$ which is a constant that normalizes the kernel of the posterior distribution. Thus, we can rewrite (3.6) as follow:

$$P(\theta/Y) \propto L(\theta;Y)P(\theta) \tag{3.7}$$

Where

$L(\theta;Y)$ denotes the likelihood function

In the Bayesian VAR forecast process, we apply the Minnesota prior and compare the value of performance gained from the traditional unrestricted VAR. The Minnesota prior is proposed by Doan et al. (1984) and Litterman (1986), sometimes referred as the Litterman prior and popular for its simplicity and good forecasting performance.

Posterior for parameters of matrix A has the form:

$$\alpha/y \sim N(\bar{\alpha}_{Mn}, \bar{V}_{Mn}) \tag{3.8}$$

Where

$$\bar{V}_{Mn} = [\underline{V}_{Mn}{}^{-1} + (\hat{\Sigma}^{-1} \otimes (X'X))]^{-1}$$

$$\bar{\alpha}_{Mn} = \bar{V}_{Mn} [\underline{V}_{Mn}{}^{-1} \underline{\alpha}_{Mn} + \hat{\Sigma}^{-1} (\otimes X)' y]$$

Thus, the posterior of variance of coefficients is combination of variance of regressors and prior and posterior of coefficients is a weighted average of Minnesota prior and ordinary least squares (OLS) estimates.

3.6 Single Equation Modelling

Single Equation method (SE) is used in econometrics to estimate models in which a single variable of interest is determined by one or more exogenous explanatory variables. In this study, we include a SE model to forecast the yields of various maturities with macroeconomic variables. The widely majority of traditional time series analyses have considered SE model. The forecasts are then derived such as the following:

$$Y_t = \beta_0 + \Sigma\beta_{1-k} X_{1-k,t-i} + \varepsilon_t, \tag{3.9}$$

Where Y_t denotes the endogenous variable at time t, X_{t-I} are 1 to k exogenous variables at time $t - I$, β_0 is constant, β_{1-k} are the parameters associated with variables X_{1-k}, and ε_t is the stochastic error term $\sim N(0, \sigma^2)$.

The SE methodology, the equation is ignored possible (non) stationarity of the variables and ordinary least squares (OLS) is provided to estimate the values of the parameters β_0, β_{1-k}. The effects of the economic factors (independent variables) may be specified to occur simultaneously (i.e., at time t or with a lag i). Doing diagnostic tests on regression models, given to the possibility that stochastic errors are correlated [i.e., $cov\ (\varepsilon_t, \varepsilon_{t-i}) \neq 0$]. Although, correlation errors do not bias parameter estimates but have effect on standard errors and impose a threat to inference by effect the size of the t ratios. The standard test for correlated errors has been the Durbin–Watson test, which tests only for first-order autocorrelation in the residuals of the estimated regression model. The conventional approach is to conclude that the errors are generated as follow process:

$$\varepsilon_t = \rho\varepsilon_{t-1} + \upsilon_t \tag{3.10}$$

Where ρ captures the relationship between temporally adjacent errors, and v_t is a "well-behaved" (uncorrelated) error process $\sim N(0, \sigma^2)$.

In this study, we will use the Random Walk forecasts as the benchmark with respect to which we will compare the forecasts of the competing other models.

The dynamics of system are identified by impulse response analysis and variance decompositions which will be presented in the next section.

3.7 Impulse Response Functions

To analyze dynamics of the estimated VAR and Bayesian VAR models and to assess the effects of shocks to macroeconomic variables on the bond yields in all different maturities. Impulse response Function (IRF) proposed by Sims (1980) to analysis is an important step in econometric analysis, which provides VAR models with the form of vector moving average. Their main purpose is to explain the evolution of model's variables in reaction to a shock in one or more variables. This feature allows to trace the transmission of a single shock within an otherwise noisy system of dynamic equations and, thus, makes them very useful tools in the assessment of economic policies. This post introduces the concept and interpretation of impulse response functions as they are commonly used in the VAR literature. In general, the core function of impulse responses is trace out the response of current and future values of each variable to a one-unit shock increase in the current value of one error in VAR models, is applied.

Different to the Generalized Impulse Response Functions (GIRF) for vector error correcting models is proposed by Koop et al. (1996) for non-linear models and developed further by Pesaran and Shin (1998), considering shocks to individual errors and integrates out the effects of the other shocks using the observed distribution of all the shocks without any orthogonalization. And the Orthogonalized Impulse Response (OIR) introduced by Sims (1980) which requires the impulse responses to be computed with respect to a set of orthogonalized shocks.

Hence, in this research, we will use originally concept of the impulse response to consider the effects of shocks to economic factors on the yields curve because it is very useful and suitable tools for the dynamic models. In general, the IRF provides useful information about the dynamics of the transmission of shocks from the economic variables to the government bond yields with respect to change in various factors, such as primary budget deficit, fed’s policy rate, capital inflow, commodity price index, VIX index, liquidity and so on. The IRF test is calculated as follows:

$$X_t = \bar{X} + \sum_{i=1}^{\infty} A_i \varepsilon_{t-1} \tag{3.11}$$

Where $\bar{X}$ denotes a vector endogenous variable

$$X_t = \bar{X} + \sum_{i=1}^{\infty} A_i B^{-1} \varepsilon_{t-1} \tag{3.12}$$

$$X_t = \bar{X} + \sum_{i=1}^{\infty} \emptyset_i \varepsilon_{t-1} \qquad ; \emptyset_i = A_i B^{-1} \tag{3.13}$$

Where $\emptyset_i$ denotes coefficient of parameter, and ε is the macroeconomic shocks.

3.8 Variance Decomposition Analysis

To investigate domestic and international determinants of bond yield fluctuation in the Thai bond market, the generalized forecast error variance of macroeconomic variables will be estimated. The variance decomposition (VD) is also developed by Koop et al. (1996) and Pesaran and Shin (1998), to analyze the variance of the forecast error into components that can be attributed to each of the endogenous variables. Specifically, it provides a breakdown of the variance of the n-step ahead forecast errors of variable *I* which is accounted for by the innovations in variable j in the VAR models. As in the case of the orthogonalized impulse response functions, the orthogonalized forecast error variables in the VAR approaches. Lange (2005) uses the VD to analyze the magnitude of the volatility in the yields on long-term maturities that can be attributed to the macroeconomic shocks.

Therefore, this paper will use the generalized VD to consider the proportion of the n-step ahead forecast errors of the variables of interesting (i.e., fed's policy rate, commodity price index, and capital inflow) which is explained by conditioning on the non-orthogonalized shocks $B^{-1}\varepsilon_t, B^{-1}\varepsilon_{t+1}, \dots, B^{-1}\varepsilon_{t+n}$ but explicitly allows for the contemporaneous correlation between these shocks and the shocks to the other equations in the system. The variance decomposition is defined as follows.

From equation (3.11), we will estimate n-period equation as:

$$X_{t+n} = \bar{X} + \sum_{i=1}^{\infty} \emptyset_i \varepsilon_{t+n-1} \tag{3.14}$$

Thus, we get n-period error forecast:

$$X_{t+n} - EX_{t+n} = \bar{X} + \sum_{i=1}^{\infty} \emptyset_i \varepsilon_{t+n-1} \tag{3.15}$$

Hence, general equation of the VD is calculated as follows:

$$X_{i,t+n} - E_t y_{i,t+n} = \emptyset_{11}(0)\varepsilon_{yi,t+n} + \emptyset_{11}(1)\varepsilon_{yi,t+n-1} + \ldots + \emptyset_{11}(\text{n-1})\varepsilon_{yi,t+1} \quad (3.16)$$
$$+ \emptyset_{12}(0)\varepsilon_{yj,t+n} + \emptyset_{12}(1)\varepsilon_{yj,t+n-1} + \ldots + \emptyset_{12}(\text{n-1})\varepsilon_{yj,t+1}$$

The portions of the variance of forecast error of X_t n steps ahead:

$$\sigma_y(n)^2, y_i = \frac{\sigma_{yi}^2 \, [\, \emptyset_{11}(0)^2 + \emptyset_{11}(1)^2 + \cdots + \emptyset_{11}(n-1)^2]}{\sigma_y(n)^2} \quad (3.17)$$

$$\sigma_y(n)^2, y_j = \frac{\sigma_{yj}^2 \, [\, \emptyset_{12}(0)^2 + \emptyset_{12}(1)^2 + \cdots + \emptyset_{12}(n-1)^2]}{\sigma_y(n)^2} \quad (3.18)$$

3.9 Forecasting Statistical Performance

In this paper, to analyze the forecasting future yields we will compare the models (Single Equation, VAR, and Bayesian VAR models) based on multiple forecasting exercises by considering the accuracy forecast error measure with the Random Walk to investigate the best performance of the forecasting yields with maturities accuracy. Given our goal, we adopt both static and dynamic forecasting with recursive and rolling-window method for the 104 in-sample and out-of-sample forecasting the yields performed.

We use five main statistical functions to measure three usual approaches, including Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE) and Theil's Inequality Coefficient. All of them will be estimated to answer for the one of objectives in our research question (What does the model provide the best performance for forecasting the yields?). The statistical equations are identified as follows.

i. MAE = $\frac{1}{n} \sum_{i=1}^{n} |y_i - \hat{y}_i|$

ii. MAPE = $\frac{1}{n} \sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right|$

iii. MSE = $\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$

iv. RMSE = $\sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}}$

v. Theil = $\frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}}{\sqrt{\sum_{i=1}^{n}(y_i)^2} + \sqrt{\sum_{i=1}^{n}(\hat{y}_i)^2}}$

From a few papers, have evaluated the forecasting performance of the models by looking at these statistical measures and discussed the procedures used in the derivation of the forecasts. For example, Giacomini and White (2006) find the new rolling forecast approached, so called "**a rolling-window method**" that it is the use of rolling window accounts to prediction uncertainty for forecasting accuracy. Additionally, Hansen and Timmermann (2012) examine that the important of handling the split point of the data set into estimation and evaluation periods in out-of-sample tests. On the related issue, Rossi and Inoue (2012) offer a robust approach to data set snooping across the length of the prediction, in rolling-window forecasting evaluations.

Almeida et al. (2017) study the forecasting the bond yields with segmented term structure models, they follow Diebold and Li (2006) to forecast both an in-sample and an out-of-sample window size equal to 84 months with the rolling-window method. However, Carriero et al. (2012) use a rolling estimation window to estimate whether the forecasts of two competing models are statistically significantly different that they follow the Giacomini and White (2006) test for forecast accuracy and use the unconditional version of the test, which is based on the same statistic of Diebold and Mariano (1995). The statistical function test is indeed valid provided that the size of the estimation window is fixed (Carriero et al., 2012).

Based on conceptual as mentioned above, in this research, we will forecast the government bond yields in various maturities with fixing an in-sample and out-of-sample window size equal to 104 quarterly datasets by using static and dynamic forecast in the Single Equation, VAR, and Bayesian VAR approaches as well as Random Walk forecasts. The dynamic forecasting consists of a sequence of one-hundred and four out-of-sample quarterly forecasts constructed with the rolling-window method.

CHAPTER 4

THE IMPACT OF MACROECONOMIC FACTORS ON BOND YIELDS IN THAILAND

4.1 Introduction

Aftermath financial crisis since 1997, the sovereign bond market of Asian countries has grown rapidly due to the massive funding needs for an investment in their countries. Likewise, Thai government bond market has grown significantly in many years ago. In part, this reflects the government attempts to the develop an alternative financing for an investment in economy system, which up until the crisis had relied heavily on bank-based intermediation of mainly short-term external credit to finance long-term domestic investments. In during the crisis, Thai's economy was unhealthy as it exposed the economy to a dual mismatch that eventually became problematic when investors lost confidence in the economy system. This realization, associated with the need to fiscalize the economy's post-crisis restructuring costs, became the motivation for the development of deep and domestic bond market in Thailand (Koosakul, 2016). As a result, the domestic bond market is not only an important source of funding for the economy, but also a market on which the central bank relies in its conduct of monetary policy.

Currently, the bond market is one of the most important assets in financial market. Government issues debt is used for the purpose of public debt financing and investment. The government bonds are the risk-free rate assets since their rate of return is known at the time of being issued, then, is neutral to the uncertainty (Caballero et al., 2017). And the government bond yield becomes a single price for using a measure of the benchmark in financial market for all investors. It is also the cost borrowing of government for an investment in infrastructure projects and refinancing of government debt in the bond market. Fluctuations in nominal government bond yields movements generate the cost problems for new government borrowing, as well as it also influences the public debt management, especially refinancing of government debt by issuing the bond, including the behavior of capital inflow into the bond market. However, the bond yield movements, like other high frequency financial economic data, are complicated to explain. Fundamental economic theories seem unable to clarify movements in bond yields behavior. In sprit of its growing importance, the impacts of economic factors that drive yield movements remains mainly based on event-specific analyses and observations. Over the years, the Thai government bond yields has exhibited a hike of fluctuation from both of domestic and external factors and it has been quite difficult to predict future yields.

However, there are standard economic theory and macroeconomic factors attempting to explain volatility on government bond yields, but it is still difficult to explain depending on the economic factors. This study addresses this question by identifying the macroeconomic factors that are most likely to impact on maturity yields in Thailand. The effects of macroeconomic variables on each bond yields could be even more amplified from all different maturities and in time varying. According to existing literature, finds that there is the relationship between macroeconomic factors and maturity yields movements. In the part evidence, shows that macroeconomic fundamentals (local shock) such as debt to GDP ratio, fiscal deficit, current account deficit, interest rate, unemployment, set index, and inflation, play a more significant as determinants of government bond yields (Bernoth et al., 2004; Doan et al., 1984; Dua & Raje, 2014; Georgoutsos & Migiakis, 2012; Kumar & Baldacci, 2010; Ludvigson & Ng, 2009; Pagano & Von Thadden, 2004; Sosvilla-Rivero & Morales-Zumaquero, 2012; Yieand & Chen, 2019).

Hence, the risk-free rate of assets, in turn, is driven by the soundness of macroeconomic fundamental (He et al., 2019). It is critical to adopt information relating to investigate the association between macroeconomic factors and bond yields movements in the bond market. This information is crucial for the policy maker and investors to monitor and predict their bond yields movements comprehensively and then to take in consideration in national policymaking, as well as possible policy providing for investors, namely institutional investors, and speculators.

However, in the literature with the focus on common economic factors above mentioned, there is still no study covering this topic, especially the lack of the role of new economic variables on expected determining the bond yields and most of these studies analyze the effects of macroeconomic fundamentals on maturity yields movements in the bond market by employing macro-finance model approaches. Recently, there are an increasing interest in applying a vector autoregressive (VAR) model proposed by Lange (2005) to examine the economic determinants of short-term and long-term interest rates. And after that Bayesian vector autoregression (BVAR) model proposed by Carriero et al. (2012) to examine a new approach to forecasting the term structure of government bond yields. In this regard, our study is more closely related to Lange (2005) and Carriero et al. (2012) who explicitly incorporate macroeconomic factors determinant into multi-factor yield models for forecasting the maturity yields. These are well-known dynamic model for time series data sample.

Hence, to fill this knowledge gap in this research field, we employ the VAR and BVAR approach to comprehensively examine macroeconomic factors drive to government bond yields movements and forecast the best performances for the different maturity yields. These approaches allow us to identify the impacts of macro shocks on the bond yields movements in the Thai bond market through modelling a multi-factor in the system in which all factors are linked. Additionally, this study needs to compare the estimated performance of several types of VAR models with macroeconomic factors accuracy for time series data. In the VAR and BVAR models, we include seven core variables, namely Thai government bond yields (short-term, medium-term, and long-term yields), primary budget deficit, fed's policy rate, VIX index (CBOE volatility index), and liquidity, adding new variables to increase forecasting power such as capital inflow, and commodity price. Quarterly data of 104 observations from 1998 to 2020 are used.

The paper is structured as follows. Section 2 review several papers and introduce our VAR and BVAR approaches. Section 3 describes the data utilized in this study. Section 4 presents the main results, the model estimation and forecast will be shortly discussed, and response of the bond yields to shocks of the macro variables. Finally, Section 5 concludes and then some policy recommendations will be proposed.

4.2 Literature Review

In the past two decades, many researchers have been interested and investigating the impacts of macroeconomic fundamentals on the bond yields movements. However, most of these studies focused on the common features, such as GDP growth, Inflation, debt to GDP, short-term interest, SET index, and exchange rate, drive yields on government bond movements. Additionally, most of research are interested the local shocks more than global shocks. Therefore, we will review the literature related to our study.

Many empirical studies on the determinants of government bond yields with different maturities movements and the power of the domestic and global macroeconomic factors in explaining yields movements, behavior is still one of key the controversies in the area. Many researchers employ event study methodology to explain the relationship between macroeconomic variables (local shocks) and bond yields movements in the bond markets (Bernoth et al., 2004; Coroneo et al., 2016; Eckhold, 1998; Georgoutsos & Migiakis, 2012; Kumar & Baldacci, 2010; Lombardi et al., 2019; Ludvigson & Ng, 2009; Pagano & Von Thadden, 2004; Sosvilla-Rivero & Morales-Zumaquero, 2012). These papers study the economic factors that there is a power to drive the maturity yields movements. The results of these studies find that macroeconomic fundamentals such as debt to GDP ratio, fiscal deficit, current account deficit, interest rate, unemployment, and inflation, have a more significant as determinants of government bond yields.

Additionally, most of the literature studies apply economic model to investigate the impacts of economic shock on the bond yields in many countries. Regrading to economic variables, many studies focus on investigating the association between several of economic factors and maturity yields. Diebold et al. (2005) apply a simple nonstructural vector autoregression (VAR) to examine the nature of linkages between the macro-finance factors driving the bond yield curve and macroeconomic fundamentals. The results of these studies suggest that there is strong evidence of the impacts of macroeconomic factors on future movements in the bond yield curve and evidence for a reverse influence as well. Chionis et al. (2014) use ordinary least squares (OLS) approaches to analyzes the impact of macroeconomic variables such as Debt to

GDP ratio, deficit, inflation, and unemployment, play a more significant role as determinants of the 10-year Greek bond yield.

Similarly, Akram and Das (2014) apply Generalized Method of Moment (GMM) approaches to investigate the relationship between long-term Japanese government bond's nominal yields (JGBs) and short-term interest rates and other factors such as low inflation and persistent deflationary pressures and tepid growth. Finding that low short-term interest rates (monetary policy) have been the key reason for JGBs' low nominal yields. Akram and Das (2019) employ an autoregressive distributive lag (ARDL) approaches to investigate the long-term determinants of the nominal yields of Indian government bonds. This study finds that in India the short-term interest rate is the main driver of the long-term government bond yield over the long run. Shareef and Shijin (2017) apply a vector autoregressive (VAR) approach to explain the behavior of the future economic conditions and hence incorporating macro factors in the term structure of interest rate model is more tractable. These empirical studies suggest that short term rates are mainly influenced by the fiscal deficit present in emerging economies, while long term rates get affected when market participants revise their expectation on yields. Dai Hung (2020) uses a time-varying structural vector autorepression (TVC-VAR) approaches to investigate the impacts of macroeconomic variables on bond yields curve. These results are in line with other empirical studies that the macroeconomic fundamentals also drive the government bond yield curve.

Regarding to monetary policy variables, Lange (2005) applies a structural vector autoregressive (SVAR) approach to examine the relationship between the long-term yield and fundamental of the monetary models in Canada. The empirical results show that a small and open economy for aggregate demand shocks and monetary policy shocks have relatively large and persistent effects on long-term yields. And find that Canada is similar to those for the USA, aggregate demand shocks have relatively large and persistent effects on long-term yields, whereas aggregate supply shocks do not have significant effects. Monetary policy shocks in Canada, on the other hand, are to have large and more effects on long-term yields than those found for the USA. Nonetheless, Perović (2015) applies a static panel model to analyze the magnitudes of effects of government debt and primary balance on long-term government bond yields in 10 Central and Eastern European countries in the period 2000 - 2013. The results of this study show that a one percentage point increase in the stock of government debt is related with an increase in government bond yields of 2.7 - 4 basis points, while a one percent point increase in the primary deficit to GDP ratio is associated with an increase in government bond yields of 12.9 - 24.3 basis points.

Furthermore, the literature empirical review on global macroeconomic factors, Cebula (1997) uses cointegration analysis approaches to analyze the impact of net capital inflows on domestic interest rates variable. The results show that there is the impact of net international capital inflow on domestic interest rates in France, may not only reduce longer term interest rates but may also offsets a large segment of the long-term yield impact of that nation's government budget deficit. This is likely to global factors through international capital inflows becomes to be the one of important drivers the yields on the domestic bond market. In addition, some empirical evidence argues that common factors such as a generalized risk aversion have effect of government bond yields (Bernoth et al., 2004; Longstaff et al., 2011; Mody, 2009; Schuknecht et al., 2010). And some research finds that there is an impact of external factors, especially spillovers from global financial markets into government bond yields (Kumar & Baldacci, 2010; Lombardi et al., 2019). Baklaci (2003) indicates that there is volatility linkage between the region and cross-reginal in East European countries, EU countries, and Asian market. This research finds that domestic factors are much more important than global factors in explaining bond yields in East European countries, whereas for the Asian and EU regions, both sets of factors are important in explaining the movements in yields.

However, these empirical papers are mostly based on a common macroeconomic factor as mentioned above, and a traditional approach such as OLS model, cointegration analysis, GMM model, and VAR model which involve global and domestic macroeconomic variables of their economies, and which are estimated for various factors. In a linkage globalized world, we need to widely analyze by adding a new variable and a new approach to estimate the effects of economic factors on the bond yields movement more accuracy. Hence, the Bayesian VAR approach has been widely employed by some authors to the forecasting performance of bond yields movements such as Carriero et al. (2012). The findings of these studies showed that the US treasury forecasting performance of the proposed model relative to most of the existing alternative specifications. The finding indicates that the proposed Bayesian VAR approach produces competitive forecasts, systematically more accurate than random walk forecast, even though the gains are small.

Hence, based on the current development economic modelling, VAR and Bayesian VAR are the most suitable model in accordance with the objectives of this study, because they enable us to comprehensively quantify the impacts of macroeconomic factors on the bond yields movements and explain the transmission of shocks with comparing the best predictability value of VAR and BVAR models.

4.3 Data

Given the objective of this study, we use end of the quarter Thai bond yield data from 1998: Q1 to 2020: Q4. This yield data is used the nominal of fixed income yields with maturities of 1-, 3-, 5-, 7-, and 10-year from the ThaiBMA. As macroeconomic factors, we consider the primary budget deficit (PB), fed's policy rate (FED), all-commodity price index (ACPI), capital inflow, VIX index (CBOE volatility index) and liquidity which are all obtained from the database of the Ministry of Finance, Bank of Thailand, and the Stock Exchange of Thailand. In addition, some variables are obtained from International Monetary Funds and CEIC Database.

We consider these factors as they are widely considered to be the common set of economic fundamentals required to capture macroeconomic dynamics, and also include the new indicators such as commodity price, and capital inflow into this study. The six variables namely represent the fiscal policy instrument, the monetary policy instrument, the financial market indexes, and international indicators, respectively. Most of dataset for domestic and international factors are available at a monthly frequency, but they are converted to base on a quarterly basis covering the period from 1998: Q1 up to 2020: Q4.

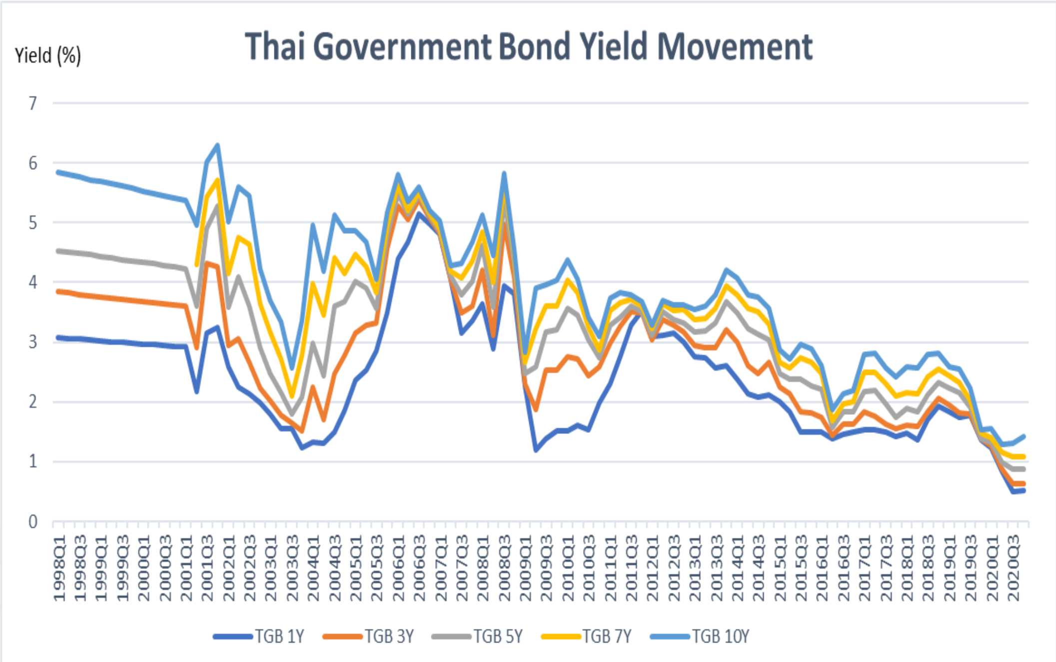


Figure 4.1 Thai Government Bond Yield Movement 1998 - 2020

Source: Authors' calculation.

4.4 Empirical Results

In this section, the empirical estimation of the effects of economic factors on the government bond yields movements based on the dynamic analysis of the multivariate models, namely the VAR and Bayesian VAR will be presented.

4.4.1 Unit Root Tests

To analyse the integration properties of the individual series, we adopt well-known accepted standard Augmented Dickey-Fuller (ADF) approach and the length provided for a unit root test is selected by Akaike Information Criterion (AIC). We will begin this section by showing that modified data satisfy the stationary condition.

According to Table 4.1 which shows the result of the unit root test based on the ADF approach, we can conclude that the data stationary condition is satisfied. Overall, the results of unit root test show that all the series do not have unit root and are stationary at the first order I(1).

Table 4.1 Unit Root Test of Yields and Macroeconomic Variables

Variables	ADF test	
	Level: I(0)	First difference: I(1)
TGB 1Y	-2.14	-7.35
TGB 3Y	-1.80	-10.31
TGB 5Y	-1.90	-10.99
TGB 7Y	-2.39	-8.99
TGB 10Y	-1.79	-8.88
PB	-4.56	-12.15
FED	-1.94	-8.89
CAPITAL INFLOW	-0.89	-10.21
ACPI	-2.04	-7.48
VIX	-5.51	-9.79
LIQUIDITY	1.77	-16.14

Source: Authors' calculation.

Note: All the series are statistically significant at 1 percent. It means that the data set are stationary at first order I(1).

This section will present the results of analysis based on the dynamic analysis of the VAR and Bayesian VAR models, including through estimating Impulse Response Function (IRF) and Variance Decomposition Analysis (VD). In addition, we will compare the results gained from the Bayesian VAR and unrestricted VAR model.

4.4.2 Yields and Economic Factors Estimation

To analyze the effect of economic factors on the bond yields with maturities of 1-, 3-, 5-, 7-, and 10-year, the data sets are investigated by using the SE, VAR, and BVAR methods in order to examine the association between macroeconomic variables and government bond yields in the Thai bond market. This study obtains the six key variables, namely the fed rate, primary budget deficit, commodity price index, capital inflow, VIX index, and liquidity. These variables are widely considered to be the fundamentals needed to capture basic macroeconomic dynamics. Many, thus, parameters must be estimated.

In Table 4.2, the results display the estimates of the parameters of the crucial macro factors and government bond yield interactions. Overall, the parameter estimates are significant, with a small associated standard deviation. The results of the VAR estimate show that the coefficient of each macroeconomic variable appears significant effects on bond yields with different maturities, but the adjustments of R-square and F-statistic are quite low. Also, the results of the Single Equation estimate are likely to be the same as the VAR's results. In contrast, compared with the Bayesian VAR estimate, the results show that in most cases, the coefficients of macro variables have a significant effect on the bond yield movements at various maturities, with very high adjustments of R-square and F-statistic of up to 0.8 and 25, respectively. This means that the BVAR approach is suitable to estimate the best predictability more accurately than another one. Furthermore, we find that new economic variables added in this area (commodity price index and capital inflow) have a significant effect on the yields at various maturities.

4.4.3 Macroeconomic to Bond Yields Interaction

4.4.3.1 Wald Tests

To consider the effect of macroeconomic variables on the yields, we employ Wald tests to link from the macroeconomy to yields with a different maturity in our estimation. It is used to ascertain whether the joint impact of the exogenous variables have a significant influence on the endogenous variable. We then compute the Wald test by using regression analysis. The Wald tests of several key exogenous variables are showed in Table 4.3.

The results report that there is clear statistical evidence in favor of link between the macroeconomic factors and yield with several maturities, except for 7-year maturity yield that there is no interaction with economic variables, p-value of 0.74. Overwhelmingly, the tests show that macro factors as if exogenous variables influence on the yields with 1-, 3-, 5-, and 10-year maturities because they give a p-value of about 0.00. Interestingly, we find that both test of fed rate, primary budget deficit, capital inflow, and commodity price have significant effect on the most of yields. Therefore, we conclude that there is a favor of link between the economic variables and the yields curve.

4.4.3.2 Confidence Bands Test with 90%

To assess the effect of economic factors on the fixed income yields, we provide the tests of confidence interval at a level of 90% to ascertain whether the joint impact of the independent variables have a significant influence on the dependent variable. We choose the 5-year yield maturity for representative of all yields and then compute the confidence bands test at a level of 90% through the VAR and BVAR model. The confidence interval test of impact of economic indicators on the yields are showed in Figure 4.2.

This figure plotted the dynamic responses of the bond yields with 5-year maturity at a level 90% confidence bands over time horizon of 10 periods. We consider the response of the fixed income yields with 5-year maturity to shock of economic indicators. In case of VAR approach, the evidence results show that the confidence interval test at a level of 90% of the yield with 5-year maturities has a significant respond directly to positive in three macro variables and negative in only one variable, except for primary budget deficit and VIX index are not significant. The yield of 5-year maturity responds almost immediately to fed rate, commodity price, and liquidity shocks in positive direction and for capital inflow shock in negative direction with confidence bands at a level of 90%.

Comparing with the BVAR approach, the bond yield in 5-year maturities reacts differently to economic factors. The evidence results find that the fixed income yield in 5-year maturity has a significant response directly to positive and negative in five macro variables at 90% confidence interval, except for the primary budget deficit is not significant. In case of positive direction, the impact of fed rate, commodity price, and capital inflow react differently to the 5-year yield maturity with confidence bands at a level of 90%. In contrast, the yield responds almost immediately to VIX index and liquidity in negative direction with 90% confidence bands.

In summary, the response at 90% confidence bands confirms that the fixed income yield responds directly to positive and negative in macroeconomic factors for all models.

Table 4.2 VAR and BVAR Model Parameter Estimate

Variables	TGB-1	TGB-2	PB-1	PB-2	FED-1	FED-2	Capital Inflow-1	Capital Inflow-2	ACPI-1	ACPI-2	VIX-1	VIX-2	Liquidity-1	Liquidity-2	Adj. R^2	F-statistic
VAR																
TGB 1y	0.03 [0.22]	0.03 [0.25]	**5.59** [2.07]	-2.51 [-1.28]	**0.19** [3.54]	0.10 [1.65]	**-7.09** [-1.71]	**-7.01** [-1.58]	**0.02** [3.75]	-0.01 [-0.21]	-0.01 [-0.69]	0.01 [0.71]	3.21 [1.34]	**-3.94** [-1.59]	0.29	3.79
TGB 3y	**-0.40** [-3.19]	-0.06 [-0.49]	**8.28** [2.32]	-5.52 [-0.20]	**0.20** [2.84]	0.19 [2.65]	**-1.17** [-2.12]	**-1.10** [-1.87]	**0.02** [3.26]	0.001 [0.12]	-0.01 [-1.47]	0.01 [0.11]	**6.93** [2.01]	-4.43 [-1.27]	0.23	2.89
TGB 5y	**-0.39** [-3.16]	-0.08 [-0.67]	**7.32** [1.88]	-1.01 [-0.33]	**0.13** [1.74]	0.24 [3.03]	**-1.61** [-2.68]	**-1.41** [-2.19]	**0.01** [2.26]	-0.001 [-0.07]	**-0.02** [-1.99]	-0.002 [-0.30]	**7.65** [2.07]	-3.50 [-0.93]	0.23	2.81
TGB 7y	0.02 [0.13]	-0.20 [-1.29]	3.01 [0.50]	-1.18 [-0.25]	0.04 [0.29]	0.29 [1.99]	-1.27 [-1.38]	-5.15 [-0.53]	0.003 [0.36]	0.002 [0.17]	-0.01 [-0.47]	0.008 [0.69]	4.33 [0.77]	-2.76 [-0.49]	0.04	0.74
TGB 10y	**-0.25** [-1.94]	-0.14 [-1.17]	6.06 [1.43]	-9.93 [-0.30]	0.05 [0.63]	**0.18** [2.19]	**-1.60** [-2.49]	**-1.18** [-1.71]	0.003 [0.43]	-0.001 [-0.13]	**-0.02** [-2.11]	-0.002 [-0.28]	**7.70** [1.92]	-3.10 [-0.76]	0.12	1.86
BVAR																
TGB 1y	**0.72** [13.96]	**0.97** [2.29]	7.42 [0.32]	-1.18 [-0.74]	**0.08** [2.62]	-0.02 [-0.66]	1.96 [0.65]	1.47 [0.80]	**0.005** [3.05]	-0.002 [-1.17]	0.001 [0.26]	0.002 [0.95]	-2.29 [-0.29]	1.15 [0.15]	0.83	34.18
TGB 3y	**0.41** [6.29]	**0.08** [1.73]	5.10 [0.17]	-1.07 [-0.52]	**0.07** [1.78]	-0.007 [0.24]	-9.34 [-0.24]	1.40 [0.59]	**0.005** [2.36]	-0.001 [-0.23]	**-0.01** [-1.98]	-0.001 [-0.32]	-4.94 [-0.50]	-4.23 [-0.42]	0.78	24.14
TGB 5y	**0.36** [5.27]	0.06 [1.45]	-5.43 [-0.17]	-1.10 [-0.50]	0.05 [1.14]	0.001 [0.01]	-2.80 [-0.67]	1.12 [0.44]	**0.004** [1.89]	-0.001 [-0.07]	**-0.01** [-2.07]	-0.001 [-0.24]	-6.82 [-0.64]	-4.86 [-0.45]	0.77	22.84
TGB 7y	**0.52** [8.45]	**0.08** [1.85]	1.72 [0.04]	-4.77 [-0.17]	**0.13** [2.30]	0.01 [0.34]	-2.59 [-0.47]	1.39 [0.41]	**0.005** [1.80]	0.001 [0.26]	-0.01 [-0.84]	0.001 [0.24]	2.20 [0.02]	-5.65 [-0.40]	0.76	20.85
TGB 10y	**0.33** [4.68]	0.04 [0.94]	-1.13 [-0.34]	-1.10 [-0.49]	0.01 [0.18]	0.005 [0.15]	-4.27 [-0.99]	5.35 [0.20]	0.001 [0.53]	-0.001 [0.07]	**-0.01** [-1.93]	-0.001 [-0.20]	-9.44 [-0.85]	-5.31 [-0.48]	0.82	29.32

Variables	TGB-1	TGB-2	PB-1	PB-2	FED-1	FED-2	Capital Inflow-1	Capital Inflow-2	ACPI-1	ACPI-2	VIX-1	VIX-2	Liquidity-1	Liquidity-2	Adj. R^2	F-statistic
VAR																
TGB 1y	0.03 [0.22]	0.03 [0.25]	**5.59** [2.07]	-2.51 [-1.28]	**0.19** [3.54]	0.10 [1.65]	**-7.09** [-1.71]	**-7.01** [-1.58]	**0.02** [3.75]	-0.01 [-0.21]	-0.01 [-0.69]	0.01 [0.71]	3.21 [1.34]	**-3.94** [-1.59]	0.29	3.79
TGB 3y	**-0.40** [-3.19]	-0.06 [-0.49]	**8.28** [2.32]	-5.52 [-0.20]	**0.20** [2.84]	0.19 [2.65]	**-1.17** [-2.12]	**-1.10** [-1.87]	**0.02** [3.26]	0.001 [0.12]	-0.01 [-1.47]	0.01 [0.11]	**6.93** [2.01]	-4.43 [-1.27]	0.23	2.89
TGB 5y	**-0.39** [-3.16]	-0.08 [-0.67]	**7.32** [1.88]	-1.01 [-0.33]	**0.13** [1.74]	0.24 [3.03]	**-1.61** [-2.68]	**-1.41** [-2.19]	**0.01** [2.26]	-0.001 [-0.07]	**-0.02** [-1.99]	-0.002 [-0.30]	**7.65** [2.07]	-3.50 [-0.93]	0.23	2.81
TGB 7y	0.02 [0.13]	-0.20 [-1.29]	3.01 [0.50]	-1.18 [-0.25]	0.04 [0.29]	0.29 [1.99]	-1.27 [-1.38]	-5.15 [-0.53]	0.003 [0.36]	0.002 [0.17]	-0.01 [-0.47]	0.008 [0.69]	4.33 [0.77]	-2.76 [-0.49]	0.04	0.74
TGB 10y	**-0.25** [-1.94]	-0.14 [-1.17]	6.06 [1.43]	-9.93 [-0.30]	0.05 [0.63]	**0.18** [2.19]	**-1.60** [-2.49]	**-1.18** [-1.71]	0.003 [0.43]	-0.001 [-0.13]	**-0.02** [-2.11]	-0.002 [-0.28]	**7.70** [1.92]	-3.10 [-0.76]	0.12	1.86
BVAR																
TGB 1y	**0.72** [13.96]	**0.97** [2.29]	7.42 [0.32]	-1.18 [-0.74]	**0.08** [2.62]	-0.02 [-0.66]	1.96 [0.65]	1.47 [0.80]	**0.005** [3.05]	-0.002 [-1.17]	0.001 [0.26]	0.002 [0.95]	-2.29 [-0.29]	1.15 [0.15]	0.83	34.18
TGB 3y	**0.41** [6.29]	**0.08** [1.73]	5.10 [0.17]	-1.07 [-0.52]	**0.07** [1.78]	-0.007 [0.24]	-9.34 [-0.24]	1.40 [0.59]	**0.005** [2.36]	-0.001 [-0.23]	**-0.01** [-1.98]	-0.001 [-0.32]	-4.94 [-0.50]	-4.23 [-0.42]	0.78	24.14
TGB 5y	**0.36** [5.27]	0.06 [1.45]	-5.43 [-0.17]	-1.10 [-0.50]	0.05 [1.14]	0.001 [0.01]	-2.80 [-0.67]	1.12 [0.44]	**0.004** [1.89]	-0.001 [-0.07]	**-0.01** [-2.07]	-0.001 [-0.24]	-6.82 [-0.64]	-4.86 [-0.45]	0.77	22.84
TGB 7y	**0.52** [8.45]	**0.08** [1.85]	1.72 [0.04]	-4.77 [-0.17]	**0.13** [2.30]	0.01 [0.34]	-2.59 [-0.47]	1.39 [0.41]	**0.005** [1.80]	0.001 [0.26]	-0.01 [-0.84]	0.001 [0.24]	2.20 [0.02]	-5.65 [-0.40]	0.76	20.85
TGB 10y	**0.33** [4.68]	0.04 [0.94]	-1.13 [-0.34]	-1.10 [-0.49]	0.01 [0.18]	0.005 [0.15]	-4.27 [-0.99]	5.35 [0.20]	0.001 [0.53]	-0.001 [0.07]	**-0.01** [-1.93]	-0.001 [-0.20]	-9.44 [-0.85]	-5.31 [-0.48]	0.82	29.32

Source: Authors' calculation.

Note: [ ] T -Statistic appears in parentheses and Bold entries denote parameter estimates significant at the 1, 5, and 10 percent level respectively.

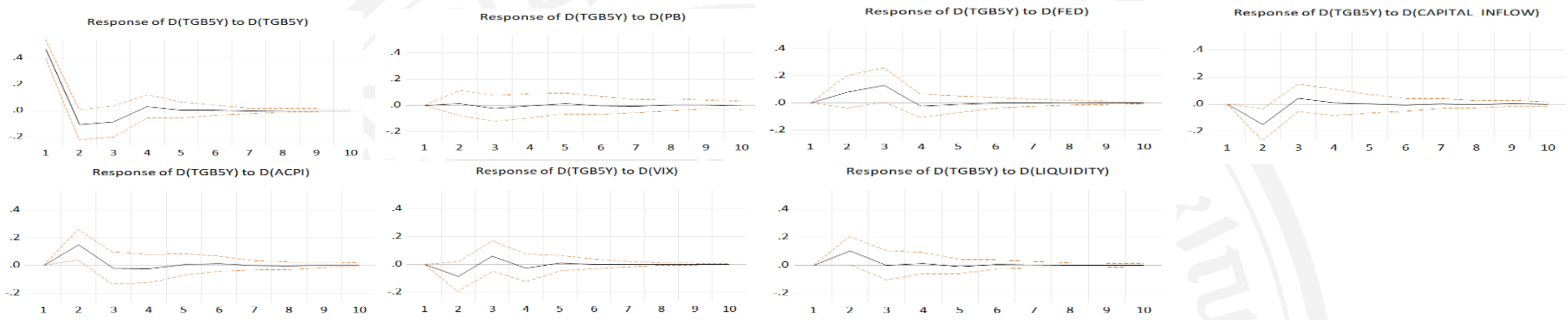
Table 4.3 Wald Test for Macroeconomic Factors to Yield

Endogenous Variables	Exogenous Variables								
	TGB (-1,-2)	PB (-1,-2)	FED (-1,-2)	Capital Inflow (-1,-2)	ACPI (-1,-2)	VIX (-1,-2)	Liquidity (-1,-2)	Overall	Chi-square
TGB 1y	0.007	**2.70***	**8.93 *****	1.65	**7.59*****	0.82	1.73	**3.74*****	**52.00*****
	[0.99]	[0.07]	[0.003]	[0.20]	[0.001]	[0.44]	[0.18]	[0.00]	[0.00]
TGB 3y	**5.10****	2.76	**7.81*****	2.35	**5.71*****	1.51	2.07	**2.89*****	**40.42*****
	[0.01]	[0.70]	[0.008]	[0.10]	[0.00]	[0.23]	[0.13]	[0.00]	[0.00]
TGB 5y	**5.03****	1.87	**6.29 *****	**3.65****	**2.73***	2.26	2.15	**2.81*****	**39.39*****
	[0.01]	[0.16]	[0.003]	[0.03]	[0.07]	[0.11]	[0.12]	[0.00]	[0.00]
TGB 7y	0.84	0.17	2.16	1.22	0.11	0.65	0.30	0.74	10.35
	[0.43]	[0.85]	[0.12]	[0.30]	[0.90]	[0.52]	[0.74]	[0.73]	[0.74]
TGB 10y	2.40	1.10	**2.64***	**3.05***	0.09	2.54	1.87	**1.87****	**26.14****
	[0.98]	[0.34]	[0.08]	[0.05]	[0.91]	[0.85]	[0.16]	[0.04]	[0.02]

Source: Authors' calculation.

Note: [ ] P-value appears in parentheses and Bold entries denote parameter estimates significant at the ***1, **5, and *10 percent level respectively.

VAR Model



BVAR Model

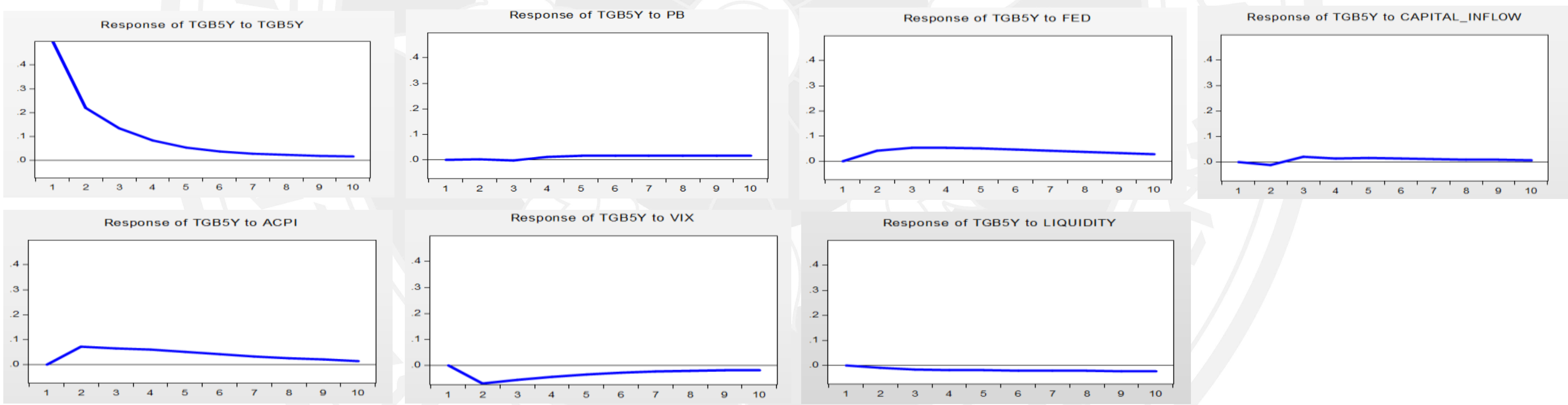


Figure 4.2 90% Confidence Band Tests for Macroeconomic Factors to Yields with 5-year Maturity

Source: Authors' calculation.

4.4.4 Response of Bond Yields Movements to Macroeconomic Shocks

To examine how bond yields movements repones to economic variables, IRFs are estimated through stimulating only one percentage point positive and negative shock to bond yields in various maturities (short-term, medium-term, and long-term yield maturities). The IRFs are showed in Figure 4.3 and 4.4 for the different two approaches respectively.

These figures plotted the dynamic responses of the bond yields over time horizon of 10 periods. Now, we will consider the response of the bond yields to shocks of the macro variables. Despite the up and down fluctuation at the beginning forecast horizon, the impulse responses maintain a stable after 5 to 10 quarters depending on cases. In most of case, the results show that the bond yields respond directly to positive shocks in macro variables (i.e., fed rate, and commodity price), except for VIX index, capital inflow, primary budget deficit, and liquidity being negative and fluctuation shocks. In addition, the pattern of the bond yields responsiveness to macroeconomic shocks, based on IRFs of both two methods, are quite different. The response of the yield maturities to the macro variables, the macro shocks seem to have transitional effect on the bonds yields when the effect of macro shocks only dies out usually after 5 to 10 quarters. Finally, these effects are significant and long lasting, however, these effects normally seem to be a small.

In IRFs of VAR approach, we will consider the bond yield in different maturities reacted strongest to macro variable shocks. The results show that the yield in various maturities responds directly to positive shocks in three macro variables. For example, the yields respond almost immediately to fed rate shocks in positive direction with a maximum increase of 0.20 percent (20 basis points) of long-term government bond yields (7-year maturity yield), and other yields in short-term and medium-term bond maturities have an increase of 13 and 15 basis points respectively. In term of commodity price shock to the yields, an increase in the commodity price almost immediately pushes up the yields is positive direction with a maximum increase approximately 0.19 percentage of 3-year bond yield. And also the response of the yields to positive shock of liquidity rises at the level of 10 basis points in medium-term and long-term bond yields (3-year and 10-year yields). Additionally, the yields reacted fluctuation to shock to primary budget deficit and VIX index which raise the level of around 10 basis points in medium-term and long-term bond yields (3-year, 5-year, 7-year, and 10-year yields). In contrast, negative shock of capital inflow causes an instantaneous fall in government bond yield in different maturities which causes a maximum decrease of 15 basis points in medium-term and long-term yields.

Comparing to the IRFs of Bayesian VAR approach, each bond yield in various maturities reacts differently to economic shocks. The results find that there are three groups of impulse response such as positive and negative shocks to bond yields, and fluctuation shocks to the yield movements. The bond yields rise immediately to positive shock from fed rate and commodity price with a maximum increase of around 10 basis points in short-term and long-term yields (1-year, and 7-year bond yields). For fluctuation shock to utilization, the bond yields have a fluctuation of responsiveness to shocks from primary budget deficit and capital inflow which raise the level of around 5 basis points and 3 basis points in long-term bond yields (7-year, and 10-year yields). On the other hand, the negative shocks of VIX index and liquidity cause immediately fall in the yields with a maximum decrease of 7 basis points and 2.5 basis points in medium-term and long-term yields (3-year, 5-year, and 10-year maturity yields) respectively.

In brief, the impulse response confirms that each macroeconomic shock from fed rate, commodity price, VIX index, capital inflow, primary budget deficit, and liquidity have a strong impact on the government bond yields in all different maturities. And the impact is transitional, usually dies out after 5 to 10 quarters but the effects of IRFs' Bayesian VAR approach seem to be long lasting more than 10 quarters.

4.4.5 Determinants of Bond Yields Fluctuation

To identify the source of disturbances to bond yields with various maturities based on factorial determinants, we estimate variance decompositions (VD) providing a popular metric for macroeconomic factors and bond yields interactions. Figures 4.5 and 4.6 provide VD of the bond yields with 1-, 3-, 5-, 7-, and 10-year yields at forecast horizons of 10 quarters. The factorial determinants of bond yield fluctuation are provided for both the VAR and BVAR models. Overall, of this study, the estimated outcomes provide a picture of the role of macro variables on the bond yields in different maturities fluctuation. This contribution is similar to the results in Diebold (2006) macro model.

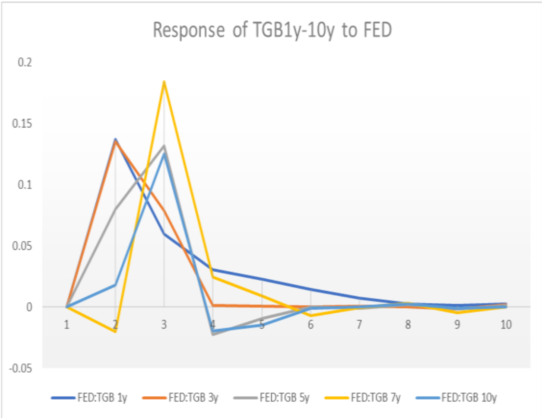
The estimation results' VAR model show that at a 1-year yield, very high of the variation in rates are driven by the fed rate and commodity price up to about 13 and 15 percent respectively by contributing since the second quarters of forecast horizon. While at medium-term bond yields (3-year and 5-year yields), macro factors, namely fed rate, commodity price, and capital inflow quickly become more influential for about 9, 12, and 8 percent respectively in the same period. Additionally, the impact of macro variables (fed rate, capital inflow, and VIX index) on the long-term yields (7-year, and 10-year yields), they account for about 6, 5, and 4 percent of the variation in rates.

Comparing to the estimation results' BVAR model, the VD emphasizes that a short-term bond yield is contributed by the effects of key economic variables: fed rate, and commodity price up to 10 and 7 percent in last period. The medium-term variation in the yield that is related to macroeconomic fundamentals (fed rate, commodity price, and VIX index) for about 7, 6.8, and 4 percent, respectively. However, at long-term yields are driven by fed rate, commodity price, and VIX index at a 10 quarters horizon, they account for about 6, 5.5, and 3 percent of the variation in rates.

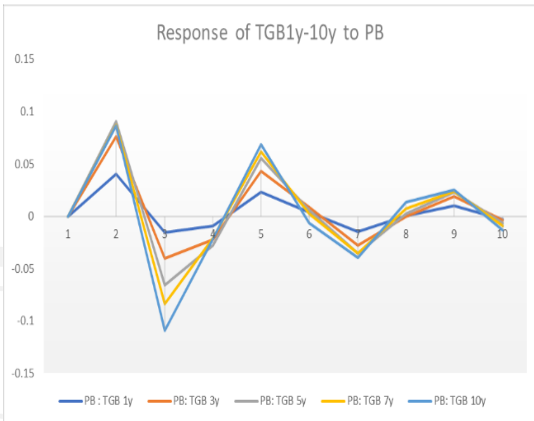
In conclusion, the variance decomposition suggests that the impacts of the macro variables on the yields are strong to contribution. Surprisingly, from the results, we find that commodity price and capital inflow as new economic variables added into this study, have a quite strong impact on the bond yields with all maturities.

4.5 Conclusion and Policy Implication

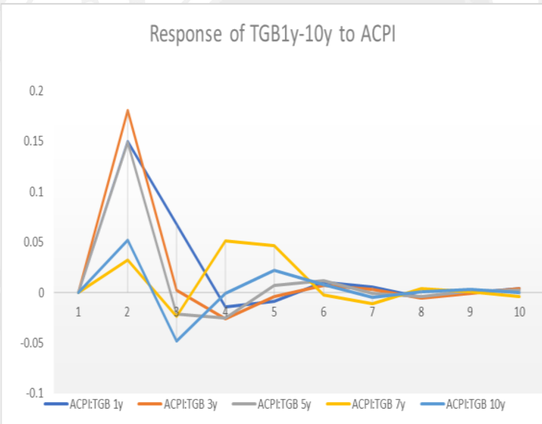
This study analyzes how and in what economic factors affect the government bond yields with various maturities (1-, 3-, 5-, 7-, and 10-year yields) in Thailand. We have specified and estimated the bond yield and macroeconomic variables (fed's policy rate, primary budget deficit, commodity price index, capital inflow, VIX index, and liquidity) by using the VAR and Bayesian VAR methods to examine the association between macroeconomic variables and government bond yields and testing of hypotheses regarding dynamic interactions between the economic variables and the yields. The empirical results provide several main findings.



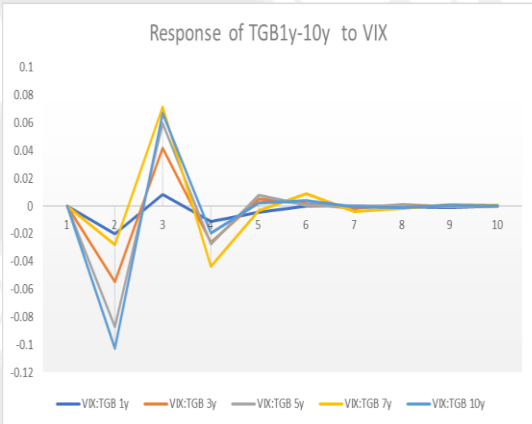
Fed Rate



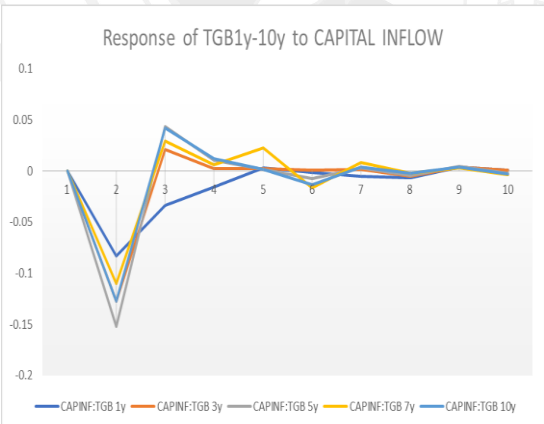
Primary Budget Deficit



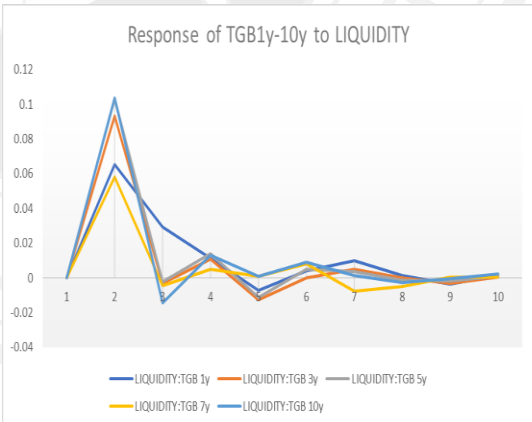
Commodity Price Index



VIX Index



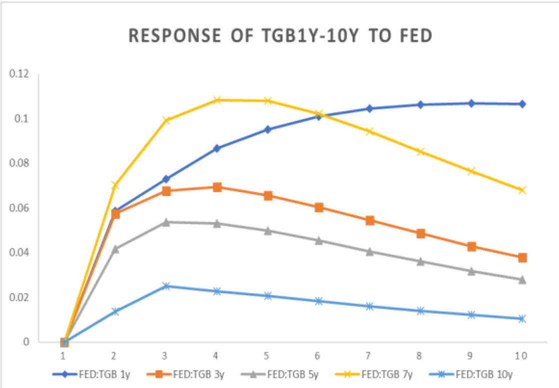
Capital Inflow



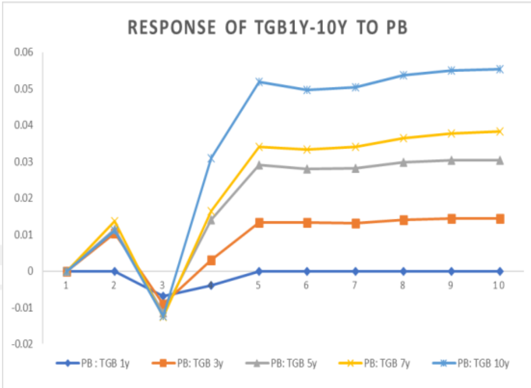
Liquidity

Figure 4.3 IRFs of Bond Yields to Economic Shocks (VAR Model) 1998-2020

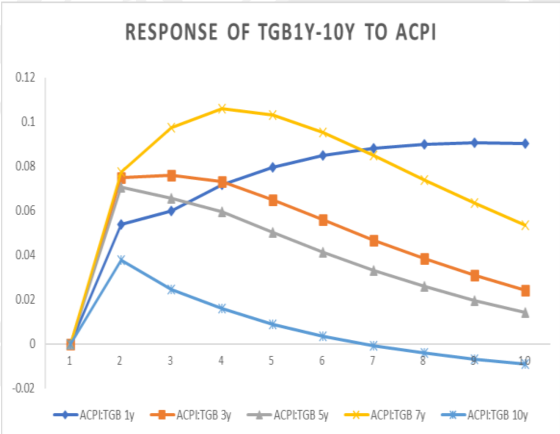
Source: Authors' calculation.



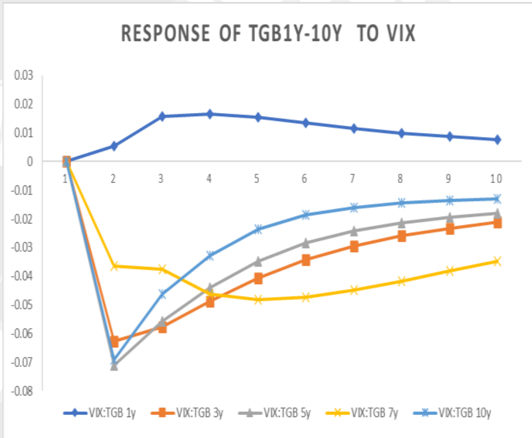
Fed Rate



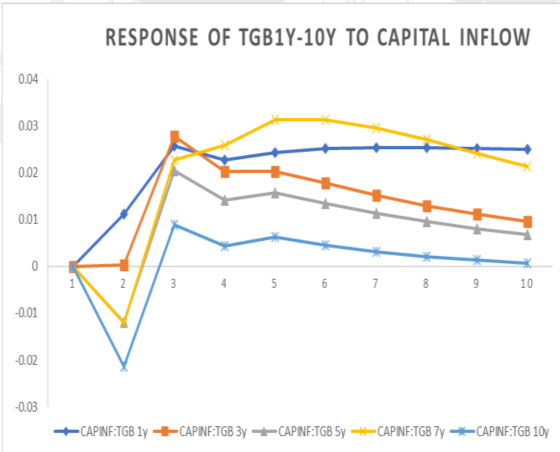
Primary Budget Deficit



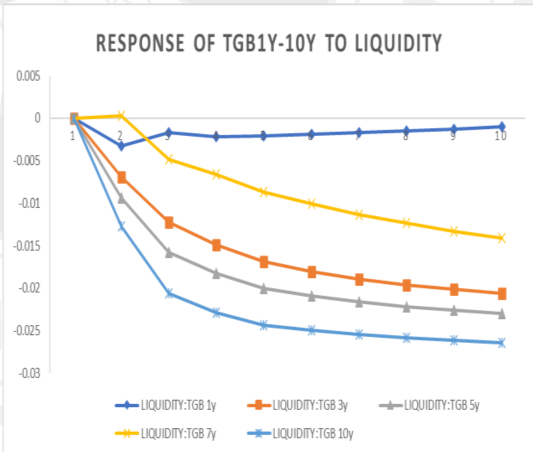
Commodity Price Index



VIX Index



Capital Inflow



Liquidity

Figure 4.4 IRFs of Bond Yields to Economic Shocks (BVAR Model) 1998-2020

Source: Authors' calculation.

Figure 4.5 Determinants of Bond Yields with Different Maturities Fluctuation (VAR Model) 1998-2020

Source: Authors' calculation.

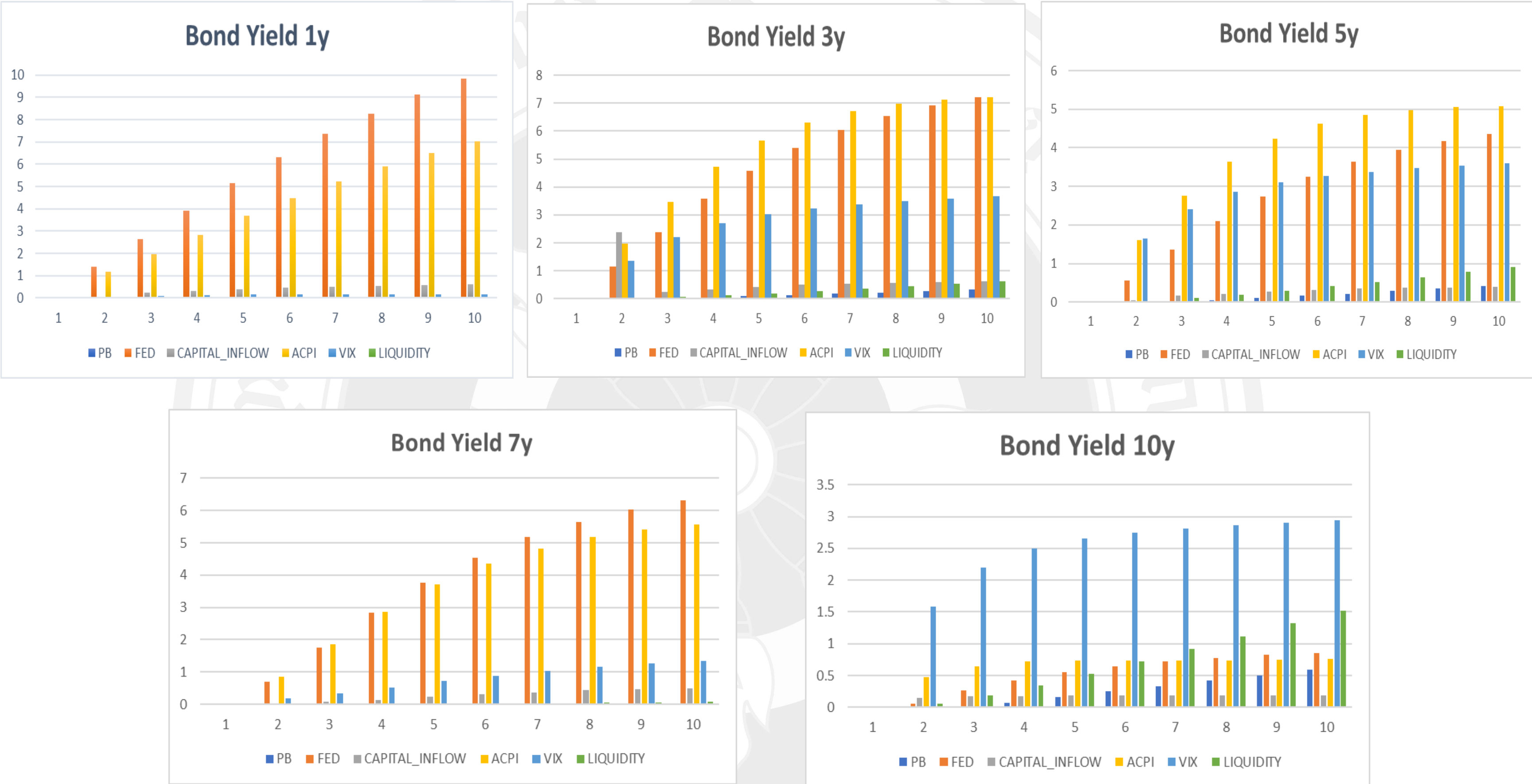


Figure 4.6 Determinants of Bond Yields with Different Maturities Fluctuation (BVAR Model) 1998-2020

Source: Authors' calculation.

First, we find strong evidence of macroeconomic effects on the yields with all maturities, the results show that the macro shocks from fed rate, commodity price, VIX index, capital inflow, primary budget deficit, and liquidity have a strong impact on the bond yields in various maturities and the impact is transitional, usually dies out after 5 to 10 quarters but the effects of IRFs' Bayesian VAR approach seem to be long lasting more than 10 quarters. Second, by comparing the bond yields responsiveness to the effects of macro shocks are varied. The short-term and medium-term yields reacts rapidly to economic factors shocks more than long-term yields. Finally, the results confirm that the impacts of domestic and international macro variables have strong fluctuation of yields, especially high impact of fed rate and commodity price on bond yields. Interestingly, from the results, we find that new economic variables intended into this study: commodity price and capital inflow, have a quite strong impact on the bond yields with all maturities.

Thus, economic policy makers should take into consideration the possible impacts that their policy such a primary budget deficit, may have effect on the bond yields, especially the fed rate, commodity price, and capital inflow which are to affect future short-term and medium-term yield in the debt market. In addition, the government may have to consider alterative options to issue a new bond of various maturities for reducing risks of funding cost and government debt refinancing.

The evidence provides important policy recommendation. Predicting the bond yields needs to account for the fluctuations of the macroeconomy, since the macroeconomic variables affect and also forecast yield movements in various maturities. Thus, the paper recommends a Bayesian VAR approach for the policy for a government, investors, and risk managers to adjust the bond yield fluctuations. In the future research, the empirical model can be extended to include the no-arbitrage restriction, then, Factor Augmented VAR approach can be employed to estimate at approximately be captured by our fitted yields because of flexible prediction to the data.

CHAPTER 5

FORECASTING GOVERNMENT BOND YIELDS IN THAILAND: A BAYESIAN VAR APPROACH

5.1 Introduction

Currently, bond yield is one of the most important market indicators in the financial market. A yield curve is the return of a bond issued by the government at different maturities. With trustworthy and reliable in the government, most of investors consider investing in the bond as risk-free rate market. The bond yield becomes the minimum requirement for return or a single price for using a measure of the benchmark in the debt market for governments, fixed income portfolio managers, financial institutions, risk managers, and individual investors. Although the rate of return of a bond is neutral to the uncertainty, as it is known at the time of being issued (Caballero et al., 2017), changes in the yield curve will directly affect the fixed income market and other market. Furthermore, they have a direct impact on government's borrowing costs for an investment in infrastructure projects and refinancing debt in portfolio. Fluctuations in nominal bond yields movements generate the borrowing cost concerns and have an impact on public debt management, particularly in government debt refinancing and risk management in portfolio benchmarks.

However, the bond yield movements, like other high-frequency financial economic data, are complicated to explain. Fundamental economic theories seem unable to clarify movements in bond yields behavior. In spite of its growing importance, the impact of economic factors that drive yield movements remains mainly based on event-specific analyses and observations. In recent years, the Thai government bond yields has exhibited a hike of fluctuation from both of domestic and international factors and it have been quite difficult to predict future yields. Hence, producing accurate yields with different maturity forecasts is crucial for policy marker, treasurers, bankers, risk managers, and fixed income portfolio managers to adjust the bond yield fluctuations.

Market participants have all attempted to construct good models of the yield curve for forecasting performance, the resulting models are very different in form and good fit. Based on different studies, there is an apparent large gap between the yield models proposed by macroeconomists, which focus on the role of economic factors in the determinants of the yields, and the models provided by financial economist, which avoid any explicit role for such determination (Diebold et al., 2006). Thus, in the past most of researchers have been interested traditional models and forecasting the future bond yields movements estimated by using only the yields without macroeconomy.

Several recent researchers have studied forecasting accuracy of yields by using various models and compared forecasting performance of traditional models and linear models for the US term structure of interest rates and other yields. For example, Diebold and Li (2006) apply the Nelson-Siegel model and a variety of models with regard to the yields to forecast the term structure of government bond yields. This study examines the out-of-sample forecasting performance of the yields by using data from the U.S. Treasury from 1985 to 2000. The results find that the Nelson-Siegel yield curve as a three-factor dynamic model (level, slope, and curvature) forecast appears much more accurate at long horizons than the RW, but the 1-month ahead forecast is no better than the RW and the other models' performances (slope regression, Fama-Bliss forward rate regression, Cochrane-Piazzesi (2002) forward curve regression, AR, VAR, and Error Correction Model (ECM)).

Moreover, Vicente and Tabak (2008) study different models for forecasting the fixed income yields in Brazil with 4 interest rate swaps maturing at different months. They compare the accuracy of out-of-sample forecasting of the Diebold-Li (2006) model, the affine term structure model, and the RW benchmark by using mean squared errors and Diebold-Mariano statistics. The empirical results suggest that the Diebold-Li (2006) model produces superior forecasts than the other models, particularly at the long-term horizon for short-term yields. In a recent paper, Almeida et al. (2017) apply segmented term structure models to forecast bond yields and then compare with successful term structure benchmarks based on out-of-sample forecasting performance by using U.S. Treasury and show that segmented models provide significantly smaller RMSE than other models produced by the RW and by some other established term structure models.

However, in the existing literature, there is still very little research to forecast future yields with maturity by using a new model for emerging markets. Most emerging countries have large debt and stock markets and receive vast inflows of foreign capital, playing an essential role in the international capital market. Thailand receives attention as it has a large debt market, with liquid derivative markets and thus represents an interesting investment opportunity for both domestic and external investors. In addition, all the forecasting models proposed so far in the economic and financial literature have a hard time producing forecasts more accurate than a simple no-change forecast. Recently, there has been an increasing interest in applying a Bayesian vector autoregression (BVAR) model proposed by Carriero et al. (2012) to examine a new approach to forecasting the term structure of government bond yields. In this regard, our study is more closely related to Carriero et al. (2012), who explicitly incorporate macroeconomic factors as determinants into multi-factor yield models for forecasting maturity yields.

Hence, to fill this knowledge gap in this research field, we provide the Single Equation, Vector Autoregression (VAR), and BVAR approaches to comprehensively examine macroeconomic factors that drive bond yield movements and forecast future yields with different maturities. In this paper, we aim to investigate key macroeconomic factors and bond yield interactions in Thai bond markets and compare the empirical forecasting performance of the proposed competitive linear models by fixing an in-sample and out-of-sample forecast horizon.

The paper is structured as follows. Section 2 reviews several papers relating to forecasting bond yields. Section 3 describes the data utilized for forecasting in this study. Section 4 proposes our BVAR approaches compared to other linear models such as the Single Equation and VAR models. Section 5 presents the main results, briefly discusses the model estimation and forecast, and presents a comparison of the forecasting performance estimated by each model. Finally, Section 6 provides conclusions and some policy recommendations.

5.2 Literature Review

In the past two decades, many researchers have been interested and forecasting future bond yield movements with macroeconomic factors. However, most of these studies focused on common factors (i.e., GDP growth, inflation, debt-to-GDP, short-term interest, SET index, and exchange rate) and the traditional models for predicting the term structure of interest rates such as a random walk, forward rate regression, affine term structure model, Fame-Bliss approach, Nelson and Siegel approach, Markov-switching Dynamic Nelson-Siegel Model, factor model, and so on. After that, most of research are interested the forecasts of bond yields with maturity by using a linear model, namely linear regression model, Single Equation, Univariate Autoregressive, and Vector Autoregression. Our, then, proposed model to forecast the fixed-income yields is the Bayesian VAR with a new strategy. Therefore, we will review the literature related to our study.

In case of impact of macro factors on the bond yields, a number of empirical studies on the determinants of government bond yields with different maturities and have demonstrated the power of domestic and global macroeconomic factors in explaining yield movements. Many researchers employ event study methodology to explain the relationship between macroeconomic variables (local shocks) and bond yield movements in the bond markets (Bernoth et al., 2004; Eckhold, 1998; Georgoutsos & Migiakis, 2012; Kumar & Baldacci, 2010; Lombardi et al., 2019; Ludvigson & Ng, 2009; Megananda et al., 2021; Pagano & Von Thadden, 2004; Sosvilla-Rivero & Morales-Zumaquero, 2012; Trinh et al., 2020). These researchers study the economic factors that have the power to drive maturity yield movements. The results of their studies indicate that macroeconomic fundamentals such as debt-to-GDP ratio, fiscal deficit, current account deficit, interest rate, unemployment, and inflation, are more significant as determinants of government bond yields.

Furthermore, Diebold et al. (2005) apply a simple-nonstructural VAR to examine the nature of linkages between the macro-finance factors driving the bond yield curve and macroeconomic fundamentals. The results of their study suggest that there is strong evidence of the impacts of macroeconomic factors on future movements in the bond yield curve and evidence of a reverse influence as well. Additionally, Perović (2015) applies a static panel model to analyze the magnitudes of the effects of government debt and primary balance on long-term government bond yields in 10 Central and Eastern European countries from 2000 to 2013. The results of this study show that a one percentage point increase in the stock of government debt is correlated with an increase in government bond yields of 2.7 – 4 basis points, while a one percentage point increase in the primary deficit to GDP ratio is associated with an increase in government bond yields of 12.9 – 24.3 basis points. Also, Dai Hung (2020) uses a time-varying structural vector autorepression (TVC-VAR) approach to investigate the impacts of macroeconomic variables on bond yield curves. These results are in line with other empirical studies that suggest that macroeconomic fundamentals also drive the government bond yields curve.

Similarly, Anwar and Suhendra (2020) employ conventional panel VAR to investigate the impact of monetary policy independence shocks on the bond yield. The results of this study reveal that monetary policy shocks have an impact on the bond yield around 6 periods after the shocks. Furthermore, according to the empirical literature review on global macroeconomic factors, Cebula (1997) uses cointegration analysis approaches to analyze the impact of net capital inflows on domestic interest rate variables. The results show that the impact of net international capital inflow on domestic interest rates in France may not only reduce long-term interest rates but may also offsets a large segment of the long-term yield impact of that nation's government budget deficit. This is likely to be due to global factors through international capital inflows, which have become one of the important drivers of the yields in the domestic bond market.

In the case of forecasting future bond yields with different maturities, most of the literature studies apply various economic models to forecast the bond yields both in-sample and out-of-sample. Most of the existing evidence focuses on statistical measures of forecast accuracy with the models. Several papers have evaluated the forecast performance of the models by looking at statistical measures (Giacomini & Rossi, 2010). Carriero et al. (2012), introduce a new statistical model for the entire term structure of interest rates (U.S. Treasury dataset using a rolling estimation window of 120 months, from 1985 to 2003) and compare the forecasting performance of the proposed model to most of the existing alternative specifications. This research uses several models for out-of-sample forecasting of U.S. yields, such as Random Walk (RW), Univariate Autoregressive (AR), Vector Autoregressive (VAR), Fama and Bliss (1987) (FB), Cochrane and Piazzesi (2005) (CP), Affine Term Structure Model (ATSM), Dynamic Nelson and Siegel Model (Diebold and Li, 2006, DL), and Bayesian VAR. The finding indicated that the proposed Bayesian VAR approach produces competitive forecasts that are, systematically more accurate than Random Walk forecasts at all maturities and forecast horizons, even though the gains are small, and it outperforms all other models. Moreover, they find that in the class of linear models, powering up produces an overall better forecast than the other models (direct approach), both for AR and VAR models.

Similarly, Almeida et al. (2017) apply segmented term structure models to forecast bond yields and then compare them with successful term structure benchmarks based on out-of-sample forecasting performance of segmented term structure models by using data from the U.S. Treasury with 8 maturity yields covering the period from 1985 to 2012. The several models used for measuring the rolling- window forecast performance with RW are the Diebold and Li model (2006) (DL), Svenson model (DSM), polynomial segmented model (Bowsher and Meeks (2008) (BM)), affine Gaussian, weak segmented (NS4) and strong segmented (NS4S), all with AR factor dynamics. The finding shows that a series of out-of-sample forecasts of U.S. Treasury yields, produced by the segmented models has a significantly lower RMSE than those produced by the RW and some other established term structure models. Also, Vicente and Tabak (2008) study different models for forecasting the fixed income yields in Brazil with 4 interest rate swaps maturing at different months. They compare the accuracy of out-of-sample forecasting of the Diebold-Li (2006) model, the affine term structure model and the RW benchmark by using mean squared errors and Diebold-Mariano statistics. The empirical results suggest that the Diebold-Li (2006) model produces superior forecasts than the other models, particularly at the long-term horizon for short-term yields.

Moreover, Diebold and Li (2006) apply the Nelson-Siegel model and a variety of models with regard to the yields to forecast the term structure of government bond yields. This study examines the out-of-sample forecasting performance of the yields by using data from the U.S. Treasury, from 1985 to 2000. The results show that the Nelson-Siegel yield curve as a three-factor dynamic model (level, slope, and curvature) forecast appears much more accurate at long horizons than the RW, but the 1-month ahead forecast is no better than the RW and the other models' performances (slope regression, Fama-Bliss forward rate regression, Cochrane-Piazzesi (2002) forward curve regression, AR, VAR, and Error Correction Model (ECM)). In additional to Noteboom (2019), employs the Markov-Switching Dynamic Nelson-Siegel model (MS-DNS) to fit and forecast the yield curve in a low interest rate environment with and without linking the yield curve to the macroeconomy, by using U.S. Treasury yields from 1986 to 2018. The evidence shows that MS-DNS with a regime-switching model allows the transition probabilities to depend on the economic factors and produces the most superior forecasts, especially at the short yield curve.

However, the aforementioned empirical papers are mostly based on the traditional approaches that are used to forecast the future term structure of fixed income yields with different maturities. Most of the models are direct approaches estimated by using only the yields without any macroeconomic consideration. In recent research, linear models have been very popular and tend to produce better overall forecasts of economic indicators and yields than other direct approach. Hence, based on the current literature above, we propose Bayesian VAR and linear models (i.e., VAR and Single Equation) with economic factors forecasts for forecasting bond yields with different maturities in accordance with the objectives of this study and compare their forecasting performance to that of competitive models and Random Walk forecasts.

5.3 Data

Given the objective of this study, we use end of the quarter Thai bond yield data from 1998: Q1 to 2020: Q4. This yield data is used to calculate the nominal fixed income yields with maturities of 1-, 3-, 5-, 7-, and 10-year from the ThaiBMA. As for macroeconomic factors, we consider the primary budget deficit (PB), the fed's policy rate (FED), the all-commodity price index (ACPI), capital inflow, the VIX index (CBOE volatility index), and liquidity which are all obtained from the database of the

Ministry of Finance, the Bank of Thailand, and the Stock Exchange of Thailand. In addition, some variables are obtained from the International Monetary Funds and the CEIC Database.

We consider these factors as they are widely recognized to be the common set of economic fundamentals required to capture macroeconomic dynamics and also include new indicators such as commodity prices, and capital inflow into this study. The six variables represent the fiscal policy instrument, the monetary policy instrument, the financial market indexes, and international indicators, respectively. Most of the datasets for domestic and international factors are available at a monthly frequency, but they are converted to a quarterly basis covering the period from 1998: Q1 up to 2020: Q4.

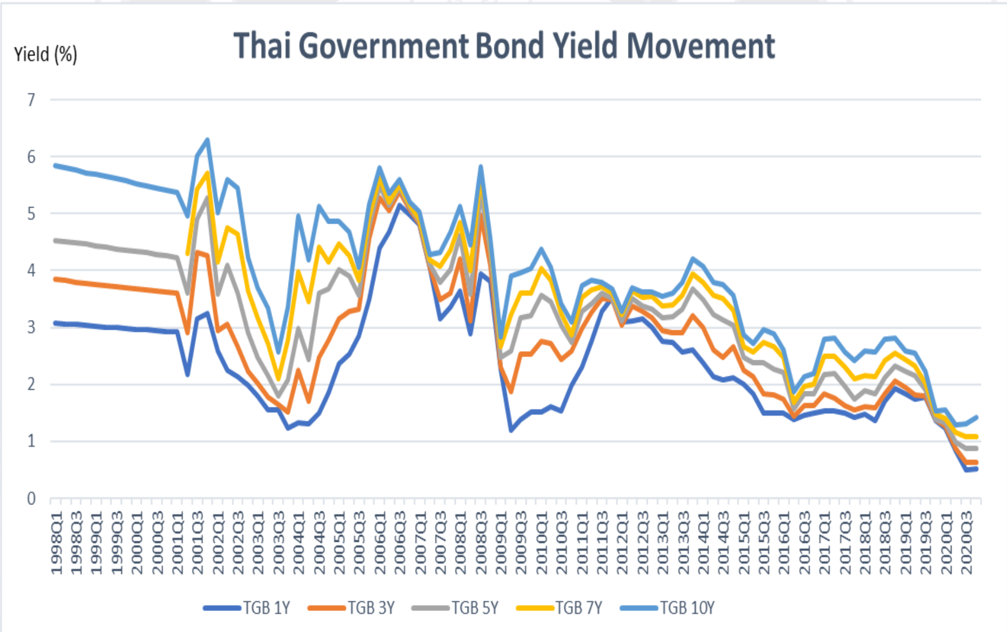


Figure 5.1 Thai Government Bond Yield Movement 1998 - 2020
Source: Authors' calculation.

5.4 Empirical Results

In this section, we present the empirical results based on forecasting government bond yields at various maturities with fixing an in-sample and out-of-sample window size equal to 104 quarterly data by estimating static and dynamic forecasts in the Single Equation, VAR, and Bayesian VAR approaches. We, then, will use the Random Walk forecasts as the benchmark with respect for comparing the forecasts of all the competing models.

5.4.1 Unit Root Tests

To analyze the integration properties of the individual series, we adopt well-known accepted standard Augmented Dickey-Fuller (ADF) approach and the length provided for a unit root test is selected by Akaike Information Criterion (AIC). We will begin this section by showing that modified data satisfy the stationary condition.

According to Table 5.1 which shows the results of the unit root test based on the ADF approach, we can conclude that the data stationary condition is satisfied. Overall, the results of the unit root test show that all the series do not have a unit root and are stationary at the first order, namely I(1).

Table 5.1 Unit Root Test of Yields and Macroeconomic Variables

Variables	**ADF test**	
	Level: I(0)	**First difference: I(1)**
TGB 1Y	-2.14	-7.35
TGB 3Y	-1.80	-10.31
TGB 5Y	-1.90	-10.99
TGB 7Y	-2.39	-8.99
TGB 10Y	-1.79	-8.88
PB	-4.56	-12.15
FED	-1.94	-8.89
CAPITAL INFLOW	-0.89	-10.21

Variables	ADF test	
	Level: I(0)	First difference: I(1)
ACPI	-2.04	-7.48
VIX	-5.51	-9.79
LIQUIDITY	1.77	-16.14

Source: Authors' calculation.
Note: All the series are statistically significant at 1 percent. It means that the data set are stationary at first order I(1).

In this paper, we will compare the results gained from the Single Equation model, unrestricted VAR model, and Bayesian VAR model, as well as Random Walk (RW) based on multiple forecasting exercises by considering the accuracy forecast error measure to investigate the best performance of the forecasting yields with maturities. We verify the role of factors' static and dynamic restrictions in linear models' forecasting performance.

5.4.2 Yield and Economic Factor Estimation

To analyze the effect of economic factors on the bond yields with maturities of 1-, 3-, 5-, 7-, and 10-year. The data sets are investigated by using the SE, VAR, and BVAR methods in order to examine the association between macroeconomic variables and government bond yields in the Thai bond market. This study obtains the six key variables, namely the fed rate, primary budget deficit, commodity price index, capital inflow, VIX index, and liquidity, which some variables are widely considered to be the fundamentals needed to capture basic macroeconomic dynamics. As discussed above, the yields with macro factors use these methods transition equation summarizing the dynamics of the vector of latent variables, and a linear measurement equation relation to the observed yields to the variables. Many, thus, parameters must be estimated.

Table 5.2 displays the estimates of the parameters of the crucial macro factors and government bond yield interactions. Overall, the parameter estimates are significant, with a small associated standard deviation. The results of the VAR estimate show that the coefficient of each macroeconomic variable has significant effects on bond yields with different maturities, but the adjustment of R-square and F-statistic are quite low. Also, the results of the Single Equation estimate are likely to be the same as the VAR's results. In contrast, compared with the Bayesian VAR estimate, the results show that in most cases, the coefficients of macro variables have a significant effect on the bond yield movements at various maturities with very high adjustments of R-square and F-statistic of up to 0.8 and 25, respectively. This means that the BVAR approach is suitable to estimate the best predictability more accurately than another one. Furthermore, we find that new economic variables added in this area (commodity price index and capital inflow) have a significant effect on the yields at various maturities.

Table 5.2 VAR Model, BVAR Model, and Single Equation Parameter Estimate

Maturity (years)	TGB-1	TGB-2	PB-1	PB-2	FED-1	FED-2	Capital Inflow-1	Capital Inflow-2	ACPI-1	ACPI-2	VIX-1	VIX-2	Liquidity-1	Liquidity-2	Adj. R^2	F-statistic
VAR																
TGB 1y	0.03 [0.22]	0.03 [0.25]	**5.59** [2.07]	-2.51 [-1.28]	**0.19** [3.54]	0.10 [1.65]	**-7.09** [-1.71]	**-7.01** [-1.58]	**0.02** [3.75]	-0.01 [-0.21]	-0.01 [-0.69]	0.01 [0.71]	3.21 [1.34]	**-3.94** [-1.59]	0.29	3.79
TGB 3y	**-0.40** [-3.19]	-0.06 [0.49]	**8.28** [2.32]	-5.52 [-0.20]	**0.20** [2.84]	0.19 [2.65]	**-1.17** [-2.12]	**-1.10** [-1.87]	**0.02** [3.26]	0.001 [0.12]	-0.01 [-1.47]	0.01 [0.11]	**6.93** [2.01]	-4.43 [-1.27]	0.23	2.89
TGB 5y	**-0.39** [-3.16]	-0.08 [-0.67]	**7.32** [1.88]	-1.01 [-0.33]	**0.13** [1.74]	0.24 [3.03]	**-1.61** [-2.68]	**-1.41** [-2.19]	**0.01** [2.26]	-0.001 [-0.07]	**-0.02** [-1.99]	-0.002 [-0.30]	**7.65** [2.07]	-3.50 [-0.93]	0.23	2.81
TGB 7y	0.02 [0.13]	-0.20 [-1.29]	3.01 [0.50]	-1.18 [-0.25]	0.04 [0.29]	0.29 [1.99]	-1.27 [-1.38]	-5.15 [-0.53]	0.003 [0.36]	0.002 [0.17]	-0.01 [-0.47]	0.008 [0.69]	4.33 [0.77]	-2.76 [-0.49]	0.04	0.74
TGB 10y	**-0.25** [-1.94]	-0.14 [-1.17]	6.06 [1.43]	-9.93 [-0.30]	0.05 [0.63]	**0.18** [2.19]	**-1.60** [-2.49]	**-1.18** [-1.71]	0.003 [0.43]	-0.001 [-0.13]	**-0.02** [-2.11]	-0.002 [-0.28]	**7.70** [1.92]	-3.10 [-0.76]	0.12	1.86
BVAR																
TGB 1y	**0.72** [13.96]	**0.97** [2.29]	7.42 [0.32]	-1.18 [-0.74]	**0.08** [2.62]	-0.02 [-0.66]	1.96 [0.65]	1.47 [0.80]	**0.005** [3.05]	-0.002 [-1.17]	0.001 [0.26]	0.002 [0.95]	-2.29 [-0.29]	1.15 [0.15]	0.83	34.18
TGB 3y	**0.41** [6.29]	**0.08** [1.73]	5.10 [0.17]	-1.07 [-0.52]	**0.07** [1.78]	-0.007 [0.24]	-9.34 [-0.24]	1.40 [0.59]	**0.005** [2.36]	-0.001 [-0.23]	**-0.01** [-1.98]	-0.001 [-0.32]	-4.94 [-0.50]	-4.23 [-0.42]	0.78	24.14
TGB 5y	**0.36** [5.27]	0.06 [1.45]	-5.43 [-0.17]	-1.10 [-0.50]	0.05 [1.14]	0.001 [0.01]	-2.80 [-0.67]	1.12 [0.44]	**0.004** [1.89]	-0.001 [-0.07]	**-0.01** [-2.07]	-0.001 [-0.24]	-6.82 [-0.64]	-4.86 [-0.45]	0.77	22.84
TGB 7y	**0.52** [8.45]	**0.08** [1.85]	1.72 [0.04]	-4.77 [-0.17]	**0.13** [2.30]	0.01 [0.34]	-2.59 [-0.47]	1.39 [0.41]	**0.005** [1.80]	0.001 [0.26]	-0.01 [-0.84]	0.001 [0.24]	2.20 [0.02]	-5.65 [-0.40]	0.76	20.85
TGB 10y	**0.33** [4.68]	0.04 [0.94]	-1.13 [-0.34]	-1.10 [-0.49]	0.01 [0.18]	0.005 [0.15]	-4.27 [-0.99]	5.35 [0.20]	0.001 [0.53]	-0.001 [0.07]	**-0.01** [-1.93]	-0.001 [-0.20]	-9.44 [-0.85]	-5.31 [-0.48]	0.82	29.32

Maturity (years)	TGB-1	TGB-2	PB-1	PB-2	FED-1	FED-2	Capital Inflow-1	Capital Inflow-2	ACPI-1	ACPI-2	VIX-1	VIX-2	Liquidity-1	Liquidity-2	Adj. R^2	F-statistic
Single EQ																
TGB 1y	0.009	0.009	**5.91**	-1.19	**0.19**	**0.10**	**-7.30**	-6.86	**0.01**	0.001	-0.004	0.002	**4.89**	-2.48	0.30	3.74
	[0.07]	[0.07]	[2.20]	[-0.56]	[3.68]	[1.84]	[-1.77]	[-1.56]	[3.78]	[0.23]	[-0.83]	[0.46]	[1.85]	[-0.94]		
TGB 3y	**-0.40**	-0.06	**8.28**	-5.52	**0.20**	**0.20**	**-1.17**	**-1.10**	**0.02**	-0.001	-0.01	0.001	**6.93**	-4.43	0.23	2.89
	[-3.19]	[-0.50]	[2.32]	[-0.19]	[2.84]	[2.65]	[-2.11]	[-1.87]	[3.26]	[0.16]	[-1.47]	[0.11]	[2.01]	[-1.27]		
TGB 5y	**-0.39**	-0.08	**7.32**	-1.00	**0.13**	**0.23**	**-1.61**	**-1.41**	**0.01**	-0.004	**-0.02**	0.002	**7.65**	-3.50	0.22	2.81
	[-3.16]	[-0.67]	[1.88]	[-0.33]	[1.74]	[3.03]	[-2.68]	[-2.91]	[2.26]	[-0.67]	[-1.99]	[0.30]	[2.07]	[-0.93]		
TGB 7y	0.02	-0.20	3.01	-1.18	0.04	**0.29**	**-1.27**	-5.15	0.003	0.001	-0.01	0.01	4.33	-2.76	0.13	0.74
	[0.13]	[-1.28]	[0.50]	[-0.25]	[0.29]	[1.99]	[-1.38]	[-0.53]	[0.35]	[0.17]	[-0.47]	[0.69]	[0.77]	[-0.48]		
TGB 10y	**-0.25**	-0.14	6.06	-9.93	0.05	**0.18**	**-1.60**	-1.17	-0.003	-0.001	**0.02**	0.002	**7.70**	-3.10	0.12	1.87
	[-1.94]	[-1.17]	[1.42]	[-0.30]	[0.63]	[2.19]	[-2.47]	[-1.71]	[-0.43]	[-0.13]	[-2.01]	[0.28]	[1.92]	[-0.76]		

Source: Authors' calculation.

Note: [ ] T -Statistic appears in parentheses and Bold entries denote parameter estimates significant at the 1, 5, and 10 percent level respectively.

5.4.3 Static Forecasting Performances of Yields

To assess the forecasting performance of the Single Equation, VAR and BVAR models, the RW forecasts are used the benchmark by looking at statistical measures. In this paper, we provide a measure of yield forecasting performance. In particular, we employ five core statistical functions to measure four usual approaches, including MAE, MAPE, MSE, RMSE, and Theil (Giacomini and Rossi (2010) develop statistical tests). Then, we consider the forecasting of government bond yields at various maturities by fixing an in-sample of 24 observations with the use of a static forecast technique in all models. The prediction is made for 2020:Q4, with an in-sample period from 2015:Q1 to 2020:Q4. Finally, the empirical forecasting results are presented.

We present comparisons of four models as mentioned above. The results show the forecasting performance of bond yields with different maturities of all the models. Overall, the results in terms of a measure of the forecasting performances of all models are displayed in Table 5.3. The results show that the BVAR model has the best performance in forecasting bond yields with various maturities, with the exception of the 10-year maturity, where the RW forecast outperforms the BVAR model. Most figures of the BVAR model of these statistical functions measured are the lowest, and the RMSE and Theil of the evaluations of all yields (short-term, medium-term, and long-term yields) are smaller than one signals, indicating that the model under consideration strongly outperforms the SE, VAR, and RW models, but the figures of the RW forecast (10-year maturity yield) beat all the models. However, overall, these model forecasts are generally more accurate than those of most of the competitive models in a robust way. For instance, the average RMSE and Theil of the BVAR method when forecasting short-term yield maturity (1-year yield) with an in-sample of 24 quarters are very low and equal to 0.1627 and 0.0543, respectively. For the poor performance of other models in the table, compared with the same yields, the values of the SE model's evaluations are high and equal to 0.1818 and 0.0604. The values of the RW's evaluations are also high and equal to 0.1888 and 0.0552. Similarly, an entry with the VAR model's evaluations has higher RMSE and Theil values than the other models, and the values are equal to 0.1902 and 0.0627, respectively.

5.4.3.1 Static Forecasting Error for the Short-Term Yields

In view of the 1-year yield, we consider the forecast error measure to investigate the best performance of the forecasting yield. The results show that all models have impressive performances, particularly the BVAR model gives fewer forecast errors in the whole period when compared with the actual short-term yield for all forecasting horizons. This is illustrated by the static forecast of 1-year yield with competitive models plotted in Figure 5.2. As for the case of the VAR model, the magnitude of forecast errors from the actual 1-year maturity is a maximum increase of 0.42% and a minimum increase of 0.01%. Explicitly, the percentage of forecast errors of the BVAR model have a small and significant effect on the actual bond yield, with a maximum increase of 0.40% and a minimum increase of 0.01%. In terms of the SE model, the percentage of forecast errors (0.41%) is relatively small compared to that of the VAR method, but its minimum error is likely to be higher than the BVAR model. For the RW forecast, the percentage of forecast errors (0.38%) is relatively small compared to that of the VAR, BVAR, and SE models, but its minimum error (0.02%) is higher than all other models.

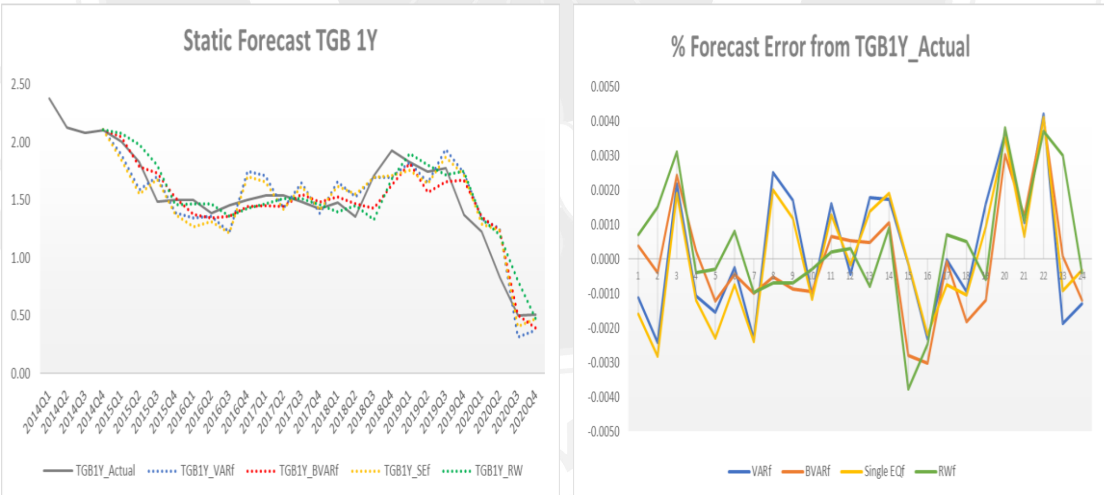


Figure 5.2 Static Forecast Error of Short-Term Yield

Source: Authors' calculation.

5.4.3.2 Static Forecasting Error for the Medium-Term Yields

In the case of medium-term yields, our evidence shows that the forecast errors of all models have fluctuated from most of the actual yields with 3- and 5-year maturities in Figure 5.3. Regarding the percentage of forecast errors for the 3-year yield, all models provide the evident errors from the actual yield with a maximum increase of 0.47% (VAR), 0.50% (BVAR), 0.50% (SE) and 0.37% (RW). In other word, their models have little errors of 0.02% (VAR), 0.00% (BVAR), 0.01% (SE), and 0.01% (RW). Considering the forecast errors for the 5-year yield, the magnitude of forecast errors of all models is a maximum increase of 0.63% (VAR), 0.47% (BVAR), 0.57% (SE), and 0.53% (RW), respectively. For small forecast errors of each model, both BVAR and RW have a value error of 0.001%, whereas the VAR and SE models have large errors of 0.03% and 0.015%, respectively.

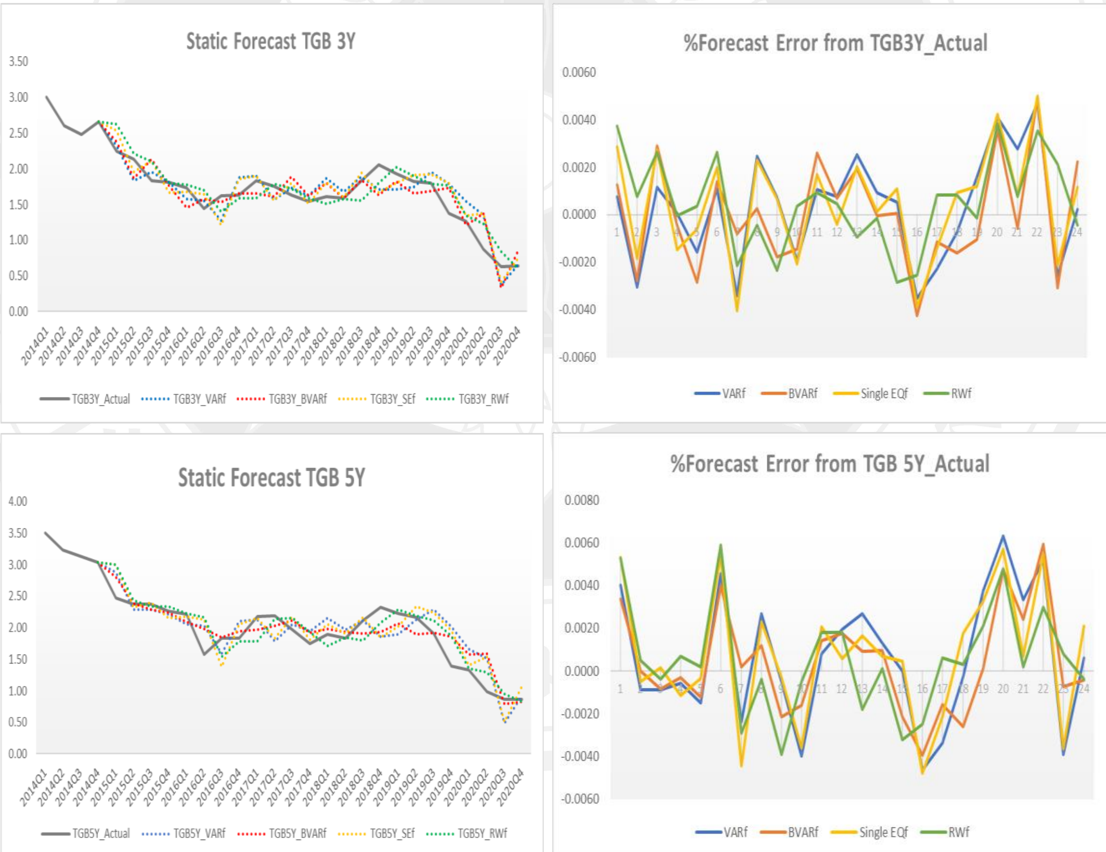


Figure 5.3 Static Forecast Error of Medium -Term Yield

Source: Authors' calculation.

5.4.3.3 Static Forecasting Error for the Long-Term Yield

In the case of long-term yields, the results show that all models generate the forecast errors from the actual bond yields at different values in Figure 5.4. In terms of the 7-year yield, unlike other cases, VAR's forecast error is smaller than that of other models, with a maximum increase of 0.74%, but the error values of the BVAR, SE, and RW models are at a high level of 0.80%, 0.75%, and 0.80%, respectively. However, the minimum of RW's forecast error is less than the others at 0.00%, while the minimum forecast errors of the VAR, BVAR, and SE models are equal to 0.02%, 0.03%, and 0.07%, respectively. In the case of the forecast errors for the 10-year yield, the magnitude errors of all models cause a change from the actual yield with a maximum increase of 0.68% (VAR), 0.68% (BVAR), 0.75% (SE), and 0.68% (RW), respectively. For lower forecast errors of each model, the BVAR and SE models have small errors of 0.004%, compared to RW and VAR's errors of 0.009% and 0.02%, respectively.

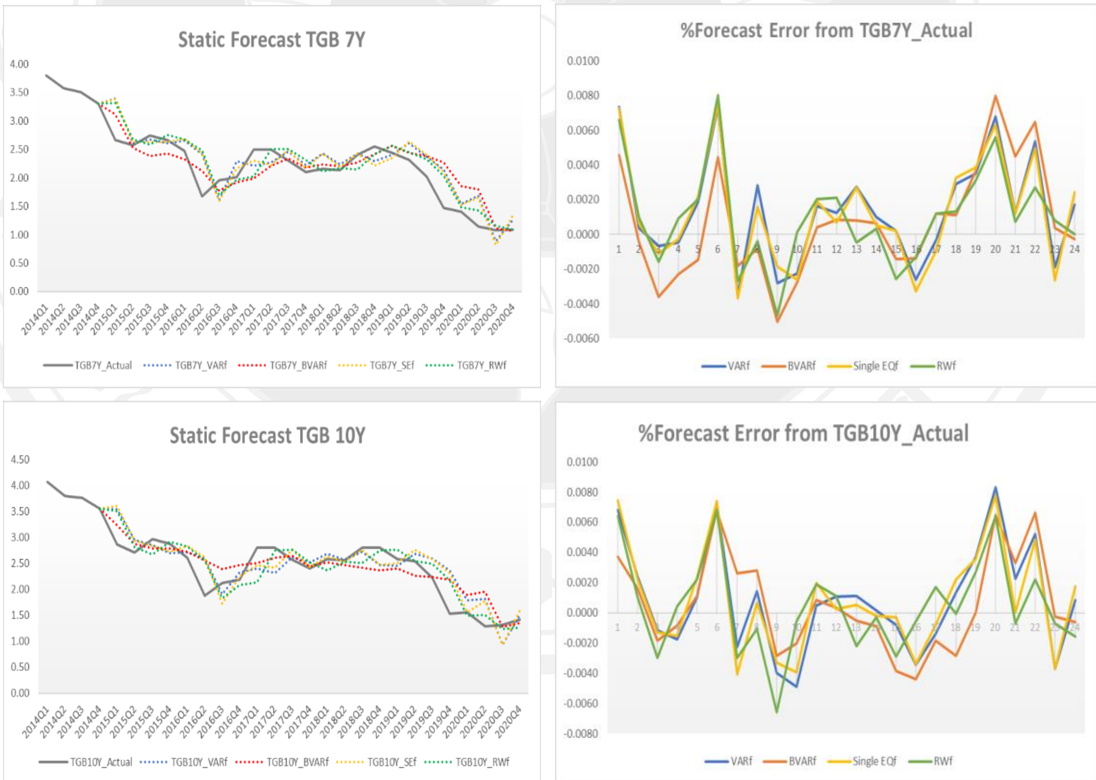


Figure 5.4 Static Forecast Error of Long -Term Yield

Source: Authors' calculation.

In conclusion, from the results indicate that in the most case of the BVAR model provides the best predictivity of bond yields at different maturities for static forecasts. Its error for forecasting the yields is smaller than the other models.

5.4.4 Dynamic Rolling Forecasting Performances of Yields

For computing our results, we use a dynamic rolling-window forecasting evaluation of 104 quarters (22 years) with only the VAR and BVAR models. In this study, we produce forecasts for all the horizons up to 3 rolling-windows ahead by presenting results for the 2-, 4-, and 8-quarter rolling ahead. The initial estimation window is from 1998:Q1 to 2016:Q3, and the initial forecast windows, are for 2-quarter rolling (2016:Q4 - 2017:Q1), 4-quarter rolling (2016:Q4 - 2017:Q3), and 8-quarter rolling (2016:Q4 - 2018:Q3). We, then, compute a rolling scheme, repeating this procedure until the last forecast window with out-of-sample 17 quarters. The empirical forecasting results are finally presented.

The results show the forecast performance of bond yields with different maturities across all models. Overall, the results in terms of the measure of the dynamic rolling forecast performances of two models are displayed in Table 5.4. The results indicate that the BVAR model has the best performance in dynamic rolling-window forecasting bond yields with various maturities of 2-, 4-, and 8-quarter rolling ahead. The statistical evaluations show that most figures of the BVAR model with all rolling forecasts are the lowest and outperform the VAR model at all maturities. Explicitly, all RMSE and Theil values of the BVAR's rolling forecast of all yields (short-term, medium-term, and long-term yields) are lower than one, which means that the BVAR model is better than the VAR model. Still, it is very interesting to note that the BVAR model with all rolling forecasts is generally more accurate than another competitive model in a robust way. For example, in the case of the 5-year yield, all RMSE and Theil values of the BVAR method with 2-, 4-, and 8-quarter rolling forecasts are lower than one (RMSE = 0.2695, 0.1369, and 0.0340 and Theil = 0.0086, 0.0044, and 0.0002). Meanwhile, the competitive model (VAR), considering the same yield with rolling forecast evaluations, produces higher values of RMSE (0.3502, 0.4692, and 0.0413) and Theil (0.0110, 0.0145, and 0.0007).

Table 5.3 Comparison with VAR Model, Bayesian VAR Model, Single Equation Model, and Random Walk Model Static Forecast Evaluation (2015-2020)

Maturity	VAR Model				Bayesian VAR Model				Single Equation Model				Random Walk Model			
	RMSE	MAE	MAPE	Theil	RMSE	MAE	MAPE	Theil	RMSE	MAE	MAPE	Theil	RMSE	MAE	MAPE	Theil
1-year yield	0.1902	0.1623	13.5800	0.0627	**0.1627**	**0.1240**	**9.3169**	**0.0543**	0.1818	0.1527	11.4930	0.0604	0.1888	0.1327	0.1130	0.0552
3-year yield	0.2239	0.1860	13.6155	0.0668	**0.2194**	**0.1768**	**13.3297**	**0.0560**	0.2321	0.1947	13.8558	0.0686	0.2401	0.1279	0.1061	0.0593
5-year yield	0.3058	0.2505	15.5848	0.0780	**0.2403**	**0.1855**	**10.0216**	**0.0618**	0.3082	0.2443	15.4911	0.0783	0.2459	0.2459	0.1063	0.0564
7-year yield	0.3350	0.2612	12.3105	0.0752	**0.3205**	**0.2431**	**11.2742**	**0.0734**	0.3356	0.2657	14.6819	0.0755	0.6884	0.2612	0.1436	0.0627
10-year yield	0.3575	0.2788	12.4948	0.0734	0.3160	0.2462	10.4755	0.0654	0.3551	0.2731	13.3894	0.0728	**0.1989**	**0.2340**	**0.1082**	**0.0035**

Source: Authors' calculation.

Note: In-Sample 24 observations from 2015q1 to 2020q4. Static forecast evaluations are Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Theil Inequality Coefficient (Theil). Bold entries denote Bayesian VAR Model and Random Walk 's forecast evaluations are the best predictability due to smallest values.

Table 5.4 Comparison with VAR Model and Bayesian VAR Model Dynamic Rolling Forecast Evaluation (2016-2020)

Maturity (years)	**VAR Model**				**Bayesian VAR Model**			
	RMSE	**MAE**	**MAPE**	**Theil**	**RMSE**	**MAE**	**MAPE**	**Theil**
TGB 1Y_Rolling								
2 Quarter	0.3894	0.2198	0.2283	0.0150	0.0774	0.2106	0.2153	0.0031
4 Quarter	0.6583	0.3030	0.3309	0.0244	0.0128	0.2587	0.2637	0.0005
8 Quarter	1.0915	0.3520	0.3673	0.0379	0.3719	0.2310	0.2216	0.0164
TGB 3Y_Rolling								
2 Quarter	0.3371	0.2025	0.1777	0.0121	0.1874	0.2091	0.1723	0.0069
4 Quarter	0.4045	0.2557	0.2401	0.0144	0.0766	0.2389	0.2133	0.0029
8 Quarter	0.2173	0.2253	0.2049	0.0080	0.1762	0.2112	0.1813	0.0069
TGB 5Y_Rolling								
2 Quarter	0.3502	0.2999	0.2068	0.0110	0.2695	0.2587	0.1848	0.0086
4 Quarter	0.4692	0.3543	0.2595	0.0145	0.1369	0.2869	0.2035	0.0044
8 Quarter	0.0413	0.3135	0.2183	0.0007	0.0340	0.2579	0.1767	0.0002
TGB 7Y_Rolling								
2 Quarter	0.8983	0.3050	0.1879	0.0237	0.6295	0.3073	0.2000	0.0171
4 Quarter	1.2315	0.3790	0.2564	0.0314	0.5607	0.3798	0.2504	0.0154
8 Quarter	1.4085	0.4314	0.3033	0.0353	0.2141	0.3940	0.2471	0.0061
TGB 10Y_Rolling								
2 Quarter	0.3598	0.3235	0.1691	0.0090	0.1527	0.2965	0.1618	0.0039
4 Quarter	0.3410	0.3974	0.2194	0.0085	0.0162	0.3438	0.1823	0.0004
8 Quarter	0.2430	0.5374	0.2759	0.0065	0.1901	0.3212	0.1640	0.0050

Source: Authors' calculation.

Note: In-Sample 17 observations from 2016q4 to 2020q4. Static forecast evaluations are RMSE, MAE, MAPE, and Theil. Bayesian VAR Model’s dynamic rolling forecast evaluations are the best predictability due to all values smallest.

5.4.4.1 Dynamic Rolling Forecast Error for the Short-Term Yields

For the 1-year yield, we find that, overall, the BVAR model with all rolling forecasts works better than the VAR model plotted in Figure 5.5. The BVAR model produces very good forecasts in all periods in which the percentage of forecast errors from the actual yield is lower than another model with a maximum-minimum value of 2-quarter (0.72%, 0.01%), 4-quarter (0.87%, 0.01%), and 8-quarter (0.69%, 0.005%). As for the VAR model, the rolling forecast errors from the actual yield are high, with a maximum-minimum value of 2-quarter (0.74%, 0.04%), 4-quarter (0.83%, 0.04%), and 8-quarter (0.85%, 0.11%).

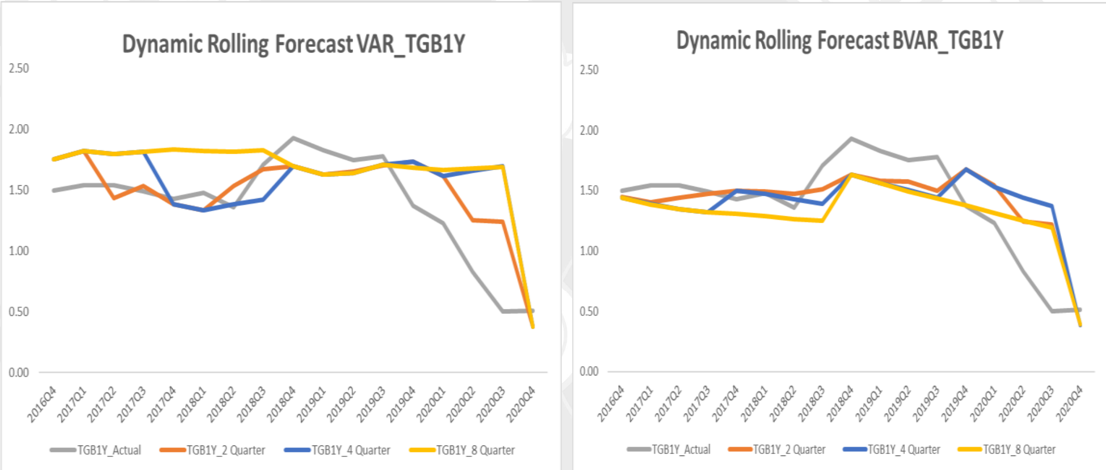


Figure 5.5 Dynamic Rolling Forecast of Short-Term Yield

Source: Authors' calculation.

5.4.4.2 Dynamic Rolling Forecast Error for the Medium-Term Yields

In terms of the medium-term yields, our evidence shows that most of the BVAR's rolling forecasts are better than those of the competing model, except in some cases where the magnitude errors of the VAR model (2- and 4-quarter rolling forecasts) are lower a plotted in Figure 5.6. The results show that the magnitude errors for the 3-year yield are less than the actual yield in the VAR's rolling forecast by a maximum increase of 0.64% (2-quarter), 0.78% (4-quarter), and 0.85% (8-quarter), respectively. The BVAR model generates higher errors only in a few cases, such as rolling forecasts of 2- and 4-quarters ahead by an increase of 0.70%, 0.80%, and 0.67%, respectively.

However, the magnitude of the minimum forecast error of the BVAR model has very little value. Its forecast error from the actual yield is lower in all cases by an increase of 0.01%.

For the 5-year yield, we find that the magnitude errors of the BVAR model are lower than those of the VAR, except in the case of 2-quarter rolling. When comparing their forecast errors, both models have a maximum increase of 2-quarter (0.67%, 0.63%), 4-quarter (0.76%, 1.0%), and 8-quarter (0.63%, 0.81%), respectively. For small forecast errors of each model, the BVAR model has low errors of 0.07%, 0.04%, and 0.04%, compared to the VAR model that has errors of 0.05% in all cases.

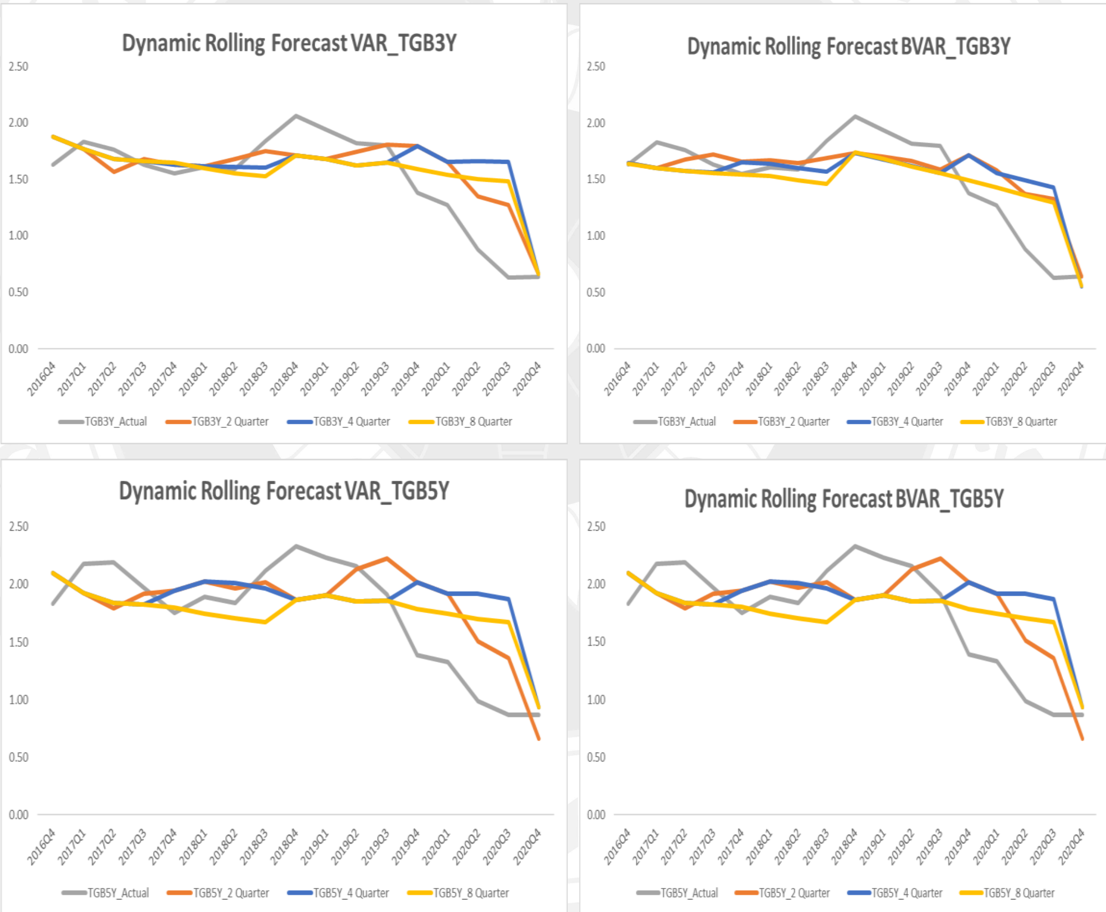


Figure 5.6 Dynamic Rolling Forecast of Medium-Term Yield

Source: Authors' calculation.

5.4.4.3 Dynamic Rolling Forecast Error for the Long-Term Yields

In the case of long-term yields, our evidence shows that BVAR's forecast errors from the actual bond yields are better than those of the VAR, as plotted in Figure 5.7.

For the 7-year yield, the magnitude errors of the BVAR model are smaller, except in the 2-quarter rolling forecast, where the BVAR model's value is higher. Their forecast errors as follows: 2-quarter (0.88%, 0.75%), 4-quarter (1.11%, 1.14%), and 8-quarter (0.96%, 1.44%). The minimum of VAR's forecast error is lower only in the 4-quarter rolling forecast by an increase of 0.0004%. For the rest, the BVAR and VAR models produce a similar error of 0.01%.

For the 10-year yield, the magnitude errors of the BVAR model cause a change from the actual yield that is lower than the VAR model, with the following maximum increases: 2-quarter (0.67%, 0.83%), 4-quarter (0.74%, 0.99%), and 8-quarter (0.61%, 1.01%). The forecast errors of the BVAR model are lower than those of the VAR model, with the following minimum increases: 2-quarter (0.01%, 0.03%), 4-quarter (0.05%, 0.03%), and 8-quarter (0.01%, 0.05%).

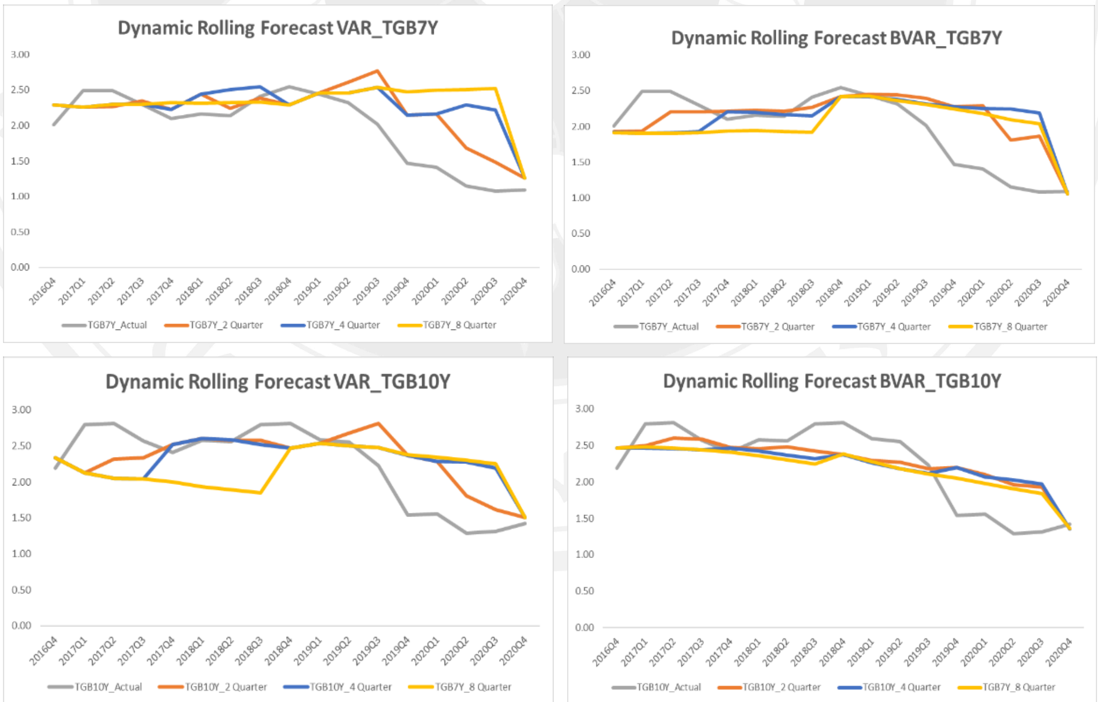


Figure 5.7 Dynamic Rolling Forecast of Long-Term Yield

Source: Authors' calculation.

In sum up, from the results indicate that in the most case of the BVAR model produces the best predictivity in out-of-sample rolling forecast accuracy than the competitive model. Its error for forecasting the yields is significantly smaller than another model. Although the 3-year yield ahead (2-, and 4-quarters) rolling forecasting results are no better than the competitor, VAR model.

Table 5.5 Dynamic Rolling Forecast Error (in%) of Bond Yields (2016-2020)

Maturity (years)	VAR Model		BVAR Model	
	Max	**Min**	**Max**	**Min**
TGB 1Y_Rolling				
2 Quarter	0.74%	0.04%	0.72%	0.01%
4 Quarter	0.83%	0.04%	0.87%	0.01%
8 Quarter	0.85%	0.11%	0.69%	0.005%
TGB 3Y_Rolling				
2 Quarter	0.64%	0.01%	0.70%	0.01%
4 Quarter	0.78%	0.01%	0.80%	0.01%
8 Quarter	0.85%	0.03%	0.67%	0.01%
TGB 5Y_Rolling				
2 Quarter	0.63%	0.05%	0.67%	0.07%
4 Quarter	1.00%	0.05%	0.76%	0.04%
8 Quarter	0.81%	0.05%	0.63%	0.04%
TGB 7Y_Rolling				
2 Quarter	0.75%	0.01%	0.88%	0.01%
4 Quarter	1.14%	0.0004%	1.11%	0.02%
8 Quarter	1.44%	0.01%	0.96%	0.01%
TGB 10Y_Rolling				
2 Quarter	0.83%	0.03%	0.67%	0.01%
4 Quarter	0.99%	0.03%	0.74%	0.05%
8 Quarter	1.01%	0.05%	0.61%	0.01%

Source: Authors' calculation.

5.4.4 Forecast the future bond yields in next 3 years (2022f – 2024f)

Regarding to the best predictability of bond yields, we find that a Bayesian VAR model is the most suitable approach because it provides a more accurate forecast at long horizons than other models. Hence, we use a Bayesian VAR model with dynamic forecast technique to predict future bond yield movements with different maturities in the next 3 years (2022f - 2024f).

From the results of BVAR's prediction, we find that, in the next 3 years, Thai government bond yields tend to increase by an average of 0.32%. In Figure 5.8, the yield curve tends to increase in short-to-long term yields and its shape is likely to steepen. The main reason why the yield curve tends to steepen in the next 3 years is that the Fed may raise short-term interest rates. An increase in the Fed's target for short-term rates usually leads to an increase in longer-term rates and probably affects the yield movements in the world's financial markets, including for policy rate of the Bank of Thailand. In addition, the yield curve tends to rise following the bond supply of the Thai government in the same period because the government needs to continue to issue new bonds of various maturities with the primary objectives being to finance the annual budget deficit, support economic development, and restructure public debt.

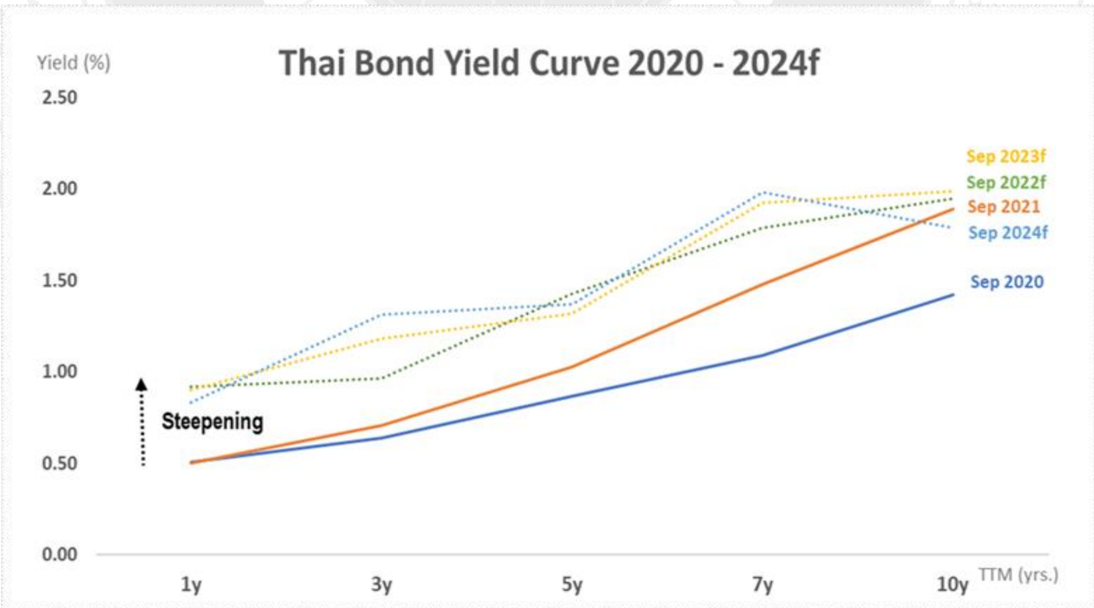


Figure 5.8 Forecast Thai Bond Yield Curve 2020 - 2024f

Source: Authors' calculation.

We discovered that over the years 2022-2024, the movements of yields with different maturities (1-, 3-, 5-,7-, and 10-year) is likely to increase in Figure 5.9. This directly reflects the high costs of a new government borrowing for funding needs, especially public debt management, refinancing of government debt, infrastructure projects, and risk management in portfolio benchmarks. Furthermore, an increase in yields may result in higher portfolio returns for investors or speculators.

Then, we examine the risks of increasing yields for bond market participants. As previously stated, any shift in the yield curve will directly reflect the government's high borrowing costs, as it is the largest issuer in the bond market. Considering the projection of funding needs for 2022 - 2024, we estimate that Thailand's funding needs will rise by an average of THB 1.6 – 2 trillion each year. When the future expected yields of each maturity have been increasing, it has affected the interest debt burden of government borrowing. We estimate that yield swings will increase by 10 to 150 basis points every year. This might increase the interest debt burden of government borrowing by an average of 1.03 percent, 0.70 percent, and 0.88 percent between 2022 and 2024.

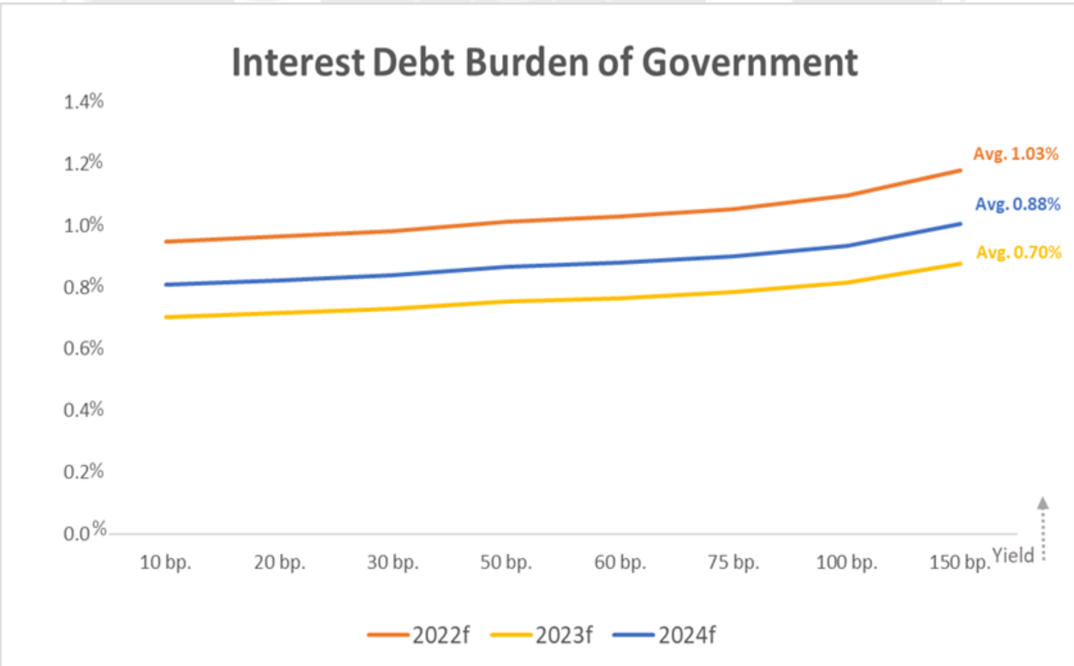


Figure 5.9 Interest Debt Burden of Government 2022f - 2024f
Source: Authors' calculation.

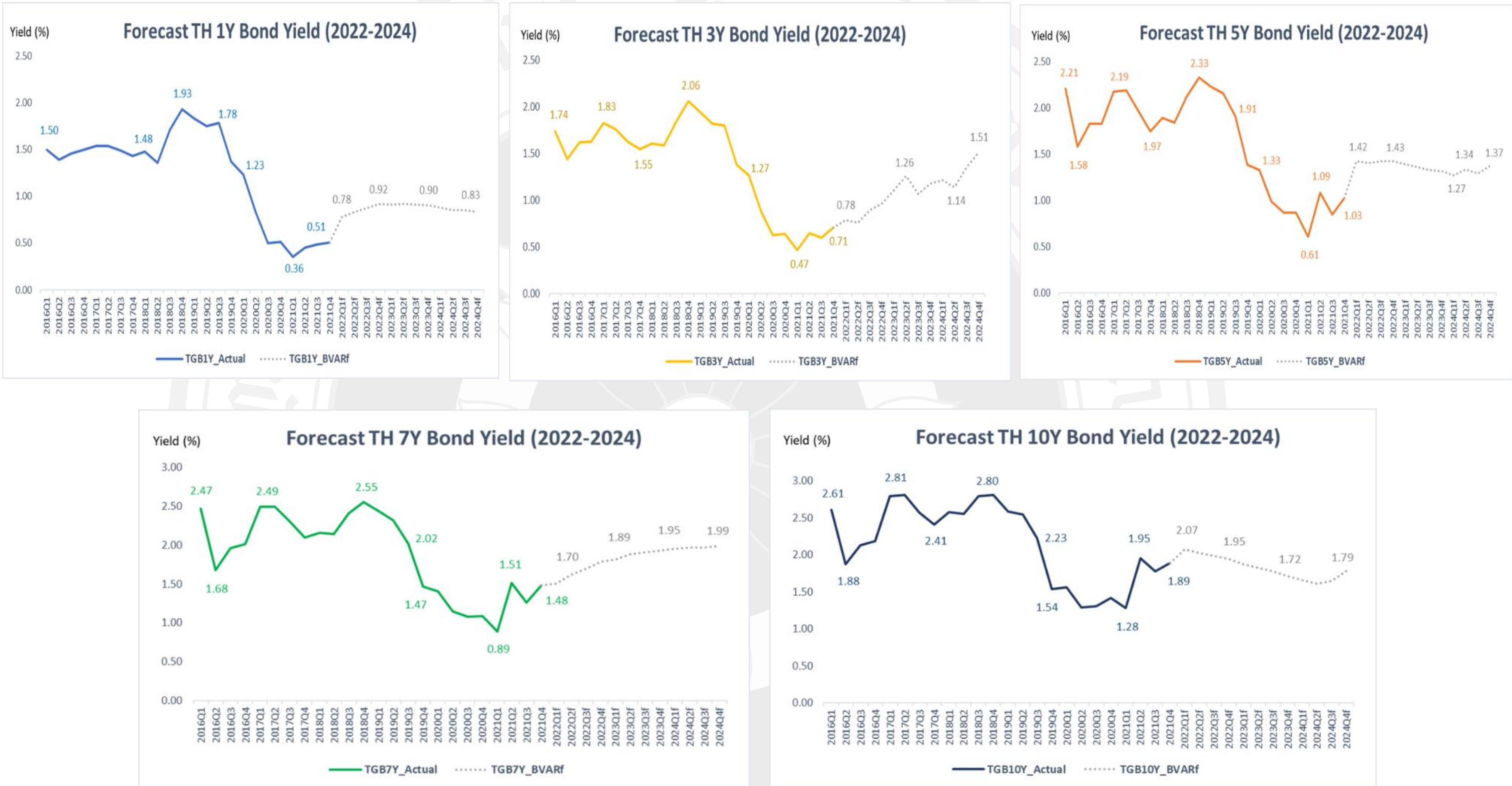


Figure 5.10 Forecast TH 1Y, 3Y, 5Y, 7Y, and 10Y Bond Yield 2022-2024

Source: Authors' calculation.

Therefore, it is the great interest of various market participants such as investors, policy makers, and risk managers to accurately predict interest rates movements. For investors, forecasting future yields may result in higher portfolio returns. However, for policy makers understanding the change in future yields might help their decision-making concerning interest debt burden of government borrowing in the future.

5.5 Conclusion and Policy Implications

In this paper, we look at how and in why macroeconomic factors affect government bond yields in Thailand for various maturities (1-, 3-, 5-, 7-, and 10-year yields). To investigate the relationship between macroeconomic variables and government bond yields, we used the SE, VAR, and Bayesian VAR methods to specify and estimate the bond yield and macroeconomic factors (fed's policy rate, primary budget deficit, commodity price index, capital inflow, VIX index, and liquidity). In addition, we propose statistical models for the entire government bond yields with various maturities and compare its forecasting performance with current most promising alternatives and random walk, considering evaluation the forecasts error in terms of static and dynamic rolling forecast technique with in-sample and out-of-sample in linear models. The empirical results provide several main findings.

First, we find that the estimates of the parameters of the crucial macro factors and government bond yields interactions. Overall, the parameter estimates are significant, with small associated standard deviation. Interestingly, from the results, we find that new economic variables: commodity price index and capital inflow added in this study appear significant effect on the bond yields with all maturities.

Second, the results of the static forecast show that most figures of the BVAR model of these statistical functions measured are the lowest, and the RMSE and Theil of the evaluations of all yields are smaller than one, indicating that the model under consideration strongly outperforms the SE and VAR models. However, for the long-term-yield (10-year maturity), RW outperforms the BVAR model. The results show that the performance of in-sample forecasting is quite good. Additionally, we discover that the static prediction of short-term yields has a lower inaccuracy than the forecast of medium-term and long-term yields for various forecasting horizons when compared to the actual yield.

Third, the results reveal that the BVAR model has the best performance in dynamic rolling-window forecasting of future bond yields with various maturities of 2-, 4-, and 8-quarter rolling ahead. The statistical evaluations show that most figures of BVAR with all rolling forecasts appear the lowest and outperform the VAR model at all maturities. Explicitly, all of the RMSE and Theil of the BVAR's rolling forecast of all yields (short-term, medium-term, and long-term yields), are lower than one, which means that the BVAR model is better than the VAR model. Still, it is very interesting to note that the BVAR model with a rolling forecast horizon is generally more accurate than those competitive models in a robust way. In addition, the advantages of a rolling scheme for forecasting, are to avoid problems of instability (Pesaran & Timmermann, 2005). It has fixed the number of observations used to forecast and the resulting time series of the forecast errors allows to test by using Giacomini and White (2006) for comparing forecast accuracy.

Finally, we verify the role of factors' static and dynamic restrictions in linear models' forecasting performance. By comparing the static forecast of the bond yields to dynamic rolling forecast technique for all models, the evidence shows that the static forecast technique is generally more accurate than rolling forecasts for each model. Notwithstanding, it cannot provide forecasting the yields with out-of-sample at long horizon.

The finding of this study lead to an important policy recommendation. The prediction of the bond yields needs to into account the fluctuations of the macroeconomy since the economic variables affect and also forecast the fixed income yield movements in various maturities with static and dynamic rolling forecast for all models. Thus, our paper recommends a Bayesian VAR approach a policy instrument for governments, fixed-income portfolio managers, financial regulators, financial institutions, risk managers and others to adjust the bond yield with different maturities fluctuations. The BVAR model provides more accurate forecasts of bond yields at long horizons than the linear models and RW forecasts.

In addition, our paper applies a Bayesian VAR approach to predict the bond yield changes in the next 3 years (2022-2024). Finding that yield curve tends to be an increase in parallel shift of short-to-long end yields average 0.32 basis points. Also, its shape is likely to steepen, and medium-to-long end yields are higher than short-to-end yield. We then estimate that Thailand's funding needs will rise by an average of THB 1.6 - 2 trillion each year. When the future expected yields of each maturity have been increasing, it has affected the interest debt burden of government borrowing. We estimate that yield swings will increase by 10 to 150 basis points every year. This might increase the interest debt burden of government borrowing by an average of 1.03 percent, 0.70 percent, and 0.88 percent between 2022 and 2024. It is confirmed that a higher yield with different maturities will induce future higher interest debt burden of government. Therefore, the government needs to choose a suitable strategy for lowering borrowing cost and risk management in portfolio benchmark.

In the future research, the empirical model can be extended to include the no-arbitrage restriction. Perhaps models that incorporate Factor Augmented VAR approach would be employed to estimate at approximately be captured by our fitted yields because of flexible prediction to the large number of datasets as well. Finally, we suggest that could employ the daily or monthly dataset for forecasting the future bond yields and it would be quite interesting to compare with Asian bond markets.

CHAPTER 6

CONCLUSION AND POLICY IMPICATION

The dissertation comprehensively investigates key macroeconomic factors and bond yield interactions in Thai bond market and analyzes the impacts of both domestic and international economic factors on the fixed income yield movements, as well as forecasts the future bond yields of different maturities with macroeconomy by applying VAR, Bayesian VAR, and Single Equation (SE) approaches.

The dissertation consists of three main topics. It starts with identifying the relationship between macroeconomic factors and government bond yields of a different maturity movements and assessing the extent, speed, and size of effects of macroeconomic factor shocks on the yields in different maturities of 1-, 3-, 5-, 7-, and 10-year. After that, the focus is moved to a specific aspect that many policy makers, investors, and risk managers of all market participants have been greatly concerned, that is how the direction of yield responsiveness to economic shocks. Explicitly, yield in various maturities responds directly to positive and negative shocks in macroeconomic indicators (i.e., six key variables: fed rate, primary budget deficit, commodity price, capital inflow, VIX index, and liquidity). This in turn indicates a need of policy and tools in order to reduce the negative impact of economic shocks on the yield movements in the bond market. Therefore, we implement the Wald test and 90% confidence band test to ascertain whether the joint impact of the key macroeconomic variables have a significant influence on the yields. Finally, we adopt various models to forecast future bond yields with macroeconomy, then comparing the best predictive yields with each model. The differences between actual and forecast will provide information about the best performance of the bond yield movements accuracy.

To sum up the key finding throughout the dissertation, they are presented in corresponding to three main objectives of the dissertation.

In the first objective, the estimation results show several main findings. Overall, fixed income yields respond strongest to the economic factor shocks. The estimates of the parameters of the crucial macro factors and government bond yields interactions. There is evidence result of the association between the macroeconomic factors and bond yield movements for all models. By comparing the model of Bayesian VAR estimate, in most of case, the coefficients of macro variables have significant effect on the bond yield movements in various maturities with very high adjustment of R-square and F-statistic around 0.80 and 25 respectively. While the models of VAR and SE estimates show that the coefficients of each macroeconomic variable appear significant effects on fixed income yields with different maturities, but adjustment of R-square and F-statistic are quite very low. Surprisingly, new economic variables such as commodity price and capital inflow added into our study appear significant effect on the yields with different maturities.

In the second objective, the results of estimating the responses of bond yields with all maturities to economic shocks display several important findings. Generally, overall evidence shows that both domestic and international macroeconomic factor shocks have a significant impact on the fixed income yields of various maturities with all models. Regarding the macro shocks from fed rate, commodity price, VIX index, capital inflow, primary budget deficit, and liquidity have a strong impact on the bond yields in all maturities and the impact is transitional, usually dies out after 5 to 10 quarters but the effects of Bayesian VAR approach seem to be long lasting more than 10 quarters. Additionally, our results show that by comparing the bond yields responsiveness to the effects of macro shocks are varied. The short-term and medium-term yields reacts rapidly to economic factors shocks more than long-term yields. This confirms that the impacts of domestic and international macro variables have strong fluctuation of yields, especially high impact of fed rate and commodity price on bond yields.

Interestingly, from the results, evidence shows that new economic variables intended into this study: commodity price and capital inflow, have a quite strong impact on the bond yields with all maturities as well. Hence, it is crucial for all participants in the bond market such as government, fixed income portfolio managers, financial institutions, risk managers, and investors to timely estimate and understand both magnitude and duration of effects of domestic and international economic shocks on the yields with all maturities. Additionally, economic policy makers should take into consideration the possible impacts that their policy may have on the bond yields in the debt market. For this reason, we try to justify this finding by investigating the effects of macroeconomic indicators on the fixed income yields.

In the third objective, RW, VAR, Bayesian VAR, and SE models are built to forecast the future bond yields in various maturities with macroeconomy. These allow for estimating static and dynamic rolling forecast technique with fixing an in-sample and out-of-sample window and comparing the best predictive yields with each model. The differences between actual and forecast will provide information about the best performance of the bond yield movements accuracy. Overall, the empirical results provide two main findings:

First, for the static forecast (in-sample) with all of four models, the strong evidence results show that the most case of the BVAR model produces the best predictivity of bond yields in a different maturity with static forecast, except for only 10-year maturity that the RW forecast beat BVAR model. Most figures of BVAR model of these statistical functions measured are the lowest and for RMSE and Theil of evaluations of all yields are smaller than one signals that the model under consideration strongly outperforms the RW, SE model, and VAR models. The results reflect that the performance in-sample forecasting is quite good. Additionally, we find that static forecast of short-term yield (1-year yield), when compared with the actual yield, has a lower error than medium-term yields (3-year and 5-year yields) and long-term yields (7-year and 10-year yields) for forecasting horizons.

Second, for the dynamic rolling forecast (out-of-sample) with both VAR and BVAR models, the evidence results confirm that BVAR model is the best performance in dynamic rolling-window forecasting the future bond yields with various maturities for 2-, 4-, and 8-quarter rolling ahead. The statistical evaluations show that the most figures of BVAR with all rolling forecasts appear the lowest and outperform the VAR at all maturities. Explicitly, all RMSE and Theil of the BVAR's rolling forecast of all yields (short-term, medium-term, and long-term yields), have a value lower than one means that the model is better than the VAR model. Still, it is very interesting to note that the BVAR model with rolling forecasts horizon are generally more accurate than those competitive model in a robust way. In addition, the advantages of a rolling scheme for forecasting, are to avoid problems of instability (Pesaran & Timmermann, 2005). It has fixed the number of observations used to forecast and there the resulting time series of the forecast errors allows to test by using Giacomini and White (2006) for comparing forecast accuracy.

Last but not the least, overall, the evidence of increasing degree of economic shocks gives several important policy implications for the fixed income yields in the bond market. First, an increasing role of the shocks from dynamic macroeconomic indicators show that movement in yields of different maturity and macroeconomic linkages is the important source of bond market. Hence, it is crucial for all participants in the bond market such as government, fixed income portfolio managers, financial institutions, risk managers, and investors to timely estimate and understand both magnitude and duration of effects of domestic and international economic shocks on the yields with all maturities. Second, the evidence of converging trend in dynamic response of bond yields to economic shocks implies that fiscal and monetary policy which will reflect to dynamic of macro factors adopted in our country and other countries in the world, particularly for the Federal fund rate are possibly to affect the bond yields in financial market indexes. From the results of our study, indicate that the effect shocks of economic indicators play a significant role of the fixed income yield movements with all maturities. Also, the results show that the macro shocks from fed rate, commodity price, VIX index, capital inflow, primary budget deficit, and liquidity have a strong impact on the bond yields in various maturities. By comparing the bond yields responsiveness to the effects of macro shocks are varied. The short-term and medium-term yields react rapidly to economic factors shocks more than long-term yields. This is the reason why yields with short-term and medium-term are very high of the variation in rates and high fluctuation.

Thus, economic policy makers should take into consideration the possible impacts that their policy such a primary budget deficit, may have on the bond yields, particularly the fed rate, commodity price, and capital inflow which are to affect the future short-term and medium-term yield in the debt market. In addition, the government may have to consider alterative options to issue a new bond of various maturities for reducing risks of funding cost and government debt refinancing.

Third, in case of forecast future yields in the next 3 years (2022-2024), we use a Bayesian VAR model with dynamic forecast technique to predict future bond yield movements with different maturities in the next 3 years (2022f - 2024f). We find that, in the next 3 years, Thai government bond yields tend to increase by an average of 0.32%. The yield curve tends to increase in short-to-long term yields and its shape is likely to steepen. Furthermore, we find that the movements of yields with different maturities (1-, 3-, 5-,7-, and 10-year) tend to slightly increase during 2022 - 2024. This directly reflects the high costs of a new government borrowing for funding needs, especially public debt management, refinancing of government debt, infrastructure projects, and risk management in portfolio benchmarks.

Then, we examine the risks of rising yields for participating in the bond market. As mentioned previously, any change in the yield curve will directly reflect the high borrowing costs of the government, which is the biggest issuer in the bond market. Considering the projection of funding needs for 2022 - 2024, we estimate that Thailand’s funding needs will increase by an average of THB 1.6 - 2 trillion per year. When the future expected yields of each maturity have been increasing, it has affected the interest debt burden of government borrowing. We estimate that yield movements have increased by a range of 10 - 150 basis points each year. This might affect the interest debt burden of government borrowing in 2022 - 2024 by an average of 1.03%, 0.70%, and 0.88%, respectively.

It is implied that a higher yield with different maturities will induce future higher debt burden of government. Therefore, the government needs to choose a suitable strategy for lowering borrowing cost and risk management in portfolio benchmark as well as plans to issue a new bond of various maturities for reducing risks of future higher debt burden of government borrowing. This obtained information in turn can help policy makers, and risk managers to conduct adequate variety of instruments in order to manage and monitor such risk, reduce and avert further increase of vulnerability the yield movements.

Additionally, the evidence provides important policy recommendation. Predicting the fixed income yields needs to account for the fluctuations of the macroeconomy, since the economic shocks affect and also forecast the fixed income yields movement in various maturities with static and dynamic rolling forecast for all models. Hence, our study recommends a Bayesian VAR approach for the policy instruments for a government, fixed-income portfolio managers, financial regulators, financial institutions, risk managers, and among others to adjust the bond yield with different maturities fluctuations. The model provides more accurate forecast at long horizons for the bond yields than the linear models and RW forecasts. However, for policy makers understanding the change in future term structure of interest rates may help their decision making concerning economic monetary and fiscal policy. Also, the results of our study carry important implication for government, and domestic and international investors by providing assistance in possibly lowering government borrowing costs and by identifying diversification portfolio gains, respectively.

In the future research, the empirical model can be extended to include the no-arbitrage restriction. Perhaps models that incorporate Factor Augmented VAR approach would be employed to estimate at approximately be captured by our fitted yields because of flexible prediction to the large number of datasets as well. Additionally, in during periods of a low interest rate environment or economic downturn, a Markov-switching dynamic Nelson-Siegel model may be used to capture the behaviour of the yield curve because lowering short term rates causes an increase in the slope of the yield curve. Finally, we suggest that could employ the daily or monthly dataset for forecasting the future bond yields and it would be quite interesting to compare with Asian bond markets.

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